Online Voltage Stability Monitoring using Artificial Neural Network

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Abstract— This paper presents an application of Artificial Neural Network (ANN) for monitoring power system voltage stability. The training of ANN is accomplished by adapting information received from local and remote measurements as inputs and fast indicators providing voltage stability information of the whole power system and one at each particular bus as outputs. The use of feature reduction techniques can decrease the number of features required and thus reduce the number of system quantities needed to be measured and transmitted. In this paper, the effectiveness of the proposed algorithm is tested under a large number of random operating conditions on the standard IEEE 14-bus system and the results are encouraging. Fast performance and accurate evaluation of voltage stability indicators have been obtained. Finally, the idea of applying load shedding based on voltage stability indicator as one of potential countermeasures is described.

Index Terms— Voltage Stability, Artificial Neural Network, Online monitoring system, Feature reduction

I. Introduction

VOLTAGE stability has been of the keen interest of industry and research sectors around the world since the power system is being operated closer to the limit whereas the network expansion is restricted due to may reasons such as lack of investment or serious concerns on environmental problems. There are several works previously proposed to predict the voltage stability and proximity to voltage collapse based on conventional approach, for example PV and QV curves, sensitivity based indices [1] and continuation methods [2]. Other methods, such as bifurcation theory [3], energy function [4] singular value decomposition [5], etc have been also reported in the literature. These methods provide complete and accurate results but they are usually hampered by the fact that they consume long computing time because of the requirement for repetitive power flow calculations.

To suit the online monitoring requirement, fast, accurate and easily interpretable indicators are desired. Few examples of pioneering but still popular indicators are the L-index [6] and Voltage Collapse Proximity Index (VCPI) [7]. These indicators provide sufficiently accurate assessments but, however, they usually require complete topological information of the system under consideration.

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Recently, the wide area monitoring system consisting of phase measurement units (PMUs) and high-speed communication links provides snapshots of current power system variables where PMUs are connected. Based on the simple method proposed in [8] for determining Thevenin equivalent parameters, few voltage stability indicators can be determined based only on voltage and current information provided by PMU at local buses. Examples of those are Power Transfer Stability Index (PTSI) [9], Power based Voltage Stability Margin (PVSM) [10]. This method is very suitable for implementing on a protective device because no communication for system data acquisition is required and its action can be autonomously undertaken.

Online voltage security assessment is a very useful but not yet becomes a widely used tool that measures the distance from the current operating condition at any time to the critical point. Artificial neural network have recently received widespread attention from researchers for this application. Most of ANN applications have been implemented using multi-layered feed-forward neural networks trained by back propagation because of their robustness to input and system noise, their capability of handling incomplete or corrupt input data. However, in typical power systems there are voluminous amount of input data. Then, the success of ANN applications also depends on the systematic approach of selecting highly important features which will result in a compact and efficient ANN. Different feature reduction methods are compared in this paper.

This paper is organized as follows. The method of real-time tracking of Thevenin equivalent and brief summary of considered indices are presented in Section II. Section III presents the design of the proposed method. Simulation results are given in section IV and section V concludes the paper and suggests the future work.

II. DETERMINATION OF FAST VOLTAGE STABILITY INDICATORS

In this part, several voltage stability indicators are calculated. It should be mentioned here that this paper aims at implementing these already proposed indicators by ANN. The capability of monitoring proximity to voltage collapse was tested beforehand, but unfortunately due to space limitation and scope of this paper the complete results cannot be presented. However, the corresponding references given in the earlier section will enable the avid readers to regenerate the same results.

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A. Tracking Thevenin Equivalent

This step is necessary for deriving two indicators which will be presented in the next section.

Consider a load bus k having a load demand of $S_k = P_k + jQ_k$ connected to the rest of power system as shown in Fig. 1.The voltage equation at bus k at time t taken from measurement j in Fig.1 (b) can be expressed as;

$$\underline{U}_{TH}^{t} = \underline{U}_{k,j}^{t} + \underline{Z}_{TH}^{t} \underline{I}_{k,j}^{t} \qquad (1)$$

Splitting (1) into two equations of real and imaginary parts, one can immediately notice that at least two set of voltage and current information of bus k at time t ($\underline{U}_{k,j}^{t}$ and $\underline{I}_{k,j}^{t}$, repectively) are required to solve such an equation. Using the above formulations with two set of measured quantities (j=2), (1) can be transformed to;

$$\begin{bmatrix} 1 & 0 & -I_{kr,1}^{t} & I_{km,1}^{t} \\ 0 & 1 & -I_{km,1}^{t} & -I_{kr,1}^{t} \\ 1 & 0 & -I_{kr,2}^{t} & I_{km,2}^{t} \\ 0 & 1 & -I_{km,2}^{t} & -I_{kr,2}^{t} \end{bmatrix} \begin{bmatrix} U_{THr}^{t} \\ U_{THm}^{t} \\ R_{TH}^{t} \\ X_{TH}^{t} \end{bmatrix} = \begin{bmatrix} U_{kr,1}^{t} \\ U_{km,1}^{t} \\ U_{kr,2}^{t} \\ U_{km,2}^{t} \end{bmatrix} \qquad (2)$$

$$\Rightarrow \mathbf{Ax=b}$$

where $I^t_{kr,j}$ and $I^t_{km,j}$ are real and imaginary part of $\underline{I}^t_{k,j}$,respectively; U^t_{THr} and U^t_{THm} are real and imaginary part of Thevenin equivalent voltage at time t ($\underline{U}^t_{TH}$), respectively; R^t_{TH} and X^t_{TH} are resistive and reactive parts of Thevenin equivalent impedance at time t ($\underline{Z}^t_{TH}$), respectively; and $U^t_{kr,j}$ and $U^t_{km,j}$ are real and imaginary part of $\underline{U}^t_{k,j}$, respectively.

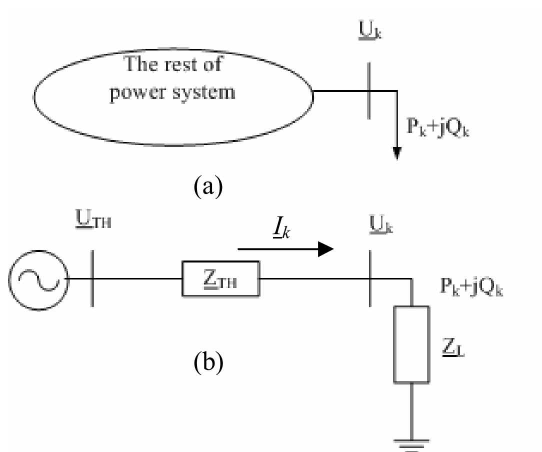

Fig.1. Representation of local bus k and the rest of system

In this paper, two measurements taken at time t are simulated by adding a very small perturbation of apparent load so that (2) becomes numerically solvable. It should be worth mentioning that the measured data $\underline{U}_k^t$ and $\underline{I}_k^t$ may practically contain some noise and error which may cause estimate of Thevein parameters inaccurate. It is therefore desirable that more than two set of measurement quantities collected from past loading conditions should be used and apply the least square technique according to (3);

$$\mathbf{A^T A x = A^T b} \qquad (3)$$

where $\mathbf{A^T}$ denotes the transpose of $\mathbf{A}$.

B. Voltage Stability Indicators

Brief description of each voltage stability indicator considered in this paper is summarized in this section. The first three require the complete system information including the network topology while the last two utilize only the information available at local buses.

Minimum Singular Value

The proximity to voltage collapse can be traced by monitoring zero-convergence of the smallest singular value. For the real $n \times n$ Jacobian matrix, the singular value decomposition is given by,

$$J = U \Sigma V^T = \sum_{i=1}^{n} u_i \sigma_i v_i^T \qquad (4)$$

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 $\sigma_1 \geq \sigma_2 \geq \ldots \geq \sigma_n$ .The matrix J under consideration in this case is the power flow Jacobian matrix (FJ) which is expressed as;

$$\begin{bmatrix} \Delta P \\ \Delta Q \end{bmatrix} = \begin{bmatrix} J_1 & J_2 \\ J_3 & J_4 \end{bmatrix} \begin{bmatrix} \Delta \delta \\ \Delta U \end{bmatrix} \qquad (5)$$

Voltage Collapse Proximity Index

The voltage collapse proximity index (VCPI) can be calculated based on the voltage phasor information of participating buses and topological data of the system. The VCPI of bus k can be found from,

$$VCPI_k = \left| 1 - \frac{\sum_{m=1, m\neq k}^{N} \underline{U}'_m}{\underline{U}_k} \right| \qquad (6)$$

$\underline{U}'_m$ in (6) is characterized by

$$\underline{U}'_m = \frac{\underline{y}_{km}}{\sum_{i=1, i\neq k}^{N} \underline{y}_{ki}} \underline{U}_m \qquad (7)$$

L-Index

The Line (L) index can be derived from information of a normal power flow solution. It can be calculated for each bus j according to,

$$L_j = \left| 1 - \sum_{i \in \alpha G} \underline{F}_{ji} \frac{\underline{U}_i}{\underline{U}_j} \right| \qquad (8)$$

where αG is the set of generator buses; $\underline{U}_j$ is the complex voltage of bus j and $\underline{F}_{ij}$ is the complex gain matrix determined by

$$\underline{F}^{LG} = -[\underline{Y}_{LL}]^{-1} [\underline{Y}_{LG}] \qquad (9)$$

where $[\underline{Y}_{LL}]$ is the load bus self admittance matrix and $[\underline{Y}_{LG}]$ is the mutual admittance matrix between generator and load buses.

Power Transfer Stability Index

The power transfer stability index (PTSI) represents the ratio of load bus apparent power to maximum allowable one .With the knowledge of Thevenin equivalent parameters, PTSI can be determined from,

$$PTSI = \frac{2S_L Z_{TH}(1+2\cos(\beta-\varphi))}{U_{TH}^2} \qquad (10)$$

where the Thevenin impedance in a polar form is $\underline{Z}_{TH} = Z_{TH}\angle\beta$; the apparent load impedance is $\underline{Z}_L = Z_L\angle\varphi$; U_{TH} is the absolute of Thevenin equivalent voltage and S_L is the apparent load power.

Power based Voltage Stability Margin

Based on the fact that the magnitude of load impedance becomes equal to the magnitude of Thevenin impedance at the maximum loadability point, the power based voltage stability margin (PVSM) can be expressed as,

$$PVSM = \frac{(Z_L - Z_{TH})^2}{Z_{TH}^2 + Z_L + 2Z_{TH}Z_L\cos(\beta-\varphi)} \qquad (11)$$

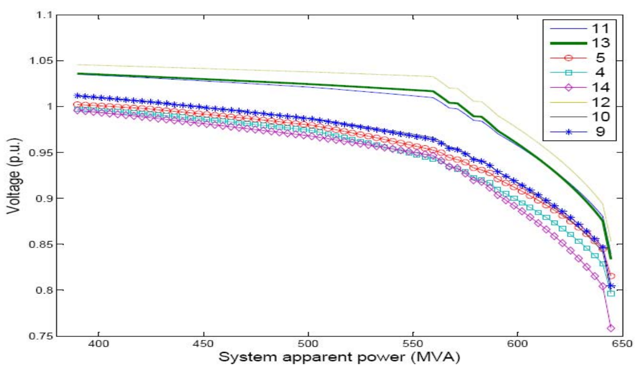

Fig.2. Voltage of load buses at various system loading levels

An extensive study was carried out on the IEEE 14-bus system whose schematic diagram is shown in Fig. A1 of the appendix, Real and reactive power demands at all load buses are uniformly increased and various indicators are calculated. During such an incident, load bus voltages are measured and plotted against the corresponding system apparent load power as shown in Fig.2. One can observe that bus voltage itself is not a good indicator of voltage collapse proximity because it changes quite slightly up to a certain system loading level but beyond that point bus voltages decline abruptly. This is an undesirable behavior of a good indicator in practical applications. System operators would prefer to have a meaningful indicator ready at their hand so that they can realize whether the system is being securely operated and how further they can load the system without jeopardizing system security.

Figs. 3 and 4 depict the characteristic of PVSM and L-index responding to such a load increase scenario discussed earlier, respectively. Each line of these two graphs indicates the value of indicator observed at the load bus. The system is approaching the voltage collapse point as reflected by the PVSM of zero and L-index of one. It could be noted that all indicators exhibit nearly the same performance in predicting the voltage collapse. The only difference is the information required for analysis.

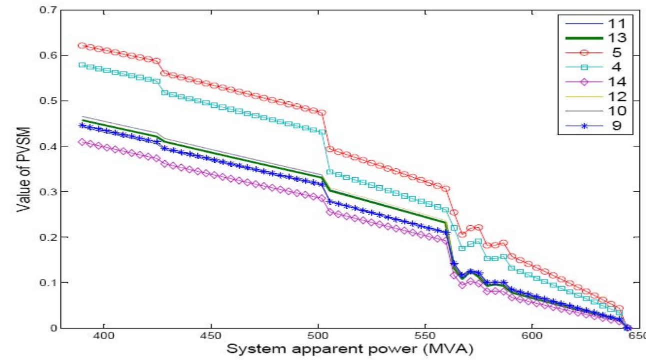

Fig.3. PVSM of load buses at various system loading levels

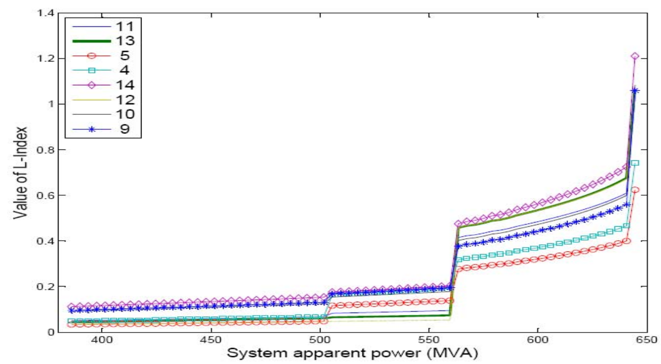

Fig.4. L-index of load buses at various system loading levels

Zero-convergence of minimum singular value of full load flow Jacobian (*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. The sub-matrix J_1 provides sensitivity information between real power injection and angle at buses (P-δ sensitivity). As seen from Fig.5, MSV of J_1 is quite insensitive to load change and thus be not a good indicator since voltage stability problem deal primarily with reactive power. 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 (5) equal to zero) where $J_{4R} = J_4 - J_3 J_1^{-1} J_2$. In this paper, as the size of test system is relatively small and Q-V sensitivity is not considered, MSV of *FJ* is used in the proposed ANN-based monitoring system.

It should be mentioned here that L-index and PVSM provide information at local buses. The most critical bus deserving special attention can be promptly identified. In this case the bus with the highest L-index value (bus 14) can represent the stability status of the whole power system, so does the case of PVSM where the lowest PVSM is the representative of the system indicator. MSV shows only the stability information of the whole system. Further analysis is required to identify the critical bus.

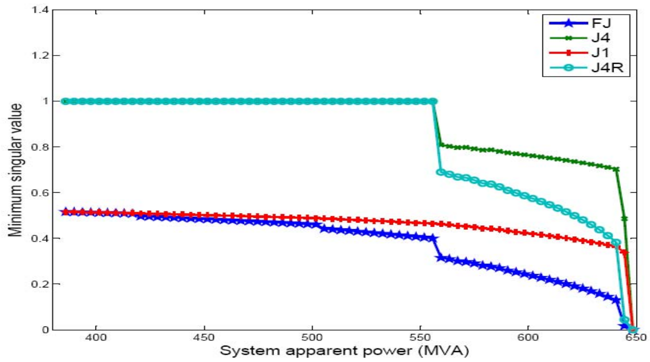

Fig.5. Minimum singular value at various loading levels

III. PROPOSED ANN-BASED METHOD

A. Generation of training data

Training data sets for ANN training are generated by varying both real and reactive loads at all the buses randomly in the range of 60% −120% of their base case values at the constant power factor and utilizing the corresponding power flow solutions. All generators in the system share the additional generation needed to meet the increased load demand equally. Power flow program is conducted at all steps and corresponding voltage stability indicators are calculated. The Power System Analysis Toolbox (PSAT) [11] was used as a computing tool. Collection of these data constitutes the training data set.

B. Feature reduction

The process of eliminating the data that are repetitive in nature and choose only those which contain maximum information regarding the whole set of input data is called feature reduction [12]. The concept of such a method can be further divided into feature selection and feature extraction. By feature selection, physical meaning of features is not changed in any way. In this paper, we adopt few clustering algorithms (as listed methods 1 to 3 in Table I) to group M available system variable to G clusters such that variables in those clusters share similar characteristics. Then, only independent features which provide significant information in each cluster are selected to form a reduced set of system variables.

On the other hand, the features are transformed to a reduced order feature space in feature extraction. Such a transformation changes the physical meaning of features. Principal component analysis (PCA), one of the well-known feature extraction techniques, is applied in this paper (as listed method 4 in Table I). It should be noted that not all principal components must be considered, but only those corresponding the largest n eigenvalues of the correlation matrix are usually sufficient. The whole concept of feature reduction technique applied to power system can be summarized as Fig.6.

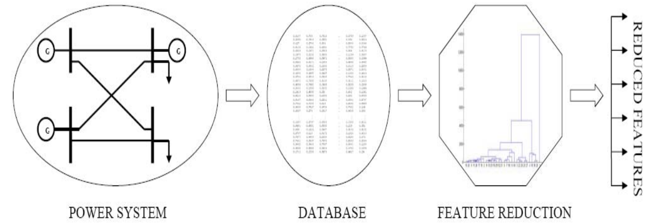

Fig.6 Framework of feature reduction system

C. Type of the 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, a hidden layer and an output layer. The number of inputs depends on the number of used features. The number of output neurons is equal to 8 for the case of PTSI, PVSM, L-index and VCPI (the latter two are not evaluated at slack and voltage controlled buses as they are always zero as long as the bus voltage is maintained) and 1 for the case of MSV. The number of neuron in hidden layer is fixed to 15.

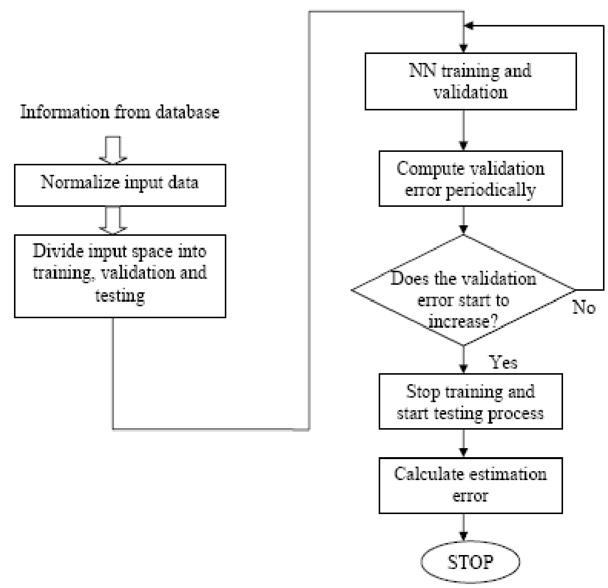

Fig.7 Procedures of ANN-based monitoring system

The designed networks are trained by the back-propagation algorithm using Lavenberg-Marquardt optimization. Early stopping regime is also applied to improve ANN generalization by preventing the training from overfitting problem [13]. In the context of neural network, overfiiting is also known as overtraining where further training will not result in better generalization. The error of validation set is periodically monitored during the training process. The training error usually decreases as the iteration grows, so does the validation error. 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 has increased for some specified number of iteration. The whole ANN process can be depicted as shown in Fig. 7 where the inputs are received from the outputs of the feature reduction system shown in Fig.6. MATLAB neural network tool box is used as a computing tool.

IV. Simulation Results

The standard IEEE 14-bus system is used to test the ability of the proposed ANN-based voltage stability monitoring system. It has a slack bus (bus 1), 4 voltage controlled buses (buses 2,3,6,8), 9 load buses without attached generation (buses 4,5,7 and 9-14) and 2 additional loads are connected to voltage controlled buses 2 and 3. The base load of the test system is 385.95 MVA. In this paper, real and reactive power demand (P_d,Q_d), real and reactive power generation (P_g,Q_g) and voltage magnitude and angle of each bus (U_b,δ) are obtained from power flow calculations of random operating states and constitute as a full set of measured quantities. Reactive power limits are imposed at all PV buses except bus 1 which is assumed to be an infinite bus. The entire data set consists of 3000 samples, with 20% validation and 20% testing.

The performance of the proposed ANN-based method is presented in terms of errors which are defined as the maximum error (e_{max}) and RMS error (e_{rms})

$$e_{max} = \max\{|T_q - O_q|\}, q = 1,2,...,NO \quad (11)$$

$$e_{rms} = \sqrt{\frac{1}{p^{\max}}\sum_{q=1}^{p^{\max}}\frac{1}{NO}\sum_{q=1}^{NO}[t_{qp} - o_{qp}]^2} \quad (12)$$

where $T_q = [t_{q1}, t_{q2}, \ldots, t_{qp^{max}}]$ is the target vector at the q^{th} neuron of the output layer, $O_q = [o_{q1}, o_{q2}, \ldots, o_{qp^{max}}]$ is the output vector at the q^{th} neuron of the output layer, p^{max} is the maximum number of patterns and NO is the number of neurons in the output layer.

Different feature reduction methods are applied in this paper and their details are shown in Table I. It can be observed that even different features were selected based on different feature selection techniques, but the most of selected features are real and reactive power quantities. One may draw some conclusion that ANN-based voltage stability monitoring problem can be sufficiently described with minimum information of voltage at buses.

TABLE I
ANN INPUT FEATURES BASED ON DIFFERENT FEATURE REDUCTION METHODS

Method No.	Feature reduction method	No. of features used	Features
1	Distance based clustering	14	Q_{d5},U_{b13},Q_{g3},U_{b14},P_{d13},δ_{12},Q_{g2}, Q_{d14},P_{d4},Q_{d12},P_{d10},Q_{g1}, δ_4, Q_{d2}
2	Hierarchical clustering	14	P_{d9},Q_{g3},P_{d2},Q_{d3},P_{d13},δ_{11},Q_{g1}, P_{d11},Q_{g6},Q_{g2},P_{d4},P_{d3},U_{b11},P_{g1}
3	Competitive learning	14	P_{d5},Q_{g2},Q_{d11},U_{b11},P_{d11},δ_{13}, P_{g1},U_{b5},P_{d13},Q_{g1},Q_{g3},P_{d3},P_{d6},Q_{g6}
4	Principal component analysis	11	Features are transformed to the new feature space and the size is reduced.

Once the ANN is well trained (confirmed by conducting post regression analysis), it is tested with the remaining 600 loading patterns. Estimation error of each pattern, defined as the ratio of difference between target and output values to its respective target, is calculated. Figs. 8 to 10 depict the estimation error at bus 14 in case of L-index and PVSM and the one of MSV for the whole system. The case of L-index is chosen as a simplified indicator derived from power flow equation, so does VCPI. Similarly, PTSI which is derived from tracking Thevenin equivalent is not shown here as it performs like PVSM. These results show and prove the ability of ANN to monitor the stability indicators for unforeseen patterns stored in the testing set as shown in Figs.8(b) to 10(b).

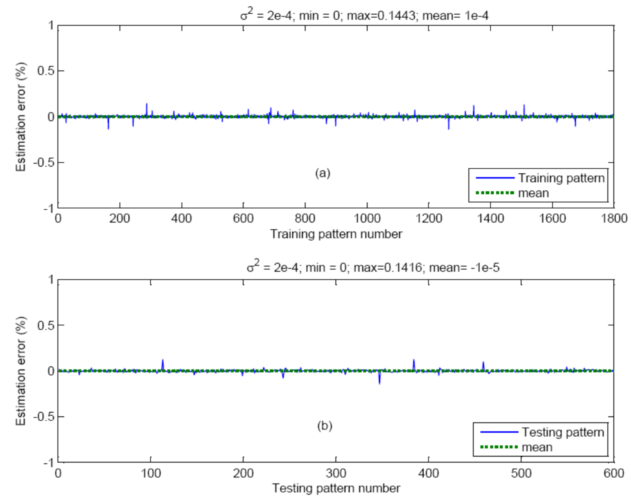

Fig.8. L-Index estimation error at bus 14 for the (a) training and (b) testing

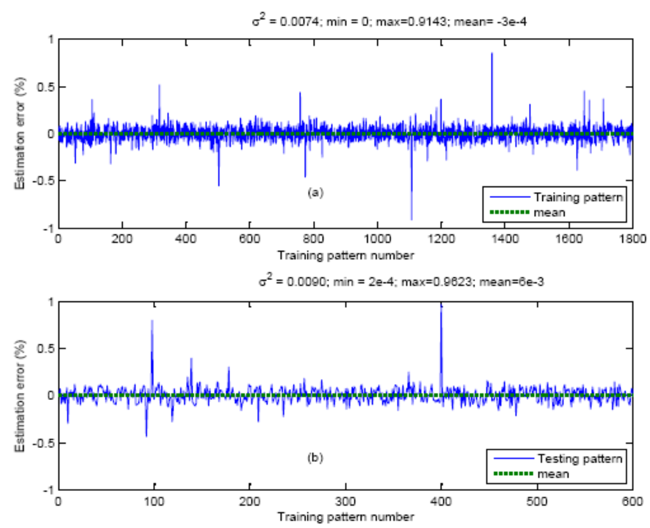

Fig.9. PVSM estimation error at bus 14 for the (a) training and (b) testing

From Figs.11 and 12, it can be seen that voltage stability indicators (L-index and PVSM, respectively) determined by the proposed ANN-based method at all load buses are very close to the solution obtained from the analytical method. Test results are compared among those considered feature reduction techniques (methods 1 to 4 as listed in Table I). Table II summarizes the maximum and rms errors for all the test patterns of all considered indicators.

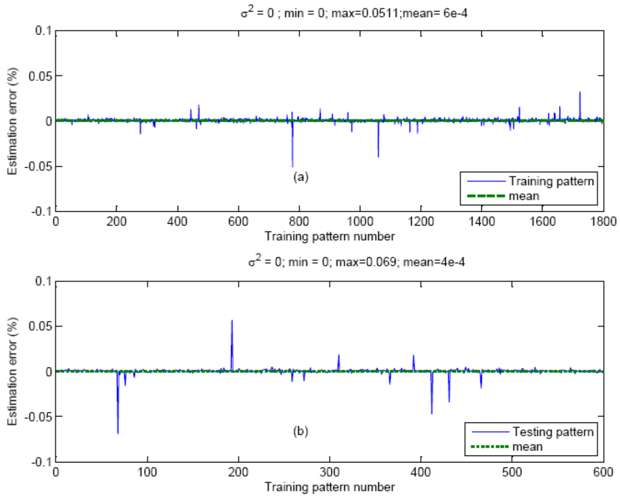

Fig.10. MSV estimation error for the (a) training and (b) testing

TABLE II
SUMMARY OF ESTIMATION ERROR BASED ON DIFFERENT FEATURE REDUCTION TECHNIQUES

	Method 1		Method 2		Method 3		Method 4	
	e_{max}	e_{rms}	e_{max}	e_{rms}	e_{max}	e_{rms}	e_{max}	e_{rms}
L	0.0006	0.0001	0.0009	0.0001	0.0005	0.0001	0.0003	0.0001
VCPI	0.0015	0.0002	0.0017	0.0003	0.0017	0.0003	0.0007	0.0001
MSV	0.0008	0.0001	0.0009	0.0001	0.0008	0.0001	0.0010	0.0003
PTSI	0.0059	0.0003	0.0065	0.0005	0.0076	0.0006	0.0026	0.0006
PVSM	0.0029	0.0003	0.0034	0.0004	0.0049	0.0005	0.0033	0.0010

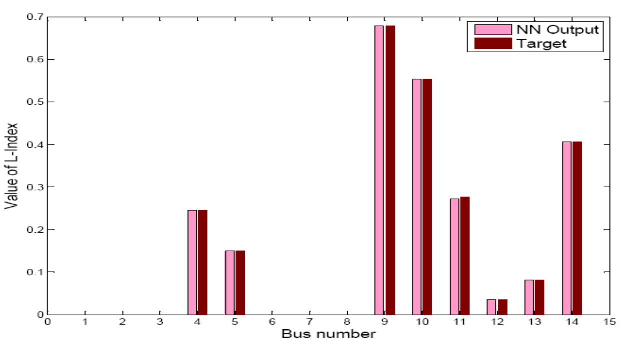

Fig.11. Comparison between NN outputs and targets in case of L-Index

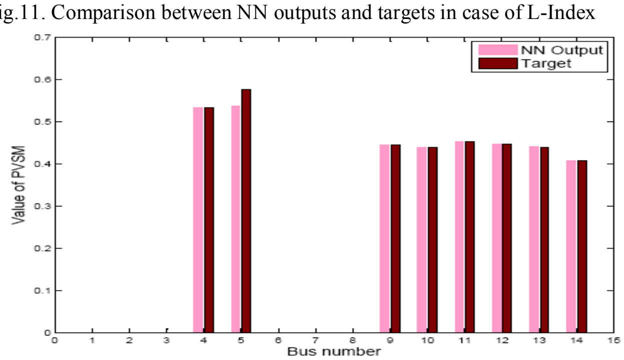

Fig.12. Comparison between NN outputs and targets in case of PVSM

This discussion below tries to exploit conceptual idea of load shedding scheme that incorporates the security feature of voltage stability. Since a fast ANN-based monitoring system was successfully developed and presented in this paper, it would be therefore productive if potential extension of such a system were presented here. As widely accepted, load shedding is among technically and economically effective countermeasures against voltage instability.

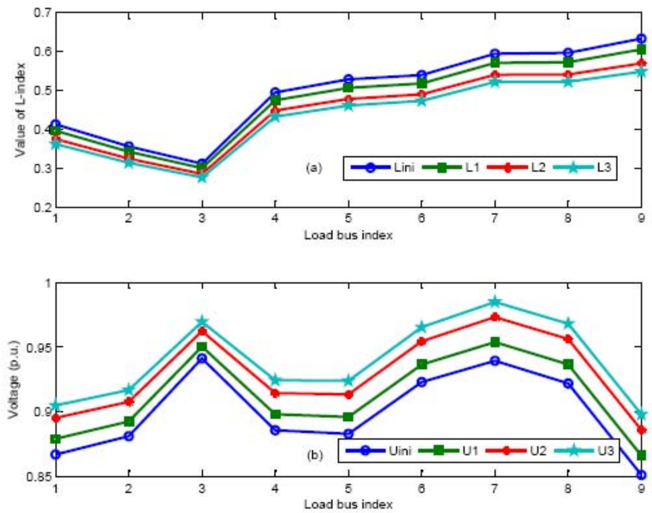

Fig.13. Conceptual idea of load shedding based on L-index (a) indicator profile in the initial case (Lini) and subsequent shedding steps (L1 to L3) (b) voltage profile in the initial case (Uini) and subsequent shedding steps (U1 to U3)

In Fig.13, the system load starts to be shed from the initial operating point (denoted by Lini and Uini in the figure) of the IEEE 14-bus system with the attempt to rise all load bus voltage above the predefined threshold (as set in this case at 0.95 pu). In this example, 1% of each load is shed in each shedding step (step 1 to 3). The corresponding bus voltages can be shown as in Fig. 13 (b). It can be seen that voltage of four (out of nine) buses become now above the threshold and the values of L-index decrease (meaning that distance to the voltage collapse point is enhanced). However, the task left to system operators is to ensure that low voltage at any bus will not occur and the system remains in a state far from voltage collapse. The current practice adopted in Fig.13 is still inadequate. A systematic approach is required in order to bring all load bus voltage above 0.95 pu and guarantee adequate voltage security margin (L indices should be above the threshold). Two important issues for a load shedding policy must be identified. These include bus location and amount of load to be shed. It should be noted that due to operating restriction, there are different maximum limits of load that can be shed at each bus. This is one of the constraints that should be included in the analysis method. Any of optimization techniques can be formulated to solve this problem.

Beside the load shedding scheme, some other countermeasures, for example generation rescheduling or managing reactive power resources can be also carried out. It is therefore very useful if fast and accurate tool become for system operators to study a large number of contingencies in offline mode so that recommendation for appropriate countermeasures can be readily devised in online operation.

V. CONCLUTIONS AND FUTURE WORKS

In this paper, a fast method for monitoring voltage stability margin using ANN is proposed. Several indicators were used to define the proximity of the system to voltage instability. The proposed ANN-based system was successfully implemented to predict the voltage stability indicators for random operating conditions of the IEEE 14-bus system. The simulation results reveal the followings;

1. The variation of the indicators presented in section II with respect to change in system load is so smooth and predictable that the system security can be periodically monitored. It should be emphasized here that only one or few indicators may be chosen in real practice. This papers aims at comparing some of those already proposed in literatures.
2. Feature reduction is crucial for the success of ANN application, although each has its own merit and demerit. Feature selection based on clustering technique can identify important parameters directly measurable from the power system. In this paper, 14 out of 49 features (28%) are shown to be adequate in describing the problem. This method has some drawbacks in that those 14 features were selected from different clusters sharing the same characteristics. These chosen features may not necessarily be to characterize the whole system. On the other hand, feature extraction is fast and highly accurate. However, this method requires full set of system information which may not be obtainable in practical cases.
3. The results of voltage stability indicators predicted by the proposed ANN-based method are very close to the actual values calculated. Additionally, the response time of the ANN model is extremely fast.

The proposed method is quite promising for real world application. Further studies can focus on artificial intelligence methods, such as particle swarm optimization or evolutionary programming, applying to optimize preventive and corrective controls with minimum cost while ensuring system security and reliability. Incomplete and noise contained input data which represent practical situations can be considered.

APPENDIX

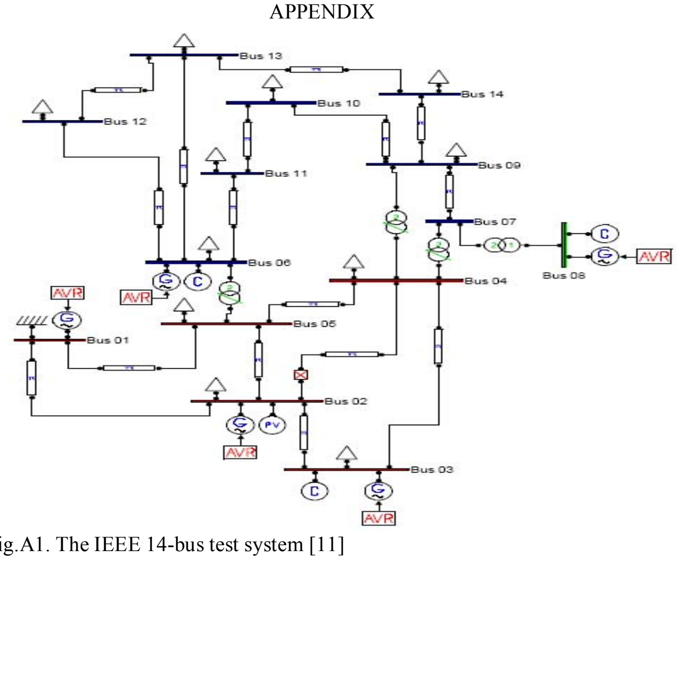

Fig.A1. The IEEE 14-bus test system [11]

REFERENCES

[1] P. Kundur, *Power System Stability and Control*. New York: McGraw-Hill, 1994.

[2] V. Ajjarapu and C. Christy, "The continuation power flow: a tool for steady state voltage stability analysis," *IEEE Trans. Power Systems,* vol. 7, pp. 416-423, Feb. 1992.

[3] C.A. Canizares, "On bifurcation, voltage collapse and load modeling," *IEEE Trans. Power Systems,* vol. 10, pp. 512-518, Feb. 1995.

[4] T.J. Overbye and C.L. Demarco, "Improved techniques for power system voltage stability assessment using energy methods," *IEEE Trans. Power Systems,* vol. 6, pp. 1446-1452, 1991.

[5] P.A. Löf, T. Smed, G. Andersson and D.J. Hill, "Fast calculation of a voltage stability index," *IEEE Trans. Power Systems,* vol. 7, pp. 54-60, 1992.

[6] T.Q. Tuan, J. Fandino, H. Hadjsaid, J.C. Sabonnadiere and H. Vu, "Emergency load shedding to avoid risks of voltage instability using indicators," *IEEE Trans. Power Systems,* vol. 9, pp. 341-348, 1994.

[7] V. Balamourougan, T.S. Sidhu and M.S. Sachdev, "Technique for online prediction of voltage collapse," *IEE Proc.-Gener. Transm. Distrb.* Vol. 151, pp.454-460, July 2004.

[8] K. Vu, M.M. Begovic, D. Novosel and M.M. Saha, "Use of local measurements to estimate voltage stability margin," *IEEE Trans. Power Systems,* vol. 14, pp. 1029-1034, August 1999.

[9] M. Nizam, A.Mohamed and A. Hussain, "Performance evaluation of voltage stability indices for dynamic voltage collapse prediction," Journal of Applied Science, vol. 6, no.5, pp. 1104-1113, 2006.

[10] M.H. Haque, "Online monitoring of maximum permissible loading of a power system within voltage stability limits," *IEE Proc.-Gener. Transm. Distrb.* Vol. 150, no.1 ,pp. 107-112, Jan. 2003.

[11] F. Milano, "An Open Source Power System Analysis Toolbox," *IEEE Trans. Power Systems,*, Vol. 20, No. 3, pp. 1199-1206, August 2005.

[12] S.P. Teeuwsen, I. Erlich, and M.A.E l-Sharkawi , "Feature Reduction for Neural Network based Small-Signal Stability Assessment," in PSCC Proceeding June 2002 Sevilla, Spain

[13] I. V. Tetko, D. J.Livingstone, A. I. Luik, "Neural network studies. 1. Comparison of overfitting and overtraining," *J. Chem. Inf. Comput.* Sci., 1995, 35, 826-833,

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