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Neural network based voltage stability enhancement in power system

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ABSTRACT: In this work, new approach for prediction and improving voltage stability margin from phase and magnitude profile of bus voltages based on sensitivity analysis of voltage stability through neural network. Bus voltage profile contains useful information about system stability margin including the effect of load-generation, line outage and reactive power compensation so, it is adopted as input pattern for voltage stability through neural network. Actually, voltage stability through neural network establishes a functionality for VSM with based on voltage profile. The proposed model has been applied on IEEE 39-bus test system which demonstrated applicability of the proposed approach.
Keywords: Feature Selection, Neural Networks, Voltage stability margin.

INTRODUCTION

Nowadays, power systems operate closer to their voltage stability limit due to existing trend toward market operation and heavier loadings of power systems, together with environmental restrictions for generation and transmission capacity expansion. Therefore, voltage stability is one of the main concerns of modern power systems. Voltage stability refers to the ability of a power system to maintain voltage such that when the load demand is increased, the load power also increases and both power and voltage are controllable [1]. Studies concerning this type of instability phenomenon deal with its evaluation and control. The former determines whether or not a power system operates in the safe operational region, while the latter takes necessary control actions in the case a power system approaches to/operates in unsafe operational region. Various methods have been proposed in the literature to deal with both lines of study for online and offline applications [2–5]. The focus of this paper is the second line of study, which is voltage stability control.

In spite of dynamical nature of voltage instability problem, static approaches are used for its analysis based on the fact that the system dynamics influencing voltage stability are usually slow [6-8], so, if system models are chosen properly, the dynamical behavior of power system may be closely approximated by a series of snapshots matching the system condition at various time frames along the time domain trajectory [6, 9]. Numerous research papers [10] have been devoted to the analysis of both static and dynamic aspects of voltage stability. In order to preserve voltage security margin at a desired level, on line assessment of stability margin is highly demanded which is a challenging task requiring more sophisticated indices. Voltage security assessment can be basically categorized into 1-model based approaches and 2- non model based approaches. In recent literatures, many voltage stability indices have been presented which are mainly model based indices evaluated from the load flow calculation. Indices evaluated from sensitivity analysis, continuation power flow [9-12], singular value of Jacobian matrix [14] and load flow feasibility [6-8] all are model based indices. Some methods utilized system Jacobian matrix [13-19] by exploiting either its sensitivity or its eigenvalue to determine its vicinity to singularity. All these methods are usually time consuming and not suitable for online applications. In [20-26] an enhanced method for estimating look-ahead load margin to voltage collapse, due to either saddle-node bifurcation or the limit-induced bifurcation, is proposed. In [1], a static approach based on optimal power flow (OPF), conventional load flow and singular value decomposition of the load flow Jacobian matrix is proposed for assessing security margin of the North-West Control Area (NWCA) of the Mexican Power System. In [16], derivative of apparent power against the admittance of load (dS/dY) is proposed for measuring proximity to voltage collapse. The techniques proposed in [2] are able to evaluate voltage stability status efficiently in both pre-contingency and post-contingency states with considering the effect of active and reactive power limits. In [5], based on the fact that the line losses in the vicinity of voltage collapse increase faster than apparent power delivery, so, by using local voltage magnitudes and angles, the change in apparent power flow of line in a time interval is exploited for computation of the voltage collapse criterion. In [27-34] by means of the singular value decomposition (SVD) of Jacobian matrix the MIMO transfer function of multi-machine power system for the analysis of the static voltage stability is developed. In [35-42], operating variable information concerning the system base condition as well as the contingency, like line flow, voltage magnitude and reactive reserve in the critical area are used to provide a complex index of the contingency severity. In [8], modal analysis and minimum singular value are used to analyze voltage stability and estimate the proximity of system condition to voltage collapse.

Artificial intelligence techniques have been used in several power system applications. In [15], a feed forward neural network is used to evaluate L index for all buses. In [19] for online voltage stability assessment of each vulnerable load bus an individual feed forward ANN is trained. In this method, ANN is trained for each vulnerable load bus and for a wide range of loading patterns. In [20], a neural network-based approach for contingency ranking of voltage collapse is proposed. For this purpose by using the singular value decomposition method, a Radial Basis Function (RBF) neural network is trained to map the operating conditions of power systems to a voltage stability indicator and contingency severity indices corresponding to transmission lines.

In this paper, a novel approach based on neural network application is proposed for online assessment and improvement of voltage stability margin. In this method, a voltage stability assessment neural network (VSANN) works as an online security estimator for assessing and enhancing voltage stability margin (VSM). In the proposed approach, VSANN uses network voltage profile. Bus voltage profile obtained by synchronous measurement of bus voltages by means of PMU’s provides an operating feature of power system which contains the effects of load-generation patterns, network structure, reactive power compensation and line outage. Therefore, voltage profile is able to reflect the effect of load-generation variation and change in structure due to line outage on the voltage stability margin. The easiness in measuring and accessibility of bus voltages recognized this approach very suitable for estimation of voltage security margin in both normal and contingent conditions.

Concept of the proposed approach

Figure (1) shows the concept of the proposed approach. In the proposed approach, at any given operating condition by synchronous measurement of bus voltages, network voltage profile including both angle and magnitude of bus voltages is provided. By presenting the network voltage profile to voltage stability assessment neural network VSANN, voltage stability margin (VSM) associated to the operating point is evaluated. If it is recognized that the system VSM is less than a specified value then it remains to enhance system voltage security. For this purpose by evaluating sensitivity of voltage stability margin with respect to reactive power compensation, the best bus will be found for reactive power compensation. The sensitivity of VSM with respect to reactive power is evaluated by using the information stored in the structure of VSANN during the training process and network voltage profile at the current operating condition.

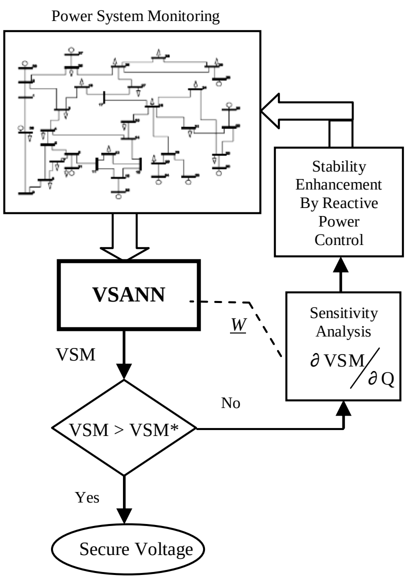

Figure 1. **Conceptual structure of the proposed approach.**

Voltage Stability Assessment Neural Network

In this paper, a multilayer feed forward neural network is used and trained evaluating voltage stability margin of the system. The function of VSANN is to map a functional relationship between system voltage profile and voltage stability margin corresponding to the system operating condition. Network voltage profile provided by synchronous measurement of bus voltages by PMU’s constitutes the input pattern of VSANN. Voltage stability margin corresponding to the presented operating condition is evaluated at the output of VSANN. The number of input neurons of VSANN is determined based on the size of the power system to be studied. There is only one output neuron which gives evaluated VSM. The number of hidden neurons is determined base on the trial and error.

One of the drawbacks of neural network applications for power system problem is dependency of its training and performance on the topology of power network which necessitates updating training process in the case of any line outage due to disturbance or repair. The input pattern of the proposed VSANN is selected in such way that eliminates the dependency of VSANN training to network topology change which may arise due to line outage. Therefore, in the case of line outage, the structure of voltage profile remains unchanged including the effect of network topology, load-generation pattern and reactive power compensation.

Training Data

In order to train VSANN, it is necessary to prepare sufficient and suitable training data. Each training data set consists of system voltage profile as input pattern and associated voltage stability margin VSM as output pattern. Each training set corresponds with an operating point of power system. For this purpose, several load-generation increase patterns are adopted. For each load increase pattern denoted as loading pattern, continuation power flow calculation is carried out by increasing load and generation through specified steps (i.e. %2) until the point of voltage collapse and loadability limit. Each loading pattern is represented by a vector α with a dimension equals to the number of network buses. The element α_k, calculated by Eq. (1) represents the contribution of load bus #k with respect to the total load increment.

$$\alpha_k = \frac{P_{loadk}}{\sum_{k=1}^{n} P_{loadk}} \qquad (1)$$

Figure (2) shows typical change of bus voltages during increase of load-generation based on a specific loading pattern toward voltage collapse. This curve is denoted as P-V curve.

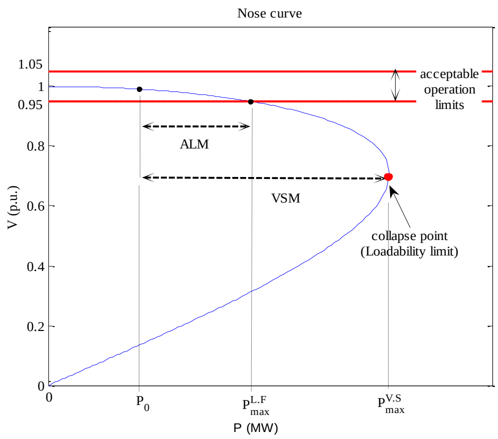

Fig. 2 Typical P-V curve showing loadability limit and VSM.

As it can be seen, each loading pattern α, corresponds with an associated loading limit denoted as loadability limit. During load-generation increase toward voltage collapse, at different steps of load increment, system takes several operating points with different corresponding voltage profiles and VSM. Figure (3) illustrates several network voltage profiles calculated for IEEE 39-bus test system corresponding to different operating points created in the trajectory of a specific loading pattern toward voltage collapse. A voltage profile consists of bus voltages which are arranged according to the bus number. For each operating point at load level Po and with a specific voltage profile there is a corresponding VSM evaluated by Eq. (2).

$$VSM_{o,i} = \frac{P_{max,i} - P_{o,i}}{P_{max,i}} \qquad (2)$$

Where,

$P_{max,i}$ is system loadability limit associated to the loading pattern i,

$P_{o,i}$ is system load level at the operating point.

In the trajectory of load increment, corresponding to a specific loading pattern, there are several operating points with different voltage profiles, load level and associated VSM. Network structure, reactive power compensation and loading pattern are the major factors affecting loadability limit and voltage security margin.

In order to reflect the effect of network topology and reactive power compensation into the voltage profile, for some loading patterns, some lines are taken out and reactive power resources are changed to produce new operating points with associated voltage profiles and VSM and added to the training patterns.

Voltage profiles include the effect of network topology, load level, loading pattern, generation pattern and reactive power compensation and contain useful information about stability status and voltage security margin of the system. Hence, bus voltage profiles are used for training of VSANN.

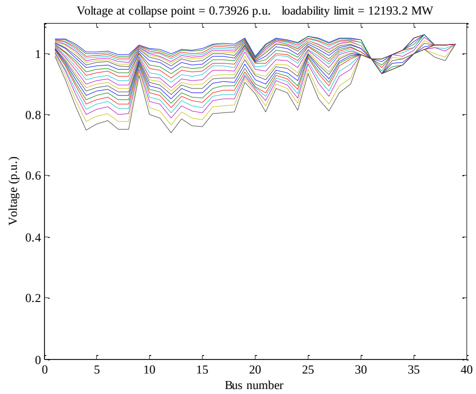

Figure 3. Bus voltage profiles during load increment toward voltage collapse.

Feature Selection

In this paper, two-stage feature selection technique of [43-49] is used, which is based on the information theoretic criteria of Mutual Information (MI) and Interaction Gain (IG). This method consists of two cascaded filters to filter out irrelevant candidate features (i.e., the features with low mutual information with the output variable) and redundant candidate features (i.e. the features that have high mutual information with each other), respectively. Since the feature selection technique is the contribution of this paper, the interested reader can refer to [50-57] for further information.

Training VSANN

The proposed VSANN is trained by the back-propagation algorithm using Levenberg Marquardt optimization. This algorithm is designed to provide fast convergence. The number of inputs depends on the number of used features. There is only one output neurons showing estimated VSM. The number of neuron in hidden layer is adopted as 30.

Early stopping regime is also applied to improve ANN generalization by preventing the training from overfitting problem [58-61]. In the context of neural network, overfitting is also known as overtraining where further training will not result in better generalization. In this technique, the available data are divided into three subsets. The first subset is the training set, which is used for computing the gradient and updating the network weights and biases. The second subset is the validation set. The error of validation set is periodically monitored during the training process. The validation error will normally decrease during the initial phase of training, as does the training set error. When the overtraining starts to occur, the validation error will typically begin to rise. Therefore, it would be useful and time saving to stop the training after the validation has increased for some specified numbers of iteration. The whole training process of VSANN consisting of data generation, preprocessing and training, can be depicted as shown in Figure (4).

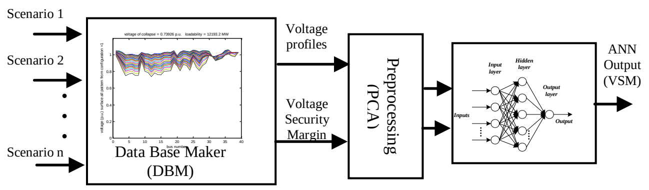

Figure 4. Whole process for VSANN training.

Sensitivity Analysis of VSANN

After training VSANN, in the working mode of the proposed approach in figure (1), if the estimated VSM by VSANN found to be low compared to a desired VSM, then it becomes necessary to enhance system stability margin by reactive power compensation. For this purpose, in order to find the most effective bus for compensation, the sensitivity analysis of VSM with respect to bus voltages is performed. The sensitivity of VSM with respect to each bus voltage magnitude can be calculated using information stored in the weighting factors of VSANN and input data by equation (5) [22]:

$$\frac{\partial \mathrm{VSM}}{\partial V_u} = \frac{\partial \psi}{\partial E}(E^o) * \left(\sum_{i=1}^{NH} W_2(i) * \frac{\partial \varphi_i}{\partial r_i}(r_i^o) * \sum_{j=1}^{n} (W_1(i,j) * T(j,u))\right) \quad (5)$$

Where:

NH: Number of hidden neurons.
n: Number of network buses.
$W_1(i,j)$: Weighting factor connecting the j^{th} input neuron to the i^{th} hidden neuron.
$W_2(i)$: Weighting factor connecting output neuron to the i^{th} hidden neuron.
r_i, φ_i: Input and output of the i^{th} hidden neuron.
E, ψ: Input and output of the output neuron.
r_i^o: Initial output value of i^{th} hidden neuron.
E^o: Initial output value of output neuron.
u: Number of uncontrolled or PQ bus.
T(j,u): Element of feature transfer matrix T.
In order to find the most effective bus compensation for VSM enhancement, it is necessary to evaluate the sensitivity of VSM with respect to reactive power compensation. For this purpose, the network Jacobain matrix as shown in eq. (6) is used. By eliminating active power variation and reducing Jacobain matrix the equation (7) is obtained which shows the sensitivity of bus voltages to reactive power injection.

$$\begin{vmatrix}\Delta P\\ \Delta Q\end{vmatrix}=\begin{vmatrix}J_1 & J_2\\ J_3 & J_4\end{vmatrix}\begin{vmatrix}\Delta\theta\\ \Delta V\end{vmatrix} \quad (6)$$

$$J_R \Delta V = \Delta Q \quad (7)$$

$$\Delta V = J_R^{-1}.Q_{Inj} = J_R^{*}.Q_{Inj} \quad (8)$$

Where:
J_R^* : Reduced Jacobian matrix equal to $=(J_4 - J_3 J_1^{-1} J_2)$
ΔV: Voltage variation of buses.
Q_{Inj}: Reactive power injection.
Using reduced Jacobian matrix, the sensitivity of VSM with respect to VAr injection at bus k^{th} is obtained as follows:

$$\Delta VSM_k = \sum_{i=1}^{Nu}\frac{\partial VSM}{\partial V_i}\Delta V_i = \sum_{i=1}^{Nu}\frac{\partial VSM}{\partial V_i}J_R^*(i,k)Q_{Inj,k} \quad (9)$$

$$S_k^{VSM} = \frac{\Delta VSM_k}{Q_{Inj,k}} = \sum_{i=1}^{Nu}\frac{\partial VSM}{\partial V_i}J_R^*(i,k) \quad (10)$$

Where:
Nu: Total number of uncontrolled or PQ buses.
$Q_{Inj,k}$: Injected reactive power at bus k^{th}.
$J^*_R(i,k)$: Element (i,k) of the reduced Jacobian matrix.
In order to increase VSM, it is required to inject the reactive power Q_{inj} at the most effective bus with highest sensitivity as obtained from equation (10).
The desired VSM is defined as a percentage of the current loading level given by eq. (11).

$$VSM^* = \beta P_0 \quad (11)$$

Where:
P_0: Loading level at the current operating point.
VSM: Voltage security margin of the operating point.
β: Desired percentage of margin with respect to P_0.

VSM Improvement by Reactive Power Control

In order to efficiently improve voltage security margin, reactive power resources installed at the buses should be effectively controlled by recognizing the most effective buses based on the sensitivity analysis of VSANN. Figure (1) shows proposed algorithm for reactive power control aimed VSM improvement.

In this algorithm, VSM is initially estimated by VSANN using initial voltage profile. If the estimated VSM is found to be greater than VSM^*, so system condition is recognized secure otherwise, sensitivity analysis of VSANN using eq. (10) is performed and the most effective buses are recognized for reactive power compensation. The process of compensation is carried out step by step and at each step, the most effective bus with highest sensitivity is selected for compensation with 50 MVAr capacitive reactive power. At each step, after applying reactive power, new voltage profile, VSM and sensitivities are updated for the next step. This process will continue until VSM reaches to the desired value VSM^*.

Simulation Studies

In order to demonstrate the capability and effectiveness of the proposed approach, it has been simulated on the New England 39-bus test system as shown in Figure (5). For this system, by using different loading patterns, system load is incrementally increased until the loadability limits lying in the range of 7000 to 12800 MW. By this way 10269 operating points with different voltage profile and VSM are generated. For some operating points, the effect of line outage and reactive power compensation are included which are reflected in the corresponding voltage profiles and VSMs. For each case, corresponding voltage profile (including magnitude and phase) and VSM are calculated.

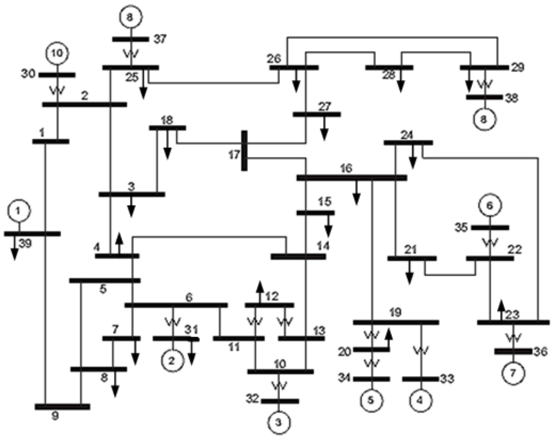

Figure 5. New England 39-bus test power system.

In this study, 10269 operating points are considered as training patterns in which voltage profile and corresponding VSM consist input and output patterns respectively. 30% of total patterns (i.e. 3081) are used for training of the VSANN and 10% for validating VSANN and the remaining 60% for testing. The training patterns are selected from those operating points whose VSM cover the whole range of feasible variation from of system including the effect of line outage and reactive power compensation. The original input pattern consists of 78 variables including 39 voltage magnitude and phase. By applying the transformation of PCA on original 78 operating variables through 3081 training patterns, they are reduced to 8 main components.

Table 1 shows the number of training, validating and test patterns and number of hidden neurons of the trained VSANN. Figure (6) shows the trend of errors corresponding to training, validating and testing VSANN. At the end of the training process of VSANN, Mean Square Error (MSE) and epoch reached to 0.0113 and 34 respectively.

Table 1 .Characteristics of the trained VSANN.

Training patterns	Validation patterns	Test patterns	Hidden neurons	Training time (sec.)
3072	1013	6101	25	54.76

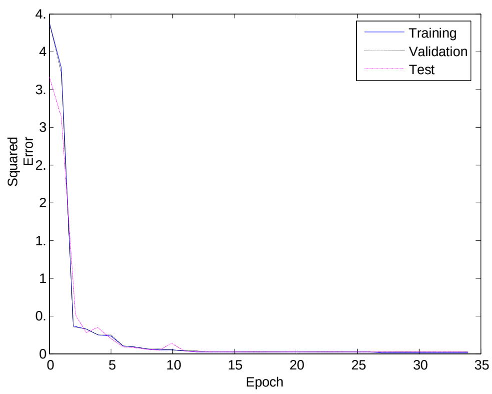

Figure 6. Trend of error corresponding to training, validation and testing in 34 epoch of training

In addition to training, validating and testing errors, another post-training analysis denoted as regression analysis has been performed relating VSANN response to the actual values to investigate the performance of the trained VSANN. For this purpose, linear regression between VSANN outputs and desired targets is used to determine the accuracy of VSANN. In figure (7), the outputs of VSANN are plotted versus the target values, while its slope and correlation coefficient are about 0.987 and 0.994 respectively which are very close to 1 indicating good performance of VSANN.

Figure (8) shows the estimated VSM by VSANN compared to the actual values, indicated for 100 samples randomly selected for testing VSANN. The normalized error between actual and estimated values of VSM lies in the range of -0.17 to 0.14.

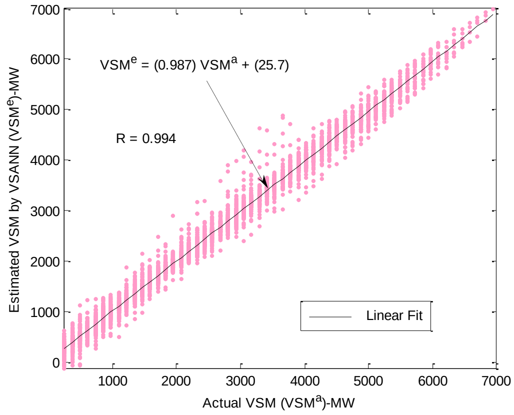

Figure 7. **Post regression analysis on TRAINLM.**

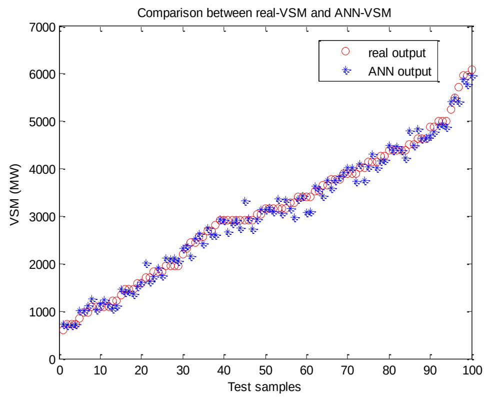

Figure 8. Comparison between real and ANN output VSM.

After training and testing VSANN, it is used in the working mode of the proposed algorithm shown in Figure (1). For any given operating point of power system, by synchronous measurement of bus voltages, voltage magnitudes and phases are extracted as input data for estimating VSM by VSANN. If the estimated VSM is less than the desired voltage stability margin VSM* then by means of sensitivity analysis the most effective bus is selected for reactive power compensation. At each step, after compensation, new voltage profile and VSM are evaluated. This process is carried out until VSM reaches VSM^*.

In this study, for an operating point with load level 7559.8 MW, the value of β in equation (13) is taken as 0.20 and two scenarios are studied in which all network buses are equipped with 200 and 100 MVAr reactive power resources respectively. Tables 2 shows the result of compensation for the first scenario in which VSM has increased from 905.8 MW to 1463.2 MW through 28 steps of compensation with total compensation 1400 MVAr. Tables 3 shows the result of compensation for the second scenario with the corresponding results. Figures 9 and 10 show voltage profiles before and after compensation through several steps of improvement for scenarios 1 and 2 respectively.

Comparing scenario 2 with 1, it can be seen that by taking smaller size of reactive power compensation, less improvement has been obtained for VSM enhancement. As it can be seen, after compensation at the most effective buses, voltage profile is moved upward and corresponding VSM is improved.

Table 2 .Results of reactive power compensation for scenario 1

Sc. No.	PL0 (MW)	Before Compensation VSM By VSANN (MW)	Before Compensation VSM by C.P.F. (MW)	After Compensation VSM By VSANN (MW)	After Compensation VSM By C.P.F. (MW)	Most Effective Buses	Injected Reactive Power (MVAr)
1	7550.8	904.8	852.52	1520.1	1461.1	2	100
						3	100
						5	50
						10	50
						13	150
						16	200
						15	200
						20	200
						24	200
						27	100
						Σ	1350

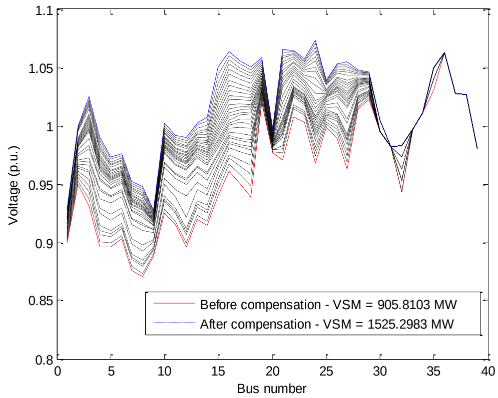

Fig 9. Voltage profiles before and after compensation-scenarios 1

Table 3 .Results of reactive power compensation for scenario 2

Sc. No.	PL0 (MW)	Before Compensation VSM By VSANN (MW)	Before Compensation VSM by C.P.F. (MW)	After Compensation VSM By VSANN (MW)	After Compensation VSM By C.P.F. (MW)	Most Effective Buses	Injected Reactive Power (MVAr)
2	7559.8	905.8	853.52	1160.9	1219.3	2	100
						4	50
						8	50
						15	50
						17	100
						20	100
						23	100
						25	100
						26	100
						Σ	750

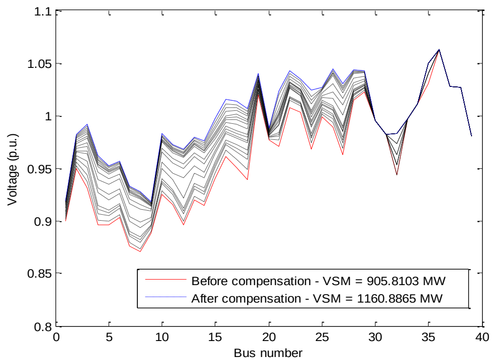

Figure 10. Voltage profiles before and after compensation-scenarios 2

CONCLUSION

In this paper, a new algorithm based on voltage profile and neural network application is proposed for estimating and enhancing voltage stability margin. In this approach, network voltage profile including both phase and magnitude of bus voltages which are measured synchronously by PMU constitutes the input pattern for VSANN. The most interesting feature of neural network application used in this paper is sensitivity analysis of VSM with respect to bus voltages and reactive power compensation. Network voltage profile is an operating variable which contains the effect of load-generation pattern, network structure, reactive power compensation and contingency with no dependency to a specific structure of the network. In order to increase the efficiency of training process of VSANN, principle component analysis has been used as feature reduction for extracting more dominant feature of voltage profile. The main advantage of the proposed approach is its ability for direct estimation of VSM from bus voltages at any moment so that the change in network structure due to line outage has no effect on VSANN performance. The simulation results demonstrate the effectiveness and suitability of the proposed approach for voltage stability assessment and enhancement in an online environment.

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