Wavelet based feature extraction of voltage profile for online voltage stability assessment using RBF neural network

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A B S T R A C T

Online voltage stability assessment is one of the vital requirements for intricate electric power systems. Due to the restructuring and liberalization, modern power systems tend to operate close to their stability limits with small security margin. In such environment, online voltage stability evaluation plays a significant role in secure operation of power systems. This paper presents a new approach for estimating voltage stability margin VSM, based on application of wavelet feature extraction method to network voltage profile. Voltage profile is adopted as the original input data for VSM estimation, because it contains sufficient information concerning network topology, load level, load-generation patterns and all system controllers. In this approach, in order to provide high discrimination between network voltage profiles, Multi-Resolution Wavelet Transform (MRWT) is utilized to extract the features of voltage profiles. Also, in order to eliminate the redundant features, principle component analysis (PCA) is used to select the most relevant features extracted by MRWT. Radial Basis Function (RBF) neural network is adopted to estimate system VSM using the dominant extracted features of the voltage profile by MRWT and PCA. Using voltage profile as the original data makes the proposed approach capable of estimating system VSM in both static and quasi dynamic conditions. The proposed approach has been implemented in New England 39-bus test system with promising results demonstrating its effectiveness and applicability.

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1. Introduction

In recent years, modern power systems tend to operate close to stability limits due to restructuring, open market and competition environments. Voltage instability has increasingly become a significant risk for secure operation of electric power systems. In the heavily loaded electric power systems, the events causing voltage instability, lead to progressive decrease in bus voltage magnitudes which may result in network islanding and blackout. For such systems, online voltage security assessment to preserve a desirable level of voltage security margin is a vital requirement for maintaining system security. Several major voltage collapse phenomena resulted in widespread blackouts [1]. A number of these collapse phenomena were reported in France, Belgium, Sweden, Germany, Japan, and the United States [2,3].

In recent years, artificial neural network applications in the field of power system security assessment have received more interest due to its ability to handle highly complex problems. In the technical literature, there are many works reported on the online voltage stability assessment, exploring the capability of ANN for approximating a functional relationship between voltage stability indicators and the measurable power system parameters. In [4], an approach based on fast voltage and line-flow contingency screening utilizing an enhanced radial basis function neural network and winner-take-all neural network is presented to examine whether the power system is secure under steady-state operating conditions. In [5], an integrated security (voltage and line flow security) assessment approach using cascade neural network developed by a combination of one screening module and two ranking modules is proposed. In [6], radial basis function neural network with reduced input features is used for estimating power system voltage stability level under contingency state. In [7], an approach is presented for power system dynamic voltage stability analysis based on the multi-input multi-output (MIMO) transfer function which is defined the critical nodal voltages as outputs and possible control variables as the input. The dynamic voltage stability analysis is carried out based on the modal analysis and singular value analysis. In [8], a method based on a modular neural network is presented for dynamic voltage stability assessment by establishing a direct mapping between operating conditions and the dynamic VSM index of individual buses. In [9], by using ANN and a regression method for selecting training feature of ANN, an approach is proposed for online voltage stability evaluation. Important features for training ANN are selected by means of the sensitivities of the voltage stability margin with respect to the
inputs using the regression models. In [10], both supervised and unsupervised training is applied to RBFN in order to reduce the number of neural networks required for voltage contingency screening and ranking. An approach based on class separability index and correlation coefficient is used to select the relevant features for the RBFNN. In [11], a RBF neural network is used to map the highly non-linear relationship between various power systems operating conditions and the corresponding voltage stability indicator evaluated by the minimum singular value (MSV) of Jacobian matrix. The MSV is used to rank various contingencies with respect to voltage stability. In [12], a method for voltage stability assessment accounting uncertainties in line parameters and settings of reactive power control variables is presented. Monte-Carlo simulation is used to evaluate probabilities of voltage collapse with respect to various operating conditions as input data for training RBF neural network. RBF neural network is trained to model probabilistic risk of voltage collapse. In [13,14], a scheme for real-time assessment of voltage stability for multiple contingencies using a single ANN is presented. A radial basis function network (RBFN) is used to provide an estimate of the voltage stability margin for different contingencies. In [13], active and reactive load powers and in [14] selected line MVA flows are used as the input features to the RBFN and the available active power margin to the point of voltage instability is used as an indicator to the voltage stability of the system.

In recent years, wavelet transform has been utilized in a lot of issues on electrical engineering such as fault detection and classification [15–17], power quality applications [18,19], load forecasting [20] and power system transient studies [21,22]. The wavelet transform is also recognized as a powerful tool for feature extraction [23]. In [24], an approach based on Artificial Neural Networks combined with Wavelet Transform is developed for single contingency screening. The violation indices namely line over load index (LOI), power margin index (PMI) and voltage stability index are used as training data. The Wavelet Transform is used to decompose the data into several coefficients which are fed to ANN for estimating the violation indices. In [25], a method for classifying power system transients utilizing wavelet entropy and artificial neural network is presented.

In this paper, an approach based on feature extraction of network voltage profile by Multi-Resolution Wavelet Transform MRWT and using radial basis function neural network RBFN is presented for estimating voltage stability margin VSM. Indeed, the wavelet coefficients are utilized as the extracted features of the voltage profile for feeding to RBFN. Also, principle component analysis (PCA) is used to reduce wavelet coefficients to the most dominant extracted features. The proposed RBFN is trained on the extracted features of the voltage profile and evaluates system VSM.

The paper is organized as follows. In Section 2, the framework of the proposed approach for evaluating VSM is explained. An introduction to multi-resolution wavelet transform is presented in Section 3. In Section 4 the application of radial basis function neural networks in this work is explained. Section 5 focuses on voltage stability analyzer neural network (VSANN). The simulation results are presented in Sections 6 and 7 summarizes the conclusions.

2. Proposed approach

Fig. 1 conceptually shows the structure and process of the proposed approach. In this approach, at each operating instant, all synchronously measured bus voltage magnitudes constitute network voltage profile for security assessment. Network voltage profile is a feature of power system containing the effect of all system attitudes like load level, load-generation pattern, reactive power compensation and network topology on the system security. Therefore, network voltage profile is considered as original indicator for estimating power system VSM. Fig. 2 illustrates a series of network voltage profiles obtained for IEEE 39-bus test system corresponding to consecutive increase of system load level toward voltage collapse. In order to extract the dominant features of the voltage profile, a Multi-Resolution Wavelet Transform (MRWT) is applied. After extracting dominant features by MRWT, in order to eliminate irrelevant and redundant data, Principle Component Analysis (PCA) is adopted and applied to reduce the size of the features. Finally, in the last stage of the process, the extracted dominant features of the voltage profile are used as input data to a Radial Basis Function Neural Network (RBFFN) for estimating system VSM. The output of RBFFN is system VSM indicating the distance of system operating point to the point of voltage collapse in term of active power load. In fact, the proposed approach provides a tool for real time and on line estimation of voltage stability margin. Generally, many system parameters and variables could be adopted as indicator for input to a security estimator neural network. However, the main drawback of other variables rather than voltage profile is dependency of the trained ANN to power network topology which necessitates retraining ANN in the case of change in network topology. Since voltage profile contains the effect of all system attitudes therefore, once the approach is trained and established for a specific system, it will be able to properly work for unforeseen conditions resulting from the change in load, generation and even network topology.

In this approach, the versatility of voltage profile for representing system status in various operating conditions without dependency on network topology is the main motivation for using it as security indicator. However, the wave shape of the voltage profile is not so rich of information for discriminating between different security levels corresponding to various operating conditions. Therefore, in order to make a clear discrimination between different voltage profiles and enhance training of RBFFN, it becomes necessary to extract main feature of the voltage profiles. For this purpose, by applying MRWT, wavelet coefficients are extracted as discriminative features of voltage profiles. Also, in order to eliminate the irrelevant data and reducing the size of wavelet coefficients, PCA is applied. The reduced wavelet coefficients are fed to RBFFN to construct a functional relationship between voltage profile and VSM. Indeed, at any instant of system operation, system dominant features in the form of wavelet coefficients are applied to RBFFN for estimating power system VSM.

3. Multi-resolution wavelet transform based feature extraction

Feature extraction is a kind of data preprocessing that transforms a pattern from its original form into a new form dominating some features. Wavelet transform is a newly developed mathematical tool for signal processing [26]. Discrete signal can be transformed by discrete wavelet transform (DWT). The discrete wavelet transform DWT provides sufficient information both for analysis and synthesis of the original signal with a significant reduction in the computation time. Feature extraction of the network voltage profile by the wavelet transform is considered as the main core of the proposed approach.

In this paper, by using multi-resolution wavelet transform a feature extraction method is developed. MRWT decomposes a given signal \( f(t) \) into its detailed and smoothed components by various levels of resolution which can be represented by two sets of functions known as scaling function \( \phi(t) \) and wavelet function \( \psi(t) \). Therefore, signal \( f(t) \) can be represented as a series expansion consisting of scaling functions and wavelets functions as shown in (1) [16,26,27]:

\[
\sum_{k} c_k \phi(t-k) + \sum_{j} \sum_{k} d_{jk} \psi_{jk}(t-k).\]
In this paper, the MRWT is applied to the network voltage profile to decompose it into detailed and smoothed components in the form of wavelet coefficients. The wavelet coefficients obtained by MRWT are considered as extracted features of the voltage profile. In order to apply MRWT to decompose network voltage profile, a mother wavelet ought to be adopted among the most popular ones including Coiflets wavelet, Meyer wavelet, Gaussian wavelet, Mexican hat wavelet, Morlet wavelet and Daubechies. In this paper, Daubechies-2 wavelet has been chosen for decomposing the voltage profile and extracting its features because it is widely used in power system application [28]. Daubechies is the most suitable mother wavelet for decomposing those signals with fast varying pattern [29]. The maximum number of wavelet decomposition levels depends on the length of original signal and mother wavelet which is determined using the following general criterion [30]:

$$\text{lev} = \frac{\log(\text{lenx})}{\log(2)}$$

where \( \text{lev} \) is the maximum number of decomposition level, \( \text{lenx} \) is length of the original signal, and \( \text{lenw} \) is the length of the mother wavelet.

In this paper, the voltage profile of IEEE 39-bus system consisting 39 bus voltage magnitudes is considered as the original signal in the decomposition process. Since the voltage profile consists of 39 bus voltage magnitudes and the length of Daubechies-2 mother wavelet is 4, the maximum number of decomposition level is computed at 3. In fact, the multi-resolution analysis contains 3 scales each containing 39 bus voltage magnitudes. The first decomposition level \((j=1)\), second level \((j=2)\) and third level \((j=3)\) have 21, 12 and 7 coefficients respectively. Fig. 3 shows the decomposition of a specific voltage profile of IEEE 39-bus system into a detailed version using the Daubechies wavelet function \(\psi_{j,m}(t)\) and approximated version using the Daubechies scaling function \(\phi(t)\).

Fig. 4 illustrates the approximation and detail coefficients of the voltage profile according to the decomposed versions shown in Fig. 3. The original voltage profile can be reconstructed, as shown in the pyramid algorithm, with combination of all details and approximation.

4. Radial basis function neural networks

Neural networks provide a generic black box function representation and have been shown to be capable of performing non-linear mapping of the input features into the output with arbitrary accuracy. Among the feed-forward neural networks, Radial Basis Function Neural Network (RBFNN), with non-linear mapping capability, has become increasingly popular in recent years due to its simple structure and training efficiency. RBFNN’s consist of two layers: a hidden radial basis layer, and an output linear layer. The hidden
layer contains neurons with non-linear functions called basis functions, whose arguments consist of the Euclidian distance between the applied input pattern and the centre of the basis function. Gaussian function is the most commonly used basis function for RBFNs\[13\]. Fig. 5 illustrates the architecture of RBFNN. In this paper, a single-output RBFNN is used to estimate the available VSM (MW margin) as an indicator for the proximity to voltage collapse point. Network voltage profile is taken as original data for deriving input data. For this purpose, by applying MRWT and PCA to voltage profile all detail and approximation coefficients are extracted and reduced to construct input data of RBFNN.

The hidden layer neurons have centroids \( c_i \) and bias \( b_i \). These neurons compute the vector distance between the input vector \( p \) and the centroid \( c_i \). A commonly used transfer function for a radial basis neuron is the Gaussian exponential function as follows:

\[
g(x) = \exp\left(-\frac{x^2}{\sigma^2}\right)
\]

For a single neuron at the output layer, the output of the RBFNN is given as follows [13,30]:

\[
y = b_1^{(2)} + \sum_{k=1}^{N} W_{1,k} \exp\left(-\left(\|p - c_k\| - b_k^{(1)}\right)^2\right)
\]

where \( W_{1,k} \) is the weight connecting kth neuron in the hidden layer to the output neuron.

Each neuron finds the Euclidean distance between the input pattern and neuron’s centroid and passes the resulting scalar through a nonlinear function. Thus, the output of the neuron is strongest when the input vector \( p \) is the nearest to the \( c_i \). The bias \( b_i \) allows the sensitivity of the radial basis neuron to be adjusted. The Euclidean distance is given by:

\[
\|p - c_k\| = \sqrt{\sum_{i=1}^{M} (x_i - c_{ki})^2}, k = 1, 2, \ldots N
\]

where \( N \) and \( M \) are the number of hidden neurons and inputs respectively.

5. Voltage stability analyzer neural network VSANN

In the proposed approach, for on line voltage stability evaluation, by using radial basis function neural network, a voltage stability analyzer neural network VSANN is adopted and trained. The
input of VSANN consists of dominant features of the network voltage profile. At each instant of power system operation including static or quasi dynamic conditions, by synchronized measurement of voltage profile and extracting its dominant features by means of MRWT and PCA, VSANN is able to evaluate system VSM associated with the given operating condition.

5.1. Training data

In order to train VSANN, it is necessary to prepare sufficient and suitable training data. Each training data set consists of dominant feature of network voltage profile as input pattern and associated voltage stability margin (VSM) as output pattern. The voltage stability margin VSM is defined as the difference between the loadability limit at collapse point and the operating load level. Each training set corresponds to a specific operating point. For this purpose, several load-generation increase patterns are created. For each load increase pattern denoted as loading pattern, continuation power flow (CPF) 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 \( a \) showing trend of load increase on load buses. The dimension of vector \( a \) is equal to the number of load buses. The element \( a_k \), calculated by (9) represents the share of load increase at bus \( #k \) with respect to the total system load increment.

\[
    a_k = \frac{P_{loadk}}{\sum_{k=1}^{n}P_{loadk}} \tag{9}
\]

Fig. 6 denoted as \( P-V \) curve, typically shows bus voltage variation toward voltage collapse during increase of load-generation based on a specific loading pattern \( a \). As shown in Fig. 6, for each loading pattern \( a \) there is a corresponding \( P-V \) curve with an associated loadability limit \( P_{max} \) denoted as loadability limit. Therefore, each loading pattern corresponds to a loadability limit. During load-generation increase toward point of voltage collapse, at different steps of load increment, system takes several operating points with different corresponding voltage profiles and VSM.

Each operating point is characterized by two parameters; load level \( P_0 \) and loading pattern \( a \). Load level \( P_0 \) creates network voltage profile while loading pattern results in loadability limit \( P_{max} \). VSM evaluated by (10) is a combinatorial feature of the two characteristics and is associated with the corresponding voltage profile.

\[
    VSM_{ai} = P_{max,i} - P_{o,i} \tag{10}
\]

where \( P_{max,i} \) is the loadability limit associated to loading pattern \( a_i \) and \( P_{o,i} \) is the system load level at the operating point.

In the trajectory of load increase based on a specific loading pattern, system takes several operating points with different load levels, voltage profiles and associated VSM. Network topology, reactive power compensation and loading pattern are the major factors affecting loadability limit and voltage security margin. In order to embed the effect of network topology and reactive power compensation into the learning ability of VSANN, for some operating points, some lines are taken out and reactive power is changed.
to produce new voltage profiles and VSM for adding to training patterns.

5.2. Feature reduction

Certain preprocessing is performed on the input data of ANN to make its training more efficient. The process of eliminating irrelevant and redundant data and choosing only dominant data is called feature reduction. For training VSANN, the dimension of the input pattern generally is related to the size of power system. In this paper, the dimension of input space is reduced by eliminating its irrelevant features by using principle component analysis (PCA) [31]. PCA is useful in situations where the dimension of the input vector is large, but the components of the vectors are highly correlated. For this purpose, after feature extraction by MRWT, the extracted features and the output target are normalized such that they have zero mean and unity standard deviation. Then, by applying PCA, the dominant features are extracted to reduce the size of input vector. By this way the input data will be transformed to an uncorrelated space. PCA is carried out using singular value decomposition as represented by (11) and (12).

$$X_{k \times t} = T_{k \times m} \times X_{m \times t}$$

(11)

where $X$ is the vector containing detail and approximate coefficients of voltages profile extracted by MRWT, $T$ is decomposition matrix

$$X'_{k \times t} = \begin{bmatrix} T_{i1} & \cdots & T_{ii} & \cdots & T_{in} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \vdots & \cdots & \vdots & \cdots & \vdots \\ T_{k1} & \cdots & T_{ki} & \cdots & T_{km} \end{bmatrix} \times X$$

(12)

$$X_{k \times t} = \begin{bmatrix} X'_{1} \\ \vdots \\ X'_{i} \\ \vdots \\ X'_{m} \end{bmatrix}$$

Table 1

<table>
<thead>
<tr>
<th>Training patterns</th>
<th>Test patterns</th>
<th>Input neurons</th>
<th>Hidden neurons</th>
<th>Training time (sec)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2568</td>
<td>2567</td>
<td>14</td>
<td>50</td>
<td>91.97</td>
</tr>
</tbody>
</table>

Table 2

<table>
<thead>
<tr>
<th>Test patterns</th>
<th>Average minimum error</th>
<th>Average maximum error</th>
</tr>
</thead>
<tbody>
<tr>
<td>2567</td>
<td>0.05</td>
<td>1.67</td>
</tr>
</tbody>
</table>

Fig. 7. New England 39-bus test power system.

Fig. 8. Trend of mean squared error through 50 epochs of training.
with rows consisting of the eigenvectors of the input covariance matrix and $X'$ is the reduced input data including $k$ uncorrelated components.

5.3. Training VSANN

In order to determine number of hidden neurons, neurons of the hidden layer are increased step by step until its training error reached to a desired value. The following steps are repeated until the network's mean squared error falls below a desired value [30].

1. Input vectors are presented to RBFNN.
2. The input vector with the greatest error is found.
3. A hidden neuron is added with the weights equal to the input vector with the greatest error.
4. The pure-line (output) layer weights are redesigned to minimize error.
5. This procedure is repeated until the desired error is met, or the maximum number of neurons is reached.

The number of inputs of VSANN depends on the number of the reduced extracted features of voltage profile. There is only one output neuron representing the estimated VSM.

6. Simulation studies and results

In order to demonstrate the effectiveness of the proposed approach, it has been implemented in New England 39-bus test system shown in Fig. 7. In order to prepare several voltage profiles with different VSM as training patterns, 26 loading patterns with different associated loadability limits in the range of 7000–12800 MW are defined [32]. For each loading pattern, system load is increased incrementally by step of 5% until the point of voltage stability limit resulting in individual loadability limits. With respect to each specific loading pattern, in the trend of load increment toward voltage stability limit a certain number of voltage profiles are created by continuation power flow calculation. In order to involve the effect of network topology and reactive power limit on the voltage profile and its associated VSM, for each loading pattern some lines or reactive sources are taken out as single contingencies. Each voltage profile including the effect of all system parameters and controllers belongs to a specific load level $P_0$ with a corresponding loadability limit ($P_{\text{max}}$) and stands as a representative for system VSM. As a result, 5135 voltage profiles are created. 2568 voltage profiles are selected as training data. The training patterns are selected such that they can reflect the effect of load level, network parameters, and the effect of network topology and reactive power limit on the voltage profile and its associated VSM.

Table 3

<table>
<thead>
<tr>
<th>Duration</th>
<th>Event</th>
<th>Exact VSM by CPF (MW)</th>
<th>Estimated VSM by VSANN (MW)</th>
<th>Error (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Initial point of simulation</td>
<td>5609</td>
<td>5487</td>
<td>–2.18</td>
</tr>
<tr>
<td>1–2</td>
<td>Load increment-under normal condition</td>
<td>2926</td>
<td>2987</td>
<td>2.08</td>
</tr>
<tr>
<td>2–3</td>
<td>Load decrement-under normal condition</td>
<td>5121</td>
<td>4876</td>
<td>–4.78</td>
</tr>
<tr>
<td>3–4</td>
<td>Small load variation</td>
<td>3365</td>
<td>5054</td>
<td>–5.80</td>
</tr>
<tr>
<td>4–5</td>
<td>Line 15–16 is out</td>
<td>2317</td>
<td>2504</td>
<td>8.07</td>
</tr>
<tr>
<td>5–6</td>
<td>Load increment-line 15–16 is out</td>
<td>1829</td>
<td>1831</td>
<td>0.11</td>
</tr>
<tr>
<td>6–7</td>
<td>Reconnection of line 15–16</td>
<td>4633</td>
<td>4365</td>
<td>–5.78</td>
</tr>
<tr>
<td>7–8</td>
<td>Small load variation</td>
<td>4511</td>
<td>4275</td>
<td>–5.23</td>
</tr>
<tr>
<td>8–9</td>
<td>Injection of 300 MVar capacitive at bus 4</td>
<td>5000</td>
<td>5149</td>
<td>2.98</td>
</tr>
<tr>
<td>9–10</td>
<td>Load increment-with injection of 300 MVar</td>
<td>4268</td>
<td>4405</td>
<td>3.32</td>
</tr>
</tbody>
</table>

Fig. 9. Bus voltage profiles during the scenario.
topology change, generation outage and reactive compensation. The original input pattern consists of 47 variables including the detail and approximation wavelet coefficients of voltage profiles. By applying PCA transformation on extracted features through 2568 training patterns, they are reduced to 14 dominant components. Table 1 shows the number of training and test patterns and also the number of hidden neurons for the trained VSANN. Fig. 8 illustrates the trend of mean squared error in 50 epochs of training. Table 2 shows the error of the trained VSANN for 2567 test patterns comprising a wide range of operating points. As it can be seen, VSANN has an average minimum error around 0.05% for a large number of test patterns and an average maximum error around 16.2% for a few patterns.

After completing training, in order to examine the performance of VSANN, it is put in the working mode of Fig. 1 and for a specific period of time, a scenario including a set of events and disturbances as shown in Table 3 is applied to the power network. Fig. 9a shows three-D illustration of network voltage profiles versus time and bus location within time duration of the scenario. Fig. 9b shows voltage variation of bus 15 versus time and Fig. 9c shows network voltage profile for a number of operating points within the scenario. In the course of the scenario, at each instant of system operation, network voltage profile is processed by MRWT and PCA and applied to the VSANN to estimate system associated VSM. Table 3 shows system VSM estimated by VSANN at different steps of the scenario compared to the exact VSM evaluated by CPF.

Fig. 10 illustrates the variation of VSM estimated by VSANN. As it can be seen, during gradual load increment or decrement under normal condition, VSM smoothly changes with a certain rate, but in the case of large events like line outage or line reconnection, the variations of VSM is sharp showing large change in system security. Also, small variation of VSM resulting from small load variation, system controllers and reactive power compensation are also detected by small error. It means that even small changes in system condition affecting system security, are reflected in the voltage profile and can be clearly recognized and discriminated by the proposed approach. Fig. 11 shows the estimated VSM compared to the exact VSM calculated by CPF. Fig. 12 shows the normalized error between exact and estimated VSMs. As it can be seen, the absolute value of errors is less than 5% in many points. The results demonstrate the ability of MRWT and PCA for extracting dominant features of voltage profile causing acceptable improvement for the performance of the proposed VSANN.

7. Conclusions

In this paper, a new approach based on feature extraction of network voltage profile by wavelet transform and neural network has been proposed for online voltage stability assessment. In the proposed approach, network voltage profile obtained by synchronized measurement of all bus voltage magnitudes provides the original data for assessment. The network voltage profile is an exhaustive representative of system operating condition including the effect of network topology (e.g. line outage), load level, load-generation patterns, reactive power compensation and system controllers. In order to make voltage profile more discriminative as input pattern for VSANN, MRWT and PCA have been utilized for extracting the most dominant features of voltage profile. Once the approach is established and VSANN is trained, as long as the number and configuration of network substation remains unchanged, VSANN can properly estimate VSM at all operating conditions including static and dynamic behavior without any need to retraining for change in topology or other controllers. The main advantage of the proposed approach is its ability for direct estimation of VSM from network voltage profile at any
moment of operation without any need to system modeling. The change in network topology resulting from line outage or new line construction has no effect on VSANN performance. Another interesting feature of this approach is its ability for capturing system security even at dynamic condition. The simulation results demonstrate the effectiveness and suitability of the proposed approach for online voltage stability assessment.

References
