Dynamic Voltage Stability Assessment and Control by Computational Intelligence

S. P. Teeuwsen, *Student Member, IEEE*, L. J. Cai, *Member, IEEE*, and I. Erlich, *Member, IEEE*

Abstract **— This paper presents a novel approach for the assessment of dynamic voltage stability. The power system dynamic voltage stability problem is modeled as a multi-input multi-output (MIMO) transfer function. By means of singular value analysis, interactions between properly defined input and output variables affecting dynamic voltage stability can be analyzed for different frequencies. The output singular vectors provide information about the level of risk at the observed nodes and the input singular vectors show which control variables are most effective for taking counter measures. Since the modal analysis and singular value analysis required for MIMO systems are very time consuming, this paper proposes using Computational Intelligence (CI) to predict the input and output singular vectors, which are of interest in an on-line power system operation. In this study, a Neural Network (NN) is used for the prediction of singular vectors. Moreover, in order to reduce the extremely high number of the NN outputs, the Principal Components (PC), instead of the full singular vectors, are suggested as NN outputs. After calculation of the PC's by the NN, the full vectors can be obtained by a simple matrix multiplication.**

Index **Dynamic Voltage Stability, Voltage Stability Assessment, Singular Value Analysis, Computational Intelligence, Neural Networks, Principal Component Analysis, Target Reduction**

I. INTRODUCTION

The voltage stability problem is one of the major concerns in power system planning and secure operation [1,2]. A large number of researches were performed in the area of voltage stability. Most of them treat the voltage stability problem with static analysis methods based on the study of the reduced (*V-Q*) Jacobian matrix, and by performing modal analysis [3-8]. The bus, branch, and generator participation factors on the static voltage stability can then be obtained. Moreover, the stability margin and the shortest distance to instability can also be determined [6,8]. However, power system is a typical large dynamic system and its dynamic behavior has great influence on the voltage stability. The latest blackouts have shown that voltage stability is very closely associated with frequency and angle stability [1,2]. Therefore, in order to get more realistic results, it is necessary to take the full dynamic system model into account. Some researches have been performed on the dynamic voltage stability analysis [7,9,10]. The general structure of the system model used is similar to that for transient stability analysis. The overall system equations comprise a set of first-order differential equations plus the algebraic equations (DAEs) [7,8,10]. In [10], the voltage stability is decoupled from the angle dynamics. The authors are assuming that all electromechanical oscillations are stable. By neglecting the power-angle dynamics, the voltage response of the unregulated power system can be approximated by the eigenvalues of the voltage stability matrix [10]. However, in large power systems, the dynamic voltage stability is associated with different modes of oscillations. Although there is extensive literature on voltage stability, very few deal with this issue.

In this paper, a novel approach for the assessment of dynamic voltage stability is proposed. The power system is treated in this approach as a MIMO system and thus the corresponding analytical methods are applied. Based on the MIMO transfer function, interactions between properly defined input and output variables affecting dynamic voltage stability can be analyzed at/for different frequencies. Because the modal analysis and singular value analysis required for MIMO systems are very time consuming, this paper suggests using Computational Intelligence (CI) to predict the input and output singular vectors, which are of interest in an on-line power system operation. For a properly defined MIMO system, the output singular vectors provide the information about the level of risk at the observed nodes. On the other hand, input singular vectors show which control variables are most effective for taking counter measures. In this study, a Neural Network (NN) is used for prediction of singular vectors. However, considering different frequencies, the number of NN outputs is extremely high. Therefore, it is suggested to use the Principal Components (PC) instead of the full singular vectors as NN outputs. After calculating the PC's by the NN, the full vectors can be achieved by a simple matrix multiplication. The proposed method is demonstrated using a small test network. However, because the order of the MIMO system is always small, the method can be applied also to large power systems.

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II. MIMO Approach for Dynamic Voltage Stability Assessment and Control

A. MIMO Model

In this paper, the dynamic voltage stability analysis is carried out based on the MIMO transfer function, which is widely used in control engineering. For this purpose, a detailed dynamic power system model including generators, governors, static exciters, Power System Stabilizers (PSS), and non-linear voltage and frequency dependent loads is necessary. Furthermore, dynamic loads may also be included. As the first step, variables that affect dynamic voltage stability have to be selected as input variables to the MIMO system. These are usually the real and reactive power at selected generator and load buses. Some other variables, such as the tap-changer position and the SVC control signals, can also be included as inputs. Furthermore, the voltage magnitudes at the most critical nodes are considered as output signals. Since the number of relevant input and output variables is usually limited, large power systems can also be analyzed using the proposed method.

In order to demonstrate the MIMO approach for the dynamic voltage stability analysis, a MIMO system transfer function matrix is derived by using all the generation and load powers of the test system as input signals. Also the set of output signals is extended to all bus voltages due to the small size of the simulated power system. The corresponding transfer function is shown in Figure 1.

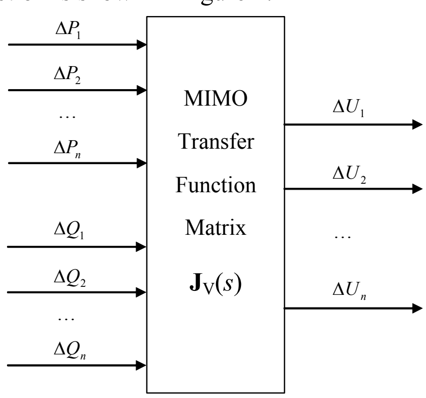

Fig. 1 Dynamic Voltage Stability Model

The MIMO transfer function matrix can then be described as:

$$\begin{aligned}&[\Delta U_1 \quad \Delta U_2 \quad \ldots \quad \Delta U_n]^T = \\ &\mathbf{J}_V(s)\cdot\left[\Delta P_1 \quad \Delta P_2 \quad \ldots \quad \Delta P_n \,\middle|\, \Delta Q_1 \quad \Delta Q_2 \quad \ldots \quad \Delta Q_n\right]^T\end{aligned} \tag{1}$$

where

$$\mathbf{J}_V(s) = \left[\begin{array}{ccc|ccc} f_{P1\_U1}(s) & \ldots & f_{Pn\_U1}(s) & f_{Q1\_U1}(s) & \ldots & f_{Qn\_U1}(s) \\ f_{P1\_U2}(s) & \ldots & f_{Pn\_U2}(s) & f_{Q1\_U2}(s) & \ldots & f_{Qn\_U2}(s) \\ & \ldots & & & \ldots & \\ f_{P1\_Un}(s) & \ldots & f_{Pn\_Un}(s) & f_{Q1\_Un}(s) & \ldots & f_{Qn\_Un}(s) \end{array}\right] \tag{2}$$

is a $n_{Output} \times n_{Input}$ transfer function matrix. Each sub-matrix in the $\mathbf{J}_V(s)$ can be obtained by applying numerical analysis to the power system dynamic model.

B. Calculation of the MIMO transfer function matrix $J_V(s)$

By means of linearization about the operating point, the linearized system model can be expressed as follows:

$$\begin{aligned}\Delta \dot{\mathbf{x}} &= \mathbf{A}\cdot\Delta\mathbf{x} + \mathbf{B}\cdot\Delta\mathbf{u} \\ \Delta\mathbf{y} &= \mathbf{C}\cdot\Delta\mathbf{x} + \mathbf{D}\cdot\Delta\mathbf{u}\end{aligned} \tag{3}$$

where

- **Δx** is the state vector of the system
- **Δy** is the output vector containing bus voltages
- **Δu** is the input vector containing load and generation modulations
- **A** is the state matrix
- **B** is the control matrix
- **C** is the output matrix
- **D** is the feedforward matrix

Therefore, the transfer function matrix $\mathbf{J}_V(s)$ expressed in (1) can be expressed as:

$$\mathbf{J}_V(s) = \frac{\Delta\mathbf{y}}{\Delta\mathbf{x}} = \mathbf{C}\cdot(s\mathbf{I}-\mathbf{A})^{-1}\mathbf{B} + \mathbf{D} \tag{4}$$

Since the number of input and output signals can be restricted even in large power systems, the dimension of the transfer function matrix $\mathbf{J}_V(s)$ is usually small. However, the order of each transfer in $\mathbf{J}_V(s)$ may be large. In this situation, it is recommended to reduce the order of the state equation (3) by means of linear techniques before calculation of the transfer functions.

C. Singular Value Analysis for Dynamic Voltage Stability

1) Singular Value Decomposition (SVD)

In order to analyze the obtained MIMO system, singular value decomposition (SVD) of $\mathbf{J}_V(s)$ is carried out at every fixed frequency [3,11-13]:

$$\mathbf{J}_v(s) = \mathbf{U}(s)\mathbf{\Sigma}(s)\mathbf{V}^T(s) \tag{5}$$

where

Σ(s) is a $n_{Output} \times n_{Input}$ matrix with k = min { n_{Output}, n_{Input}} non-negative singular values, $\sigma_i(s)$, arranged in descending order along its main diagonal; the other entries are zero. The singular values are the positive square roots of the eigenvalues of $\mathbf{J}_V^T(s)\times\mathbf{J}_V(s)$, where

$\mathbf{J}_V^T(s)$ is the complex conjugate transpose of $\mathbf{J}_V(s)$ [13].

$$\sigma_i(\mathbf{J}_V(s)) = \sqrt{\lambda_i\left(\mathbf{J}_V^T(s) \times \mathbf{J}_V(s)\right)} \tag{6}$$

U(s) is a $n_{Output} \times n_{Output}$ unitary matrix of output singular vectors, $\mathbf{u}_i$

V(s) is a $n_{Input} \times n_{Input}$ unitary matrix of input singular vectors, $\mathbf{v}_i$

The maximal singular values of $\mathbf{J}_V(s)$ correspond to the maximal gain between input and output variables for selected frequencies. It describes how the observed outputs can be influenced by the inputs [13].

2) Singular Vectors

The column vectors of **U**, denoted $\mathbf{u}_i$, represent the directions of the output variables. They are orthogonal and of unit length. Likewise, the column vectors of **V**, denoted $\mathbf{v}_i$, represent the directions of input variables. These input and output directions are related through the singular values [13].

For dynamic analysis, the singular values and their associated directions vary with the frequency. However, in power system dynamic voltage stability analysis, critical frequencies corresponding to poorly damped dominant modes must be considered. By analyzing the maximum singular values and their related input and output singular vectors, the relationship between input and output can be obtained at each frequency. The output singular vector shows at which bus the voltage magnitude is most critical. The input singular vector indicates which input has the greatest influence on the corresponding output. Therefore, by means of the singular value analysis, the dynamic voltage stability can be assessed. Furthermore, this method allows selecting the most suitable variables steering the system to a more stable state.

III. Singular Value Analysis of a Test System

A. Power System Model

A typical four-machine two-area power system model [6,11], as shown in Figure 2, is used for demonstration of the proposed method. The corresponding dynamic model consists of generators with 6th order model, governors, static exciters, PSS, and non-linear voltage and frequency dependent loads.

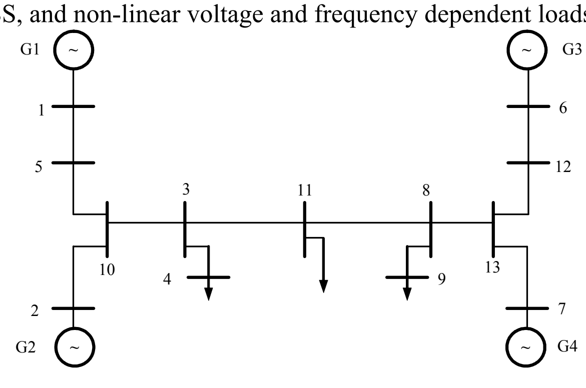

Fig. 2 Four-Machine Two-Area Power System Model

The dynamic voltage stability assessment of the test power system will be demonstrated in the next section.

B. Dynamic Voltage Stability Analysis – Singular Value Approach

Based on the detailed dynamic power system model, the transfer function matrix $\mathbf{J}_V(s)$ is calculated using numerical methods. The maximal singular value of $\mathbf{J}_V(s)$ over the frequency range of [0.01Hz~100Hz] is shown in Figure 3. It is clear that the peaks of the maximal singular value plot correspond to the inter-area mode and exciter mode 1 respectively (The exciter mode 1 and inter-area mode are determined using the modal analysis).

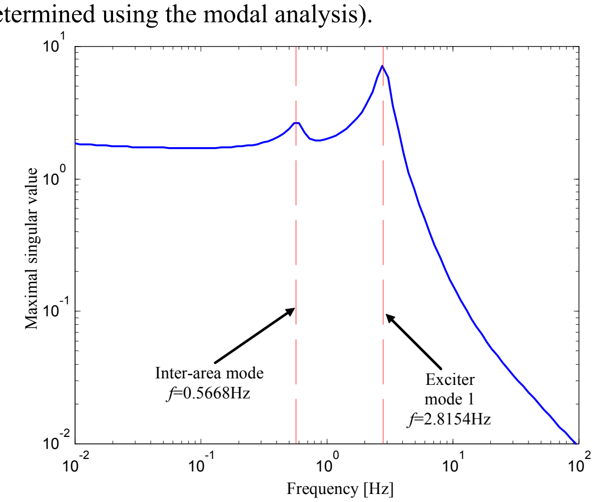

Fig. 3 Maximal Singular Value Plot

Therefore, the singular value analysis is carried out for the two critical oscillation mode frequencies. The output singular vector corresponding to the maximum singular value at the exciter mode frequency is given in Figure 4. It can be seen that buses 7, 8, 11 and 13 are related to the dynamic voltage stability with Bus 11 standing out as the most critical. The input singular vectors associated with this mode shows that the input signals of Q_{G4}, Q_{G2}, Q_{G3} and Q_{G1} (Input number 26, 24, 25 and 23) are the most suitable signals for this mode of dynamic voltage stability control. Other input signals have relatively weak influence, as can be seen in Figure 5.

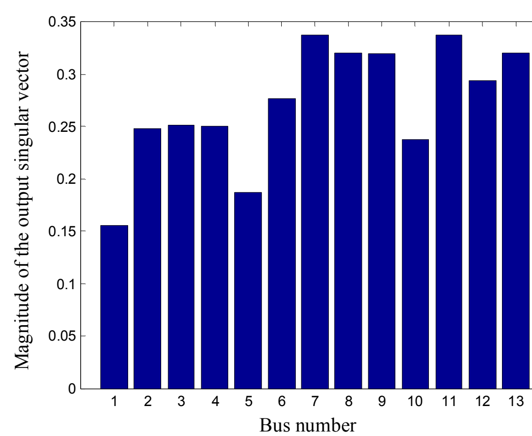

Fig. 4 Output Singular Vector Associated with Exciter Mode 1

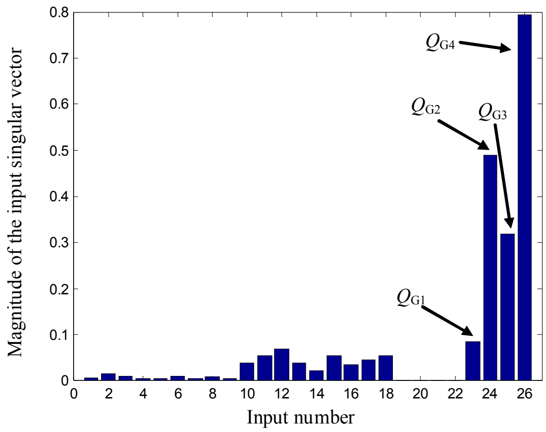

Fig. 5 Input Singular Vector Associated with Exciter Mode 1

The critical output singular vector associated with the inter-area mode is given in Figure 6. From this follows that the buses 1, 5, 3 and 4 are the most critical. In comparison with the exciter mode 1, this mode has larger output singular vectors. The input singular vectors, as can be seen in Figure 7, with this mode shows that the input signal of Q_{G2}, Q_{G1} Q_{G4} and Q_{G3} (Input number 24, 23, 26 and 25) are the most suitable signals for dynamic voltage stability control.

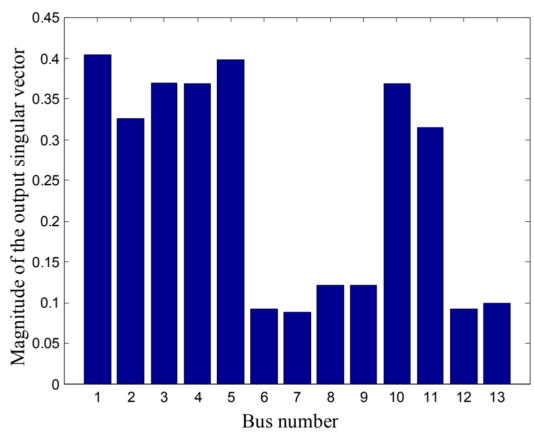

Fig. 6 Output Singular Vector Associated with Inter-Area Mode

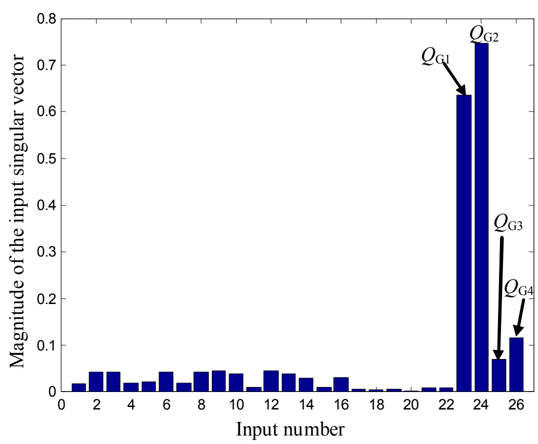

Fig. 7 Input Singular Vector Associated with Inter-Area Mode

As can be seen from the input singular vector plots given in Figures 5 and 7, the generator reactive power controls (Input number 23-26) will always have maximum influence on the dynamic voltage stability.

For assessment of static voltage stability, the MIMO transfer function matrix $\mathbf{J}_V(s)$ can be analyzed at s=0. The simulation result is similar to that of the traditional steady state voltage stability analysis [6,8].

IV. Dynamic Voltage Stability Assessment and Control using CI

The introduced singular value approach has proved to be very useful for dynamic voltage stability analysis. Especially the singular vectors provide very valuable information concerning the nodes, which are most at risk, and how the system can be controlled effectively. Therefore, the input and output singular vectors may be of interest also for Transmission System Operators (TSO) for real-time application/control. However, for real-time application, singular value analysis is too time-consuming. Furthermore, analytical computation of singular values and vectors always needs the complete power system data including the dynamic characteristics of generators and loads. Moreover, these data are not available to the TSO.

In this paper the authors suggest the use of CI, implemented to predict the singular vectors in real-time. CI works very fast and does not need the complete power system data. CI is built/based on training patterns, which can be calculated off-line and therefore without any time restrictions. Once the CI is trained properly, it is able to predict the singular vectors on-line with high accuracy. Another advantage of CI is the flexibility in terms of operating conditions. Different operating conditions, load flow scenarios, and changes in the network topology can be considered in advance and thus included in the training patterns. However, if necessary, different CI tools can be trained independently on different network scenarios.

A. Neural Networks based Approach

This study applies a NN as CI method since they are highly applicable for modeling complex and non-linear relationships. When the NN is implemented for singular vector prediction, the NN outputs must be assigned to the elements of the input and output singular vectors. However, these vectors are computed for various frequencies and therefore the NN output vector and thus the corresponding training patterns would contain thousands of elements. The power system investigated in this study results in 26 input singular vectors and 13 output singular vectors. Furthermore, each vector is computed for 97 different frequencies. Thus, the corresponding NN should be built for 3,783 outputs. Considering the 249 training patterns used in the study, it becomes obvious that this exceeds the capability of reasonable NN training. Figure 8 shows the desired NN structure.

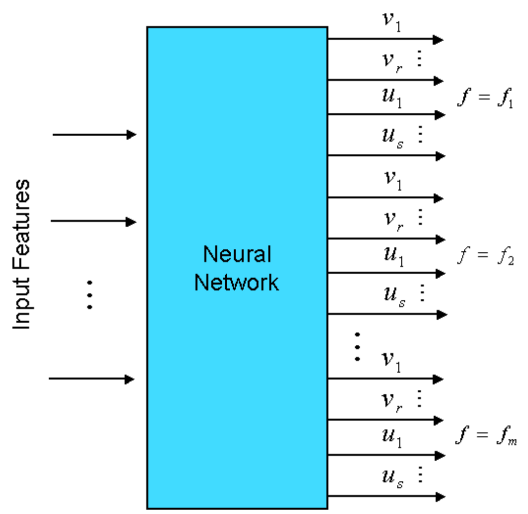

Fig. 8 Neural Network Structure when the Singular Vectors under different Frequencies are used as NN Outputs

A solution to the problem is a reduction of the dimension of the NN targets. However, it requires that the information content can be described also by a smaller data set. Moreover, the back transformation into the original space must be not only possible but also definite. The suggested dimensional reduction of the target vector based on the Principal Component Analysis (PCA) is discussed in the following subsection. The basic idea is shown in Figure 9.

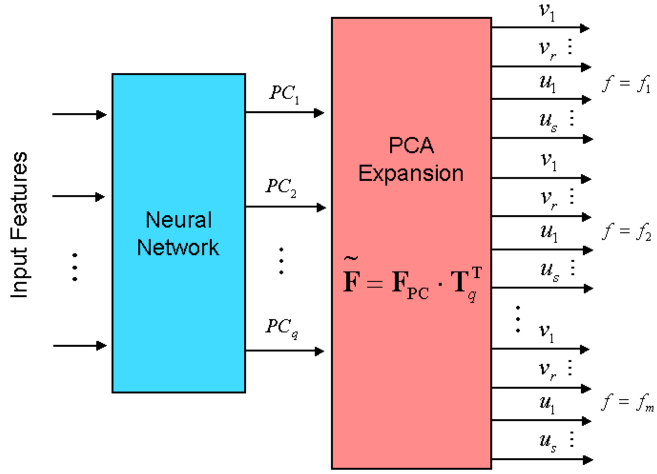

Fig. 9 Neural Network Structure when built for Principal Components; the Output Singular Vectors under different Frequencies are obtained in the original Dimension after PCA Expansion

B. NN Target Data Reduction

The PCA technique is fast and can be applied to large data sets [14]. Let $\mathbf{F}$ be a matrix of dimension, $p \times n$ where n is the number of the original targets and p is the number of patterns. The empirical covariance matrix $\mathbf{C}$ of the normalized $\mathbf{F}$ is computed by

$$\mathbf{C} = \frac{1}{p-1} \cdot \mathbf{F}^{\mathrm{T}} \cdot \mathbf{F} \tag{7}$$

Let $\mathbf{T}$ be a $n \times n$ matrix of the eigenvectors of $\mathbf{C}$, and the diagonal variance matrix $\mathbf{\Sigma}^2$ is given by

$$\mathbf{\Sigma}^2 = \mathbf{T}^{\mathrm{T}} \cdot \mathbf{C} \cdot \mathbf{T} \tag{8}$$

$\mathbf{\Sigma}^2$ includes the variances σ_x^2. Notice that the eigenvalues λ_k of the covariance matrix $\mathbf{C}$ are equal to the elements of the variance matrix $\mathbf{\Sigma}^2$. The standard deviation σ_k is also the singular value of $\mathbf{F}$:

$$\sigma_k^2 = \lambda_k \qquad (1 \le k \le n) \tag{9}$$

The n eigenvalues of $\mathbf{C}$ can be determined and sorted in descending order $\lambda_1 \ge \lambda_2 \ge \ldots \ge \lambda_n$. While $\mathbf{T}$ is an n-dimensional quadratic matrix whose columns are the eigenvectors of $\mathbf{C}$, $\mathbf{T}_q$ is a $n \times q$ matrix including q eigenvectors of $\mathbf{C}$ corresponding to the q largest eigenvalues of $\mathbf{C}$. The value of q determines the size of the new dimension of the features and is smaller than n. It also determines the retained variability of the features, which is the ratio between the first q eigenvalues and the sum of all n eigenvalues [14].

$$\upsilon = \frac{\sum_{i=1}^{q} \lambda_i}{\sum_{i=1}^{n} \lambda_i} \tag{10}$$

However, the data are transformed by the basic PCA equation

$$\mathbf{F}_{\mathrm{PC}} = \mathbf{F} \cdot \mathbf{T}_q \tag{11}$$

to the reduced data matrix $\mathbf{F}_{\mathrm{PC}}$ of dimension $p \times q$. The NN can be trained easily with these patterns for any small number of targets. Once the NN is trained successfully, the NN outputs are transformed back into the original data space by

$$\tilde{\mathbf{F}} = \mathbf{F}_{\mathrm{PC}} \cdot \mathbf{T}_q^{\mathrm{T}} \tag{12}$$

whereby $\tilde{\mathbf{F}}$ contains the information in the original space $p \times n$. In the case without reduction, where $q = n$, $\mathbf{F}$ and $\tilde{\mathbf{F}}$ are identical. The error between both matrices is defined as the Sum Squared Error (SSE) according to

$$E = \frac{1}{p \cdot n} \cdot \sum_{j=1}^{p} \sum_{i=1}^{n} \left(F_{ji} - \tilde{F}_{ji} \right)^2 \tag{13}$$

The transformation is performed on the computed sample data from the test system for 249 patterns and 3,783 original targets. Figure 10 shows the variability (10) and the transformation error (13) versus the number of used principal components without NN training. Therefore, the error results only from the loss of information during the transformation Hereby, the error is scaled on the maximum error, which occurs at $q = 1$, to obtain a percentile error.

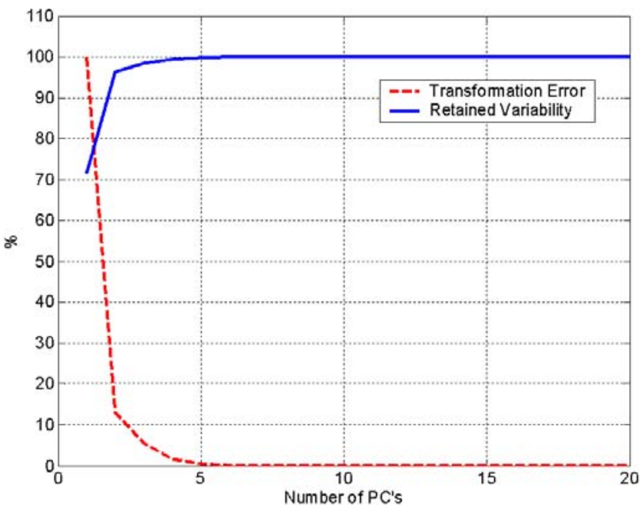

Fig. 10 Retained Variability and Transformation Error versus the Principal Components for $1 \leq q \leq 20$

The value for q is chosen depending on the required variability and the tolerated transformation error. Both the variability plot and the error plot show that the first 5 – 10 principal components contain already most of the information in the data set.

V. NN Results

In the following, various NNs are trained with patterns from the reduced data matrix. Hereby, the number of inputs is kept constant at 20 inputs for each NN. Different NNs are trained with reduced data under variable reduction rates. The highest (applied) reduction rate in this study results in only 5 NN outputs. The lowest reduction rate results in 25 NN outputs. The NN errors for training and testing are shown in Figure 11. The figure shows a high dependency of the error on the number of NN outputs. When the number of NN outputs is low (high reduction), the error increases because the transformation error is high (see Figure 10). When the number of NN outputs is high (low reduction), the error increases as well because the constant number of NN inputs cannot provide enough information to predict the NN output values with low errors. However, for about 10 – 15 NN outputs the error drops to a minimum. Figure 12 shows the NN results after training with 20 inputs. The data are reduced to 10 principal components (NN outputs). The upper figure shows both the normalized original input and output singular vectors over all frequencies for one pattern and its approximation result by the NN. Both curves are nearly identical and therefore the difference between both curves (error) is plot in the bottom figure.

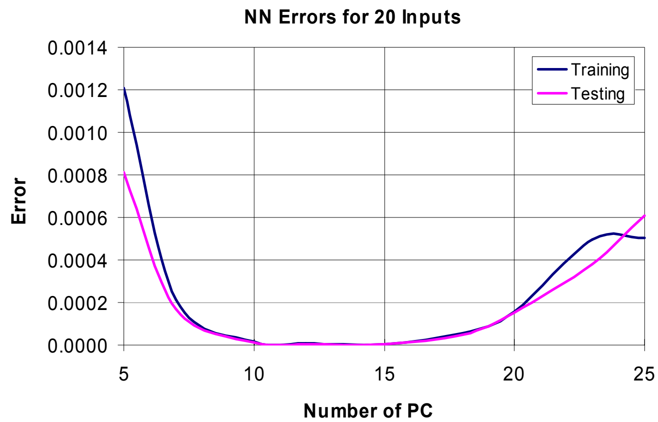

Fig. 11 NN Results after Training with different Reduction Rates and 20 Inputs

The error shown in Figure 12 is noticeably small, which demonstrates the excellent approximation capability of the NN. The reasons for the small errors are the size of the used test system, the power flow conditions considered, and the high number of training patterns. Since the test system consists of 4 generators and 13 bus nodes, the number of 249 patterns contains enough information for proper NN training. This can be seen even clearer when the original singular vectors and the NN results are compared. Figure 13 shows the magnitudes of the original output singular vectors and the NN results for one frequency (inter-area mode) and one particular load flow situation. The NN results match the original output singular vectors completely and show no noticeable difference.

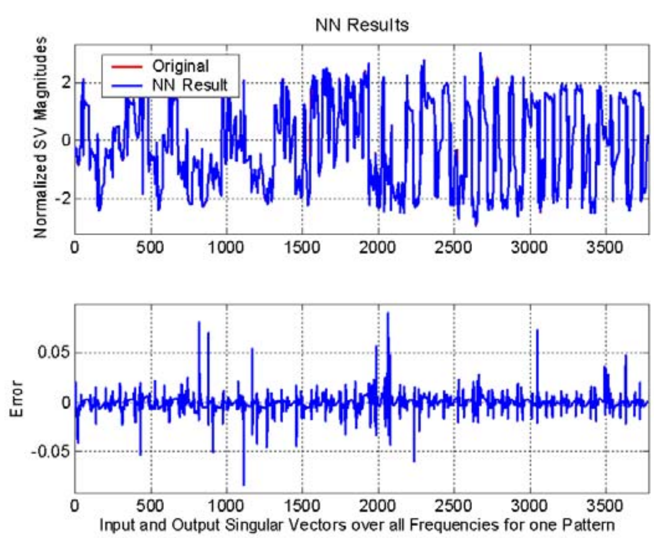

Fig. 12 Normalized Original Singular Vector Magnitudes and NN Results after Training with 20 Inputs and 10 PC's for one Pattern (Top Figure) and Error (Bottom Figure)

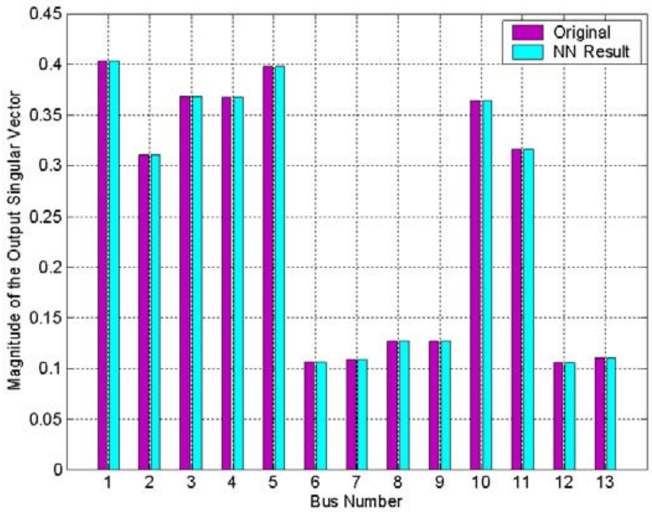

Fig. 13 Magnitudes of Original Output Singular Vectors and NN Results associated with Inter-Area Mode for one particular Load Flow Situation

All patterns used in this study are normalized on their mean and Standard Deviation (STD) before being passed on to the NN. After NN training, the results are renormalized to the original value range. Figure 14 shows the maximum, minimum as well as the mean values of the original output singular vectors for the inter-area mode under all computed load flow scenarios. The figure illustrates the range between minimum and maximum. All patterns are renormalized to this range. Therefore, even NN results with high errors fall into this range, most likely close to the mean value. Therefore, accurate NN results, that are applicable for dynamic voltage stability assessment in real-time, must result in minimal errors such as the one shown in Figure 12 and Figure 13.

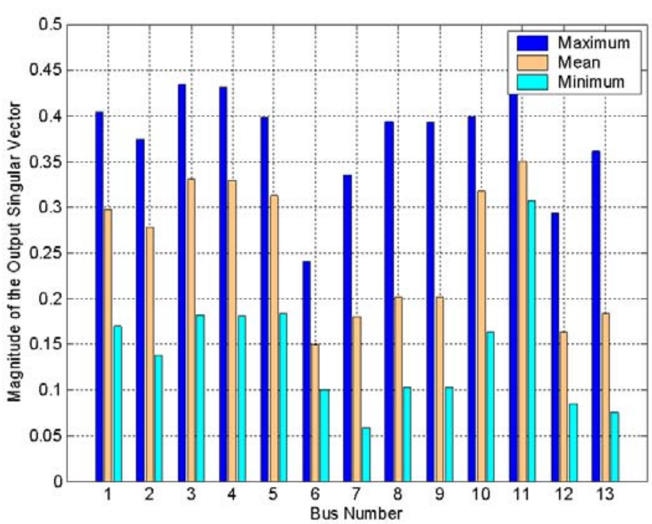

Fig. 14 Maximum, Minimum, and Mean of the Magnitudes of the Original Output Singular Vectors associated with Inter-Area Mode

VI. Conclusion

This paper introduced a new method for dynamic voltage stability assessment. The method is based on the MIMO transfer function. Interactions between properly defined input and output variables affecting the dynamic voltage stability are analyzed at different frequencies. The paper suggests the use of NN for fast calculation of input and output singular vectors. After training, the NN is able to provide valuable information to the TSO concerning dynamic voltage stability in real-time for any given new scenario in the power system.

Since the original data dimension is large and cannot be managed by a NN, the output dimension is reduced by the PCA. After NN training, the data are expanded back to the original data space. Hereby, the errors – both by the reduction and the NN training – are noticeably small. The method is highly accurate and suitable for real-time dynamic stability assessment also for large power systems.

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