Neuro-Fuzzy Networks for Voltage Security Monitoring Based on Synchronized Phasor Measurements

Chih-Wen Liu Chen-Sung Chang
Department of Electrical Engineering
National Taiwan University
Taipei, Taiwan

Mu-Chun Su
Department of Electrical Engineering
Tamkang University
Taipei, Taiwan

Abstract The ability to rapidly acquire synchronized phasor measurements from around the system open up new possibilities for power system operation and control. A novel neuro-fuzzy network, Fuzzy Hyperrectangular Composite Neural Network, is proposed for voltage security monitoring **(VSM)** using synchronized phasor measurements as input patterns. This paper demonstrates how neuro-fuzzy networks can be constructed off-line and then utilized on-line for monitoring voltage security. The neuro-fuzzy network is tested on 3000 simulated datas from randomly generated operating conditions on the IEEE 30-bus system to indicate its high classification rate for voltage security monitoring.

1. Introduction

In recent years an instability, usually termed a voltage instability, has been observed and been responsible for several major network collapses in many countries [1, 2]. The phenomenon was not always in response to a contingency such as the loss of an important transmission line or a generator, but rather in response to an unexpected raise in the load level, sometimes in combination with an inadequate VAR support at critical network buses.

Significant research efforts have been devoted to understanding voltage phenomena. A large portion of this research in focused on the steady-state aspects of voltage stability. Indeed, a lot of researchers have proposed the concept of voltage security margin which show how close the current operating point of a power system is to the voltage collapse point [3-15] as monitoring of voltage security. Specifically, Tiranuchit [3] proposed the minimum singular value of the Jacobian of the load flow equation as a voltage security index. The concept of multiple load flow solutions was proposed to deal with voltage security problems [4, 5]. Löf [6] presented a fast method to calculate the minimum singular value and the corresponding (left and right) singular vectors. Continuation methods were also applied to compute the exact collapse point and the voltage security margin in MW [7-9]. Van Cutsem [10] used the solution of a reactive power optimization problem as the voltage security. Gao [11] used the modal analysis technique to compute the voltage security. One main disadvantage of aforementioned techniques is that they require large computations and are not efficient for on-line use in control center. For on-line applications there is a need for tool which can provide timely evaluation of voltage security such that operators may observe advance warning signals in order to steer the system away from a developing voltage collapse whenever possible.

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Except the above methods, there is another class of techniques applied to voltage security monitoring (VSM) which are artificial intelligence methods in nature. Specifically, there are Artificial Neural Network [12-14], and Decision Tree [15] for VSM. The artificial intelligence methods can learn in off-line from training set and are used in on-line to classify new data much faster than would be possible by solving the model analytically.

With the advent of systems capable of making synchronized phasor measurements, the on-line monitoring of the voltage security has become an possibility [16-18]. Commercially available systems based on GPS (Global Positioning System) satellite time transmissions can provide synchronization to 1 microsecond accuracy. By communicating time-tagged phasor measurements to a central location, the state of the system can be tracked on-line. Utility experience indicates that communication bandwidths can handle 12 complete set of phasor measurements per second [19]. In this paper, we propose a two-layer Fuzzy Hyperrectangular Composite Neural Network **(FHRCNN)** using synchronized phasor measurements as input patterns for VSM. The FHRCNN first introduced in [20] has been proved to have several advantages over traditional Feed-forward Artificial Neural Network (ANN) in the context of pattern recognition. In particular, FHRCNN can provide explanations of their responses, i.e., explicit IF-THEN rules or logical reasoning processes. This expert system like property makes FHRCNN especially suitable for VSM since a trained FHRCNN can explicitly provide the security range of input

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patterns, which is useful for power system operator to identify the key influencing patterns. The minimum singular value and corresponding right singular vector are adopted to train and test FHRCNN.

The paper is organized as follows. Section 2 briefly explains the measuring technique of synchronized phasor measurements. The FHRCNN is described in Sec. 3. The adopted voltage security index and weak bus identification are described in Sec. 4. In section 5, the proposed scheme is simulated on IEEE 30-bus system. Finally, a summary conclusion is given in Sec. 6.

2. Synchronized Phasor Measurements

A detailed description of phasor measurement units (**PMUs**) utilizing time synchronized sampling over an entire power system to simultaneously obtain the phasor measurements can be found in [16-18]. Here a brief description of this technique is provided below for the case of reference. Let y(t) represent a voltage or current in sine-cosine form where $\varepsilon(t)$ represents noise like signals

$$y(t) = Y_c \cos \omega_0 t + Y_s \sin \omega_0 t + \varepsilon(t)$$

Estimates of the values $\hat{Y}_c$ and $\hat{Y}_s$ can be obtained with a Fourier calculation where there are N samples per cycle or half-cycle of the fundamental frequency ω_0 (the nominal power system frequency, 50. or 60 Hz..

$$\hat{Y}_s = \frac{2}{N}\sum_{n=0}^{N-1} y(n\Delta T)\sin\omega_0 n\Delta T \qquad (1a)$$

$$\hat{Y}_c = \frac{2}{N}\sum_{n=0}^{N-1} y(n\Delta T)\cos\omega_0 n\Delta T \qquad (1b)$$

If y(t) is a pure sinusoid that equals $\cos(\omega_0 t + \delta)$, the complex number $\hat{Y}$ computed from eqns. 1a and 1b has the angle δ . If y(t) is a bus voltage the resulting complex voltage phasor can be thought as the state of the system for many applications. As the window of N samples moves in time [the sums in eqns. a and b taken from n=k to n=N+k-1] the angle of $\hat{Y}$ rotates. A reference angle can be established and the calculations made recursively by writing the equation with ϕ equal to $\omega_0 \Delta T$ and $\hat{Y}^L$ as the phasor computed using N sample values ending at sample L .

$$\hat{Y}^L = Y^{L-1} + (\tfrac{2}{N})[y_L - y_{L-N}\exp(jN\phi)]\exp(-jL\phi) \qquad (2)$$

The recursive calculation is computationally efficient since only one multiplication is performed in eqn.(2). Even more importantly, if the signal y(t) is a pure sinusoid at the nominal frequency ω_0, then $\hat{Y}^L$ is stationary in phase with a phase angle equal to the angle δ at the instant at which the recursion was begun. Currently, one limiting factor to this technology is the availability of an accurate sampling clock synchronism system. The use of a navigation broadcast system such as the global positioning system (GPS) has made it possible to produce synchronizing pulses once every second with accuracy of 1 microsecond.

3. The Proposed FHRCNN

A two-layer FHRCNN with hybrid training algorithm is developed to monitor voltage security in this section. A description of basic elements of two-layer FHRCNN (shown in Fig. 1) follows.

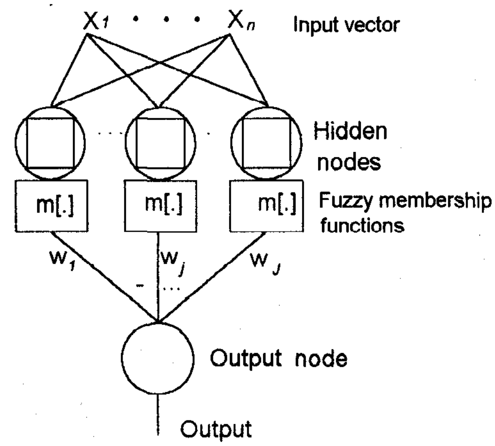

Fig. 1 A two-layer FHRCNN

Input Vector

$\underline{\hat{x}}$(=[x_1 , x_2 ,... , x_n]) is an input vector and should be properly chosen for the success of FHRCNN application in VSM. Since the GPS based synchronized voltage phasors provide the on-line information of system state, in this paper, we choose the set of voltage phasors of monitored buses as the input vector. Thus the input vector, $\hat{x}$, is of the following form:

$$\hat{x} = [|V_1|,\ \theta_1,\ |V_2|,\ \theta_2,\ \cdots,\ |V_n|,\ \theta_n]$$

Output variable

The magnitude of output variable is employed to label the voltage security levels. Suppose the study power system voltage security levels are classified into 5 levels according to the magnitude of the minimum singular value, s_n: very secure level ($s_n \geq$ 0.4450), secure level (0.4449 $\geq s_n \geq$ 0.3600), alert level (0.3599$\geq s_n \geq$ 0.1950), dangerous level (0.1949 $\geq s_n \geq$ 0.1000), very dangerous level (0.0999 $\geq s_n >$ 0.0). Of course, the determination of range of the minimum singular value depends heavily on the specific power system under operation. On possible way to do this is to extensively conduct simulations off-line for the study power system under various operating conditions to statistically determine the range. We use five integers to label the 5 levels as output values like this :

5 →very secure level
4 →secure level
3 →alert level
2 →dangerous level

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1 →very dangerous level

I - O mapping

The relationships between input vector and output variable of FHRCNN can be described by the following equation.

$$output = \sum_{j=1}^{J} w_j m_j(\hat{x}) + \theta \tag{3}$$

where

$$m_j(\hat{x}) = \frac{vol_j}{vol_j + s_j^2 (vol_j(\hat{x}) - vol_j)} \tag{4}$$

$$vol_j = \prod_{i=1}^{n} (M_{ji} - m_{ji}) \tag{5}$$

$$vol_j(\hat{x}) = \prod_{i=1}^{n} \max(M_{ji} - m_{ji}, x_i - m_{ji}, M_{ji} - x_i) \tag{6}$$

And, w_j, θ, s_j, M_{ji}, m_{ji} : scalar parameters adjusted by hybrid training algorithm.

Hybrid Training Algorithm

The supervised decision-directed learning (SDDL) algorithm and back-propagation (BP) algorithm are combined to train FHRCNN. The SDDL is based on an approach that divides the input vector space into proper subsets (i.e. hyperrectangles). Each hyperrectangle, corresponding to a hidden node, is n-dimensional and defined by $[m_{j1}, M_{j1}] \times \cdots \times [m_{jn}, M_{jn}]$ in R^n space. Once the number of hyperrectangles and initial parameters, m_{j1}, M_{j1}, $\cdots$, m_{jn}, M_{jn}, are determined by SDDL. The BP algorithm is used to adjust parameters, w_j, θ, s_j, M_{ji}, m_{ji}, such that the following error function is minimized.

$$Error = \sum_p E_p = \sum_p \frac{1}{2}\left(Out_p - t_p\right)^2 \tag{7}$$

where

t_p : desired output value of the p-th input vector,
Out_p : output value from FHRCNN.

A detailed description of the hybrid training algorithm is given in [20].

IF-THEN Rules

After sufficient training, the synaptic of a trained FHRCNN with hidden nodes can be utilized to extract the classification knowledge which are then represented as a set of IF-THEN rules such as the following examples:

IF ($\hat{x} \in HR_1$), THEN output is 5.
IF ($\hat{x} \in HR_2$), THEN output is 4.
IF ($\hat{x} \in HR_3$), THEN output is 3.
IF ($\hat{x} \in HR_4$), THEN output is 2.
IF ($\hat{x} \in HR_5$), THEN output is 1.

Where HR_j represent an n-dimensional hyperrectangle defined by $[m_{j1}, M_{j1}] \times [m_{j2}, M_{j2}] \times \cdots \times [m_{jn}, M_{jn}]$, j=1,2, ... , 5.

4. The Adopted Voltage Security Index and Weak Bus Identification

The goal of a static voltage security index is to measure how "close" a specific operating point is to the point of voltage collapse, i.e. to estimate the steady state voltage stability margin of the power system. One suggestion for a static voltage security index is to use the minimum singular value of the power flow jacobian matrix. The use of this index, obtained from a singular value decomposition of the power flow jacobian matrix, has been proposed and verified by Tiranuchit and Thomas in [3]. In this paper, the minimum singular value, s_n, and its corresponding (righ and left) singular vector, R_n, L_n, are adopted to obtain the attributes of training and test patterns for FHRCNN.

Consider the following well-known linear power flow equation,

$$\begin{bmatrix} \Delta P \\ \Delta Q \end{bmatrix} = J \begin{bmatrix} \Delta\theta \\ \Delta V \end{bmatrix} \tag{8}$$

Where P and Q are the active and reactive power, respectively, θ and V are the node angles and voltage magnitudes, respectively, and J is the Jacobian matrix of power flow equations. According to Eq. (6), The effect on the $[\Delta\theta , \Delta V]^T$ vector of a small change in the active and reactive power injections can be rewritten as

$$\begin{bmatrix} \Delta\theta \\ \Delta V \end{bmatrix} = J^{-1} \begin{bmatrix} \Delta P \\ \Delta Q \end{bmatrix} \tag{9}$$

The singular value decomposition is applied to the power flow Jacobian matrix, J. The matrix $J_{n\times n}$ then has form

$$J = LSR^T = \sum_{i=1}^{n} L_i S_i R_i^T \tag{10}$$

where L and R are n by n orthonormal matrices, the singular vector L_i and R_i are the columns of the matrices L and R, respectively, S is a diagonal matrix, and s_i is a singular value of matrix J.. As a result, Eq. (9) can be rewritten as

$$\begin{bmatrix} \Delta\theta \\ \Delta V \end{bmatrix} = RS^{-1}L^T \begin{bmatrix} \Delta P \\ \Delta Q \end{bmatrix}$$

$$= [R_1, R_2, ...R_n] \begin{bmatrix} s_1^{-1} & 0 & . & 0 \\ 0 & s_2^{-1} & & . \\ . & & . & 0 \\ 0 & . & 0 & s_n^{-1} \end{bmatrix} [L_1, L_2, ...L_n]^T \begin{bmatrix} \Delta P \\ \Delta Q \end{bmatrix} \tag{11}$$

where $s_1 \geq s_2 \geq s_3 \geq \cdots \geq s_n \geq 0$. From Eq. (11), if the minimum singular value, s_n, is equal to zero then the Jacobian matrix is singular and no power flow solution can be obtained. At the point where $s_n = 0$ is called a Static Bifurcation Point which is associated with voltage collapse phenomena [3]. Therefore, the smaller of the magnitude of s_n is, the closer to voltage collapse of the operating point is.

If we let

$$\begin{bmatrix} \Delta P \\ \Delta Q \end{bmatrix} = L_n \tag{12}$$

where L_n is the last column of L, then from Eq. (11)

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$$\begin{bmatrix} \Delta\theta \\ \Delta V \end{bmatrix} = s_n^{-1} R_n \qquad (13)$$

where R_n is the last column of R.

A summary of the above analysis is :

1. The minimum singular value, s_n, is an indicator of the proximity to the steady-state voltage stability limit;
2. The right singular vector, R_n, corresponding to s_n , indicates sensitive voltages (and angles).
3. The left singular vector, L_n, corresponding to s_n, indicates the most sensitive direction for changes of the active and the reactive power injections.

In this paper, we focus on the right singular vector, R_n, indicating sensitive voltages. Let

$$R_n = [r_1, r_2, \cdots, r_m, r_{m+1}, \cdots, r_n]^T \qquad (14)$$

where r_i, i=1, 2, ... , m are the elements which correspond to bus angle changes in vector R_n and r_i, i=m, m+1, ..., n are the elements which correspond to bus voltage magnitude change in vector R_n. The weakest bus would imply the largest value of r_i, i=m, m+1, ..., n, i.e. the largest change in voltage magnitudes. As a result, if bus k is the weakest node, then

$$r_k = \max_{i \in J_L} \{r_i\} \qquad (15)$$

where J_L is a set of all load buses. Based on the value of (index) r_i , the system buses may be arranged in order of weakness.

Training and test patterns of FHRCNN for VSM have been designed according to the above analysis. The minimum singular value, s_n, is employed to classify voltage security level. The right singular vector, R_n, is used to identify weak buses, and the location and number of PMUs to be installed in power system is determined according to the ranking of weak buses under heavy load condition. That is, we install PMUs in weak buses to monitor voltage security. Moreover, the voltage phasor measurements from PMU form the input vector of FHRCNN.

5. Numerical Example and Results

The IEEE 30-bus system with PMUs (shown in Fig. 2) was used to test the effectiveness of FHRCNN for VSM.

Fast calculations of the minimum singular value and corresponding singular vector based on [6] were adopted to prepare for the training patterns and test patterns. The 2500 training patterns and 500 test patterns were generated from a extensive power flows by considering random load changes (light load to critical load), effects of on-load tap changers (OLTCs), generator power limits (reactive power limits on generators), VAR compensators, and various contingencies.

The simulation program were developed on a SUN SPARC II in C++ and MATLAB. The power flow results of critical load conditions is shown in Table 1. Under critical

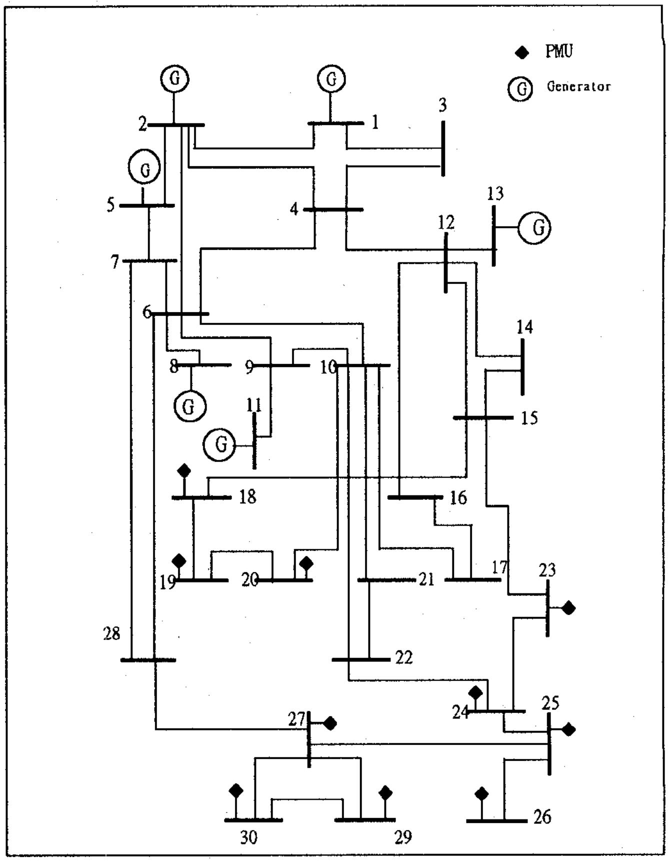

Fig. 2 IEEE 30-bus system with 10 PMUs

load condition, all generator buses (PV) except the swing bus are converted to PQ buses.

10 phasor measurement units (PMUs) were installed on bus 30, 26, 29, 25, 27, 24, 23, 19, 18, 20 based on weak bus ranking of the test system under heavy load condition. The result of the weak bus ranking under heavy load condition is presented in Table 2.

Table 1 power flow results under critical load condition
(minimum singular value=0.0068)

Bus	Type	voltage	angle	P_g	Q_g	P_d	Q_d
1	1	1.060	0.000	4.748	2.798	0.000	0.000
2	3	0.912	-9.300	0.400	0.500	0.394	0.230
3	3	0.852	-13.980	0.000	0.000	0.036	0.018
4	3	0.812	-17.417	0.000	0.000	0.114	0.024
5	3	0.760	-30.020	0.000	0.400	1.507	0.304
6	3	0.778	-21.462	0.000	0.000	0.000	0.000
7	3	0.752	-26.298	0.000	0.000	0.344	0.164
8	3	0.767	-23.206	0.000	0.400	0.462	0.456
9	3	0.750	-30.853	0.000	0.000	0.000	0.000
10	3	0.720	-36.209	0.000	0.190	0.087	0.030
11	3	0.811	-30.853	0.000	0.240	0.000	0.000
12	3	0.720	-33.766	0.000	0.000	0.169	0.113
13	3	0.764	-33.766	0.000	0.240	0.000	0.000
14	3	0.689	-36.712	0.000	0.000	0.093	0.024
15	3	0.680	-37.064	0.000	0.000	0.124	0.037
16	3	0.703	-35.721	0.000	0.000	0.052	0.027
17	3	0.703	-36.753	0.000	0.000	0.136	0.087
18	3	0.665	-39.178	0.000	0.000	0.048	0.013
19	3	0.664	-39.759	0.000	0.000	0.143	0.051
20	3	0.671	-39.038	0.000	0.000	0.033	0.010
21	3	0.690	-37.693	0.000	0.000	0.264	0.169
22	3	0.691	-37.654	0.000	0.000	0.000	0.000

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23	3	0.661	-38.415	0.000	0.000	0.048	0.024
24	3	0.656	-38.990	0.000	0.043	0.131	0.101
25	3	0.648	-37.677	0.000	0.000	0.000	0.000
26	3	0.603	-39.330	0.000	0.000	0.052	0.034
27	3	0.664	-35.908	0.000	0.000	0.000	0.000
28	3	0.761	-22.894	0.000	0.000	0.000	0.000
29	3	0.610	-40.619	0.000	0.000	0.036	0.013
30	3	0.579	-44.380	0.000	0.000	0.160	0.028

* type 1:swing bus, 2: PV bus, 3: PO bus
** PV buses change sequence: bus {13, 11, 2, 5, 8}
*** ___ input variables from PMU

Table 2 Weak buses ranking under heavy load condition

Rank	r_i index Bus	r_i	voltage	angle	load demand MW	MVAR	PMU
1	30	0.261	0.752	-34.979	15.9	2.8	+
2	26	0.256	0.766	-31.953	5.3	3.6	+
3	29	0.250	0.775	-32.717	3.6	1.4	+
4	25	0.231	0.800	-30.909	0.0	0.0	+
5	27	0.220	0.815	-29.719	0.0	0.0	+
6	24	0.218	0.804	-31.819	13.1	10.1	+
7	23	0.214	0.817	-31.672	4.8	2.4	+
8	19	0.212	0.815	-32.496	14.3	5.1	+
9	18	0.211	0.820	-32.200	4.8	1.4	+
10	20	0.208	0.822	-31.970	3.3	1.0	+
11	15	0.202	0.838	-30.959	12.3	3.8	-
12	22	0.200	0.876	-28.943	0.0	0.0	-
13	21	0.199	0.827	-30.936	26.2	16.8	-
14	14	0.198	0.848	-30.855	9.3	2.4	-
15	17	0.193	0.841	-30.391	13.5	8.7	-
16	16	0.192	0.852	-29.957	5.3	2.7	-
17	10	0.188	0.851	-29.904	8.7	3.0	-
18	12	0.183	0.876	-28.943	16.8	11.3	-
19	13	0.179	0.913	-28.943	0.0	0.0	-
20	9	0.167	0.874	-26.132	0.0	0.0	-
21	11	0.161	0.928	-26.132	0.0	0.0	-
22	28	0.130	0.842	-20.080	0.0	0.0	-
23	8	0.121	0.848	-20.225	42.0	42.0	-
24	6	0.117	0.855	-18.858	0.0	0.0	-
25	7	0.112	0.838	-22.297	34.2	16.3	-
26	4	0.102	0.875	-15.634	11.4	2.4	-
27	5	0.097	0.852	-24.557	131.9	26.6	-
28	3	0.085	0.905	-12.704	3.6	1.8	-
29	2	0.053	0.958	-8.460	32.6	19.0	-

The voltage security level is divided into 5 levels based on the magnitude of the minimum singular value : very secure level ($s_n \geq 0.4450$), secure level ($0.4449 \geq s_n \geq 0.3600$), alert level ($0.3599 \geq s_n \geq 0.1950$), dangerous level ($0.1949 \geq s_n \geq 0.1000$), and very dangerous level ($0.0999 \geq s_n \geq 0.0$). Therefore, the training patterns were divided into five clusters according to the learning characteristics of hybrid training algorithm of FHRCNN to train the FHRCNN. Training parameters of the network are shown in Table 3.

After training , **FHRCNN** extracted **21 IF-THEN** rules for **VSM**, which were represented as hyperrectangulars (i.e. hidden nodes) in input vector space. These IF-THEN rules can provide utility operators with an expert-system like tool to analyze bus voltage phasor sensitivity to the minimum singular value. Table 4 shows the lower and upper bounds of hyperrectangles (IF-THEN rules) for various voltage security levels. A look of Table 4 reveals that the lower

Table 3 Training parameters of FHRCNN for 30-bus system

No. of dimension of input data	20	number of clusters	5
No. of records of training data	2,500	number of rules	21
No. of record of testing data	500	number of iteration	10,000
value of learning rate	4.0000e-04	bias	0.23~0.27
value of tolerance	1.0000e-04	weight	0.1~0.21

range of voltage limits for insecurity levels seems to be extremely low compared to practical system. The reason is that the range of the magnitude of s_n determine the range of voltage limits. And it should be emphasized that the range of the magnitudes of s_n for each security level selected above is just for the ease of illustration of numerical test. We suggest that the range of s_n for each security level should be determined by conducting extensive power flows taking into account of various situations as the proposed scheme is applied to the realistic power system.

A multi-layer feed-forward artificial neural network (ANN) with back-propagation (BP) learning algorithm has been applied for voltage stability monitoring [12-14]. For a comparison, we conducted simulation results on three-layer ANN with back-propagation algorithm using the same training set and test set. The comparison between classification rates of FHRCNN and ANN are shown in Table 5.

The supervisory control and data acquisition (SCADA) system is used for power system operation and control. Automatic monitoring and control features have long been a part of the SCADA system. Therefore, for a comparison, we approach to voltage security monitoring using simulated P/Q measurements from SCADA as an input vector for FHRCNN. The comparison among the classification rates of FHRCNN for PMU measurements and SCADA P/Q measurements are shown in Table 6. In the above numerical test, the FHRCNN is tested with the same number of dimensions of input vector, same number of training and test patterns for PMU and SCADA.

From numerical examples and test results, one has the following observations :

(1) FHRCNN has a pretty high classification rate.
(2) FHRCNN has better performance than traditional ANN.
(3) FHRCNN combined with PMUs has better performance than FHRCNN combined with SCADA.
(4) FHRCNN combined with PMUs has the potential to be an effective on-line tool for VSM.

6. Conclusions

In this paper, we have demonstrated the success of properly trained FHRCNN for voltage security monitoring based on synchronized phasor measurements. Extensive

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Table 4 The upper(U) and lower(L) bounds of hyperrectangles

	Very dangerous level Rule 1~3				Dangerous level Rule 4~8				Alert level Rule 9~14				Secure level Rule 15~18				Very secure level Rule 19~21			
	voltage magnitude		voltage angle		voltage magnitude		voltage angle		voltage magnitude		voltage angle		voltage magnitude		voltage angle		voltage magnitude		voltage angle	
Bus	L	U	L	U	L	U	L	U	L	U	L	U	L	U	L	U	L	U	L	U
30	0.578	0.822	-0.774	-0.489	0.699	0.93	-0.645	-0.399	0.76	0.954	-0.628	-0.287	0.889	0.978	-0.439	-0.221	0.909	1	-0.356	-0.2
29	0.609	0.831	-0..708	-0.459	0.723	0.944	-0.596	-0.321	0.784	0.964	-0.583	-0.272	0.901	0.982	-0.409	-0.216	0.92	1	-0.332	-0.2
26	0.603	0.827	-0.684	-0.451	0.715	0.947	-0.398	-0.317	0.793	0.968	-0.569	-0.27	0.905	0.969	-0.409	-0.211	0.925	1	-0.332	-0.2
25	0.648	0.855	-0.657	-0.437	0.897	0.966	-0.566	-0.308	0.821	0.984	-0.549	-0.263	0.914	0.985	-0.397	-0.211	0.951	1	-0.324	-0.2
27	0.664	0.864	-0.626	-0.418	0.773	0.967	-0.533	-0.295	0.824	0.982	-0.528	-0.252	0.934	0.982	-0.371	-0.208	0.947	1	-0.303	-0.2
24	0.656	0.873	-0.68	-0.453	0.75	0.98	-0.566	-0.321	0.836	0.999	-0.569	-0.275	0.937	1.001	-0.412	-0.215	1.007	1.066	-0.336	-0.2
23	0.661	0.871	-0.67	-0.447	0.756	0.975	-0.586	-0.316	0.834	0.993	-0.561	-0.27	0.932	0.995	-0.406	-0.213	0.952	1.06	-0.331	-0.2
19	0.664	0.874	-0.693	-0.46	0.756	0.979	-0.579	-0.325	0.837	0.996	-0.579	-0.277	0.936	1	-0.414	-0.217	0.957	1.065	-0.464	-0.2
18	0.665	0.873	-0.683	-0.454	0.759	0.976	-0.596	-0.321	0.835	0.993	-0.571	-0.273	0.933	0.997	-0.41	-0.215	0.954	1.062	-0.334	-0.2
20	0.676	0.883	-0.681	-0.444	0.758	0.987	-0.605	-0.321	0.851	0.999	-0.57	-0.274	0.944	1.007	-0.426	-0.146	0.963	1.071	-0.351	-0.146

Table 5 The classification rates of FHRCNN and ANN for IEEE 30-bus system

Network Type	Pattern	Voltage Security Level				
		Very Secure	Secure	Alert	Dangerous	Very Dangerous
FHRCNN	Training set	100%	100%	100%	100%	100%
	Test set	97.72%	98.17%	98.30%	98.54%	98.02%
ANN	Training set	93.18%	95.61%	94.75%	97.13%	95.08%
	Test set	84.21%	88.78%	89.00%	87.27%	87.32%

Table 6 The classification rates of FHRCNN input vector selected based on synchronized phasor measurements (PMUs) and SCADA systems

Device	Input Vector (20 dimensions)	Pattern	Voltage Security Level				
			Very Secure	Secure	Alert	Dangerous	Very Dangerous
PMU	V_n, θ_n, n= 30, 26, 29, 25, 27, 24, 23, 19,18, 20	Training set	100%	100%	100%	100%	100%
		Test set	97.72%	98.17%	98.30%	98.54%	98.02%
SCADA	P_{dn}, Q_{dn} ,n=30,26, 29, 25, 27, 24, 23, 19, 18, 20	Training set	94.18%	95.30%	92.75%	93.53%	92.42%
		Test set	76.24%	78.78%	75.60%	77.27%	77.02%
	P_{gi} ,Q_{gi}i=2,5,8,13 P_{dk} ,Q_{dk} , k=30,29, 26, 24,20, 19	Training set	99.10%	98.25%	97.06%	95.13%	95.08%
		Test set	90.72%	89.98%	87.27%	86.45%	85.83%

testing was performed on the IEEE 30-bus system under various operating conditions. Accuracies in excess of 97% were also obtained for these testings. The FHRCNN was constructed off-line from simulated data. The computational burden proved to be quite reasonable, and larger system could be handled. Once the FHRCNN is constructed in off-line, the on-line VSM response is extremely fast. We suggest that a FHRCNN methodology can automate the process of transforming off-line simulation studies into on-line decision rules.

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Biographies

Chih-Wen Liu received the B.S. degree in electrical engineering from National Taiwan University in 1987, Ph.D. degree in electrical engineering from Cornell University in 1994. Since 1994, he has been with National Taiwan University, where he is associate professor of electrical engineering. His research interests include power system computer applications.

Chen-Sung Chang received the diploma in Electrical Engineering from National Taipei Institute of Technology. He is currently working toward his Ph.D. degree at National Taiwan University. His research interests include power system voltage stability and applications of artificial intelligence in power system .

Mu-Chun Su received the B. S. degree in electronics engineering from National Chiao Tung University, Taiwan, Republic of China, in 1986, and the M. S. and Ph.D. degree in electrical engineering from University of Maryland, College Park, MD, in 1990 and 1993, respectively. He was the 1992 IEEE Franklin V. Talor Award recipient for the most outstanding paper co-authored with Dr. N. DeClaris. He is an Associate Professor of Electrical Engineering at Tamkang University, Taiwan, Republic of China. His current interests include neural networks, fuzzy systems, computer-aided medical systems, pattern recognition and speech processing.

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