Mansoura Engineering Journal, (MEJ), Vol. 24, No. 2, June 1999. E. 1

KOHONEN NEURAL NETWORK BASED APPROACH FOR VOLTAGE SECURITY MONITORING OF POWER SYSTEMS

مدخل شبكة كوهين العصبية لمراقبة أمان الجهد بنظم القوى الكهربية

M. E. El-Said **E. Abd-Raboh**

Electrical Power & Machines Dept., Faculty of Engineering, Mansoura University

ملخص البحث :يقدم البحث مدخلا جديدا لمراقبة درجة أمان الجهد بنظم القوى الكهربية باستخدام شبكة كوهين العصبية. تعتمد نمذجة الشبكة العصبية لكوهين على مبدأ التعلم الذاتى للخلايا العصبية لطبقة كوهين وقدرتها فى التعرف على ملامح اشارات الدخل. تم إعداد خوارزم لتدريب الشبكة العصبية لكوهين بمساعدة بيانات تحليل سريان القدرة وطريقة أقل قيمة مفردة وذلك لكى تعطى مؤشرات الأمان للجهد عند نقط التحميل المختلفة وكذلك للنظام ككل. تم أختبار مقدرة شبكة كوهين العصبية المقترحة تحت ظروف تشغيل عديدة ومختلفة بالنسبة لزيادة الأحمال وحالات الخروج المفاجىء لمحطات التوليد وخطوط النقل، وقد تم تطبيق الطريقة المقترحة على نظام قوى كهربى من النوع القياسى IEEE 30-bus ، حيث أظهرت النتائج مدى مقدرتها فى مراقبة درجة أمان الجهد فى ظل ظروف التشغيل العادية والغير عادية لنظم القوى الكهربية.

ABSTRACT:

This paper utilizes the artificial neural network of Kohonen for monitoring voltage security of electric power systems. The Kohonen model is based on the self-organization feature mapping technique that transforms input patterns into neurons on the two dimensional grid. By using the power flow analysis and the minimum singular value method a Kohonen Neural Network (KNN) is trained to give the expected values of voltage stability index at each load bus as well as for the whole system. Special emphasis is placed on the selection of input information and analysis of the network output results. The generalization capability of the KNN under various operating conditions has been tested. Test results on IEEE 30-bus system show the effectiveness of the proposed approach for monitoring voltage security in power systems.

KEY WORDS: Voltage security monitoring, Artificial Neural Networks, Kohonen self organizing networks.

Accepted May 2, 1999

1. INTRODUCTION

Voltage instability in power systems has gained increasing attention as a result of the voltage collapse incidents. The phenomenon is closely related to a shortage of reactive power supply, which is characterised by a progressive decrease in voltage magnitude, starting at a particular location and then spreading out across the whole system causing a complete or partial voltage collapse in the power system [1].

At present, one of the major goals is to develop computer-aided procedures for use in real time applications to evaluate voltage security of the power system. In particular, two important functions should be implemented, the voltage stability monitoring and the voltage stability assessment [2]. Using appropriate indicators, computed by on-line data from the state estimator, the monitoring function evaluates the status of voltage stability for the present operating point of the system. The assessment function predicts the voltage stability of a near future power system condition and involves the ability to analyse hundreds of contingencies.

In recent years, a great deal of effort has been devoted to the development of practical tools to analyse the static voltage stability of power systems. A number of analytical methods have been proposed in the literature for voltage stability analysis. These methods can be classified as, Power flow -based methods [3,4]; voltage collapse proximity indicators [5]; minimum singular value method [6]; modal analysis [7]; and energy-based sensitivity method [8].

In more recent years, ANNs have been proposed as an alternative method for solving certain difficult power system problems [9,10] where the conventional techniques have not achieved the desired speed, accuracy and efficiency. However, most of the published work in the area of voltage stability [11,12] has utilized multilayer perceptron networks trained by back propagation for quantifying voltage stability margins. However, approaches which simulate back propagation networks have some shortcomings, particularly in respect of the relatively long time needed for learning, sticking at local minima and accuracy is highly dependent on the number of training data. Thus, a large number of inputs are needed, including contingency and system configuration. This obviously poses problems in practical applications.

As an attractive alternative to the multilayer perceptron, KNNs offer some advantages, particularly in the applications of clustering type problems. Results of applications to power system static security assessment and contingency analysis are very encouraging [13,14]. KNN is an unsupervised neural network which maps high dimensional input vectors into a two-dimensional surface outputs. Input patterns with similar features, which contain sufficient information about the voltage stability of power systems, are clustered together in the output map. The weight vectors associated with the output map neurons are then used to find the voltage stability margin. Thus, power system conditions can be effectively monitored in terms of voltage instability and effective preventive control actions can be implemented to enhance the overall system performance.

2. VOLTAGE STABILITY INDICATOR

The aim of this section is to illustrate a comprehensive procedure for voltage stability analysis and to define voltage-collapse proximity indicator suitable for on-line voltage stability monitoring. The purpose of voltage stability indicator is to quantify how a particular operating point is close to the point of voltage collapse. In this paper, the minimum singular value (MSV) method [6], is employed as a reference with which the proposed KNN-based approach will be compared. The MSV is a mathematical measure of the distance between the studied operating point and the steady state voltage stability limit. The two singular vectors obtained together with the MSV give a valuable information about the studied operating point of the power system. In this section, a brief introduction to the method is given.

The linear power flow equations under normal operating conditions are given by

$$\begin{bmatrix}\Delta P\\ \Delta Q\end{bmatrix}=[J]\begin{bmatrix}\Delta\theta\\ \Delta V\end{bmatrix} \qquad (1)$$

Now, if the singular value decomposition is applied to the power flow Jacobian matrix , J , the so obtained matrix decomposition can be written as

$$J = U\Sigma V^T = \sum_{i=1}^{n}\sigma_i.u_i.v_i^T \qquad (2)$$

where U and V are n by n matrices, the singular vectors ui and vi are the columns of the matrices U and V respectively, and Σ is a diagonal matrix with

$$\sum(J)=\text{diag}[\sigma_i(J)]\ ,\ i=1,2\ .....,n \qquad (3)$$

where $\sigma i \geq 0$ for all i. The diagonal elements in the matrix Σ are usually ordered so that $\sigma_1 \geq \sigma_2 \geq ..... \geq \sigma_n \geq 0$. The MSV, σn (J), is a measure of how the system operating point close to singularity of the Jacobian matrix. If the minimum singular value is equal to zero, then the studied matrix is singular and no power flow solution can be obtained. The effect on the $[\Delta\theta\ \ \Delta V]^T$ vector of a small change in the active and reactive power injections can be written as

$$\begin{bmatrix}\Delta\theta\\ \Delta V\end{bmatrix}=[J]^{-1}\begin{bmatrix}\Delta P\\ \Delta Q\end{bmatrix}=\sum_{i=1}^{n}\sigma_i^{-1}.v_i.u_i^T.\begin{bmatrix}\Delta P\\ \Delta Q\end{bmatrix} \qquad (4)$$

Close to a voltage collapse point, when a singular value is almost zero, the system response is determined by the MSV σ_n^{-1}, with singular vectors vn and un. Hence

$$\begin{bmatrix}\Delta\theta\\ \Delta V\end{bmatrix}=\sigma_n^{-1}.v_n.u_n^T\begin{bmatrix}\Delta P\\ \Delta Q\end{bmatrix} \qquad (5)$$

let

$$\begin{bmatrix}\Delta P\\ \Delta Q\end{bmatrix}=u_n \qquad (6)$$

where un, vn are the last column of U and V respectively, then

$$\begin{bmatrix}\Delta\theta\\ \Delta V\end{bmatrix}=\sigma_n^{-1}.v_n \qquad (7)$$

From the above analysis, the following remarks can be made
(i) The smallest singular value, σn, is an indicator to the static voltage stability limit.
(ii) The weak buses can be ordered by using the elements of the right singular vector, vn, corresponding to the σn. An indicator for the weakness of a bus is defined as

$$VSIj = Vj / \max \{vi\}, i=1,2,....n \tag{8}$$

where V_j is the element of vector V_n corresponding to the voltage of bus j. Therefore, if VSIj is less than a threshold value, the corresponding bus belongs to the critical bus. The above defined indicators allow an implementation of voltage stability monitoring and control for the power system.

3. KOHONEN SELF-ORGANIZING NEURAL NETWORK

The KNN belongs to a class of unsupervised neural networks which are very effective for pattern classification problems [15]. There is no target output for evaluating an error function in these self organising networks. The learning of the synaptic weights is unsupervised, which means that, upon presentation of new input vectors, the network determines these weights dynamically, such that input vectors which are closely related will excite neurons which are close together or clustered.

3.1 Architecture of KNN

The KNN is an array of specific number of neurons. If these neurons are arranged on a grid in a plane, the network is called two-dimensional, since this network maps high dimensional input vectors into a two-dimensional surface. Figure 1 shows a Kohonen network which consists of an input layer and a two-dimensional Kohonen layer. The network maps an n-dimensional input vectors into two dimensions in a nonlinear way. The input vectors are fully connected to each Kohonen neuron. With the KNN, input data with similar features are mapped to continuos clusters after enough input vectors have been presented. The similarity between input vectors can be measured by the Euclidean distance between two input patterns. The algorithm that forms the output map requires a neighborhood to be defined around each neuron. This neighborhood slowly decreases in size as the learning algorithm proceeds and finally just one neuron is fired to give the output of the network as shown in figure 1.

3.2 The Training Algorithm for KNN

During the learning phase the input vectors are presented randomly. At each step of the learning process, every neuron of the network calculates a scalar activation function which depends on the input vector and on its own weight vector. This function is chosen to represent a distance $\|.\|$ between the input vector and the weight vector of the neuron under consideration. Possible choices are the Euclidean distance or the scalar product [15]. Kohonen proposed a simplified rules for carrying out the unsupervised learning. This method is based on firing the neuron with the weight vector closest to the input pattern. Therefore, the weights of fired neuron as well as the weight vectors of its neighborhood is updated. Now let the input vector of dimension n is given by

$$X(t) = \left(X_1(t), X_2(t), \ldots\ldots, X_n(t)\right)^T \tag{9}$$

where t is the input pattern number (t =1, 2, 3,...., tmax), tmax is the number of input patterns and n is the number of input units. The input of output neuron i at learning step k can be expressed as

$$I_i(k)=\sum_j X_j(t).w_{ij}(k) \tag{10}$$

where wij (k) is the weight between neurons i and j.
The output of output neuron i at learning step k is given by

$$O_i(k)=\sigma(I_i(k)) \tag{11}$$

where σ(*) is a nonlinear function (see figure 2) such that

$$\sigma(I_i(k))=\begin{cases}1 & \text{if} \quad I_i(k)>1 \\ I_i(k) & \text{if} \quad 0\le I_i(k)\le 1 \\ 0 & \text{if} \quad I_i(k)<0\end{cases} \tag{12}$$

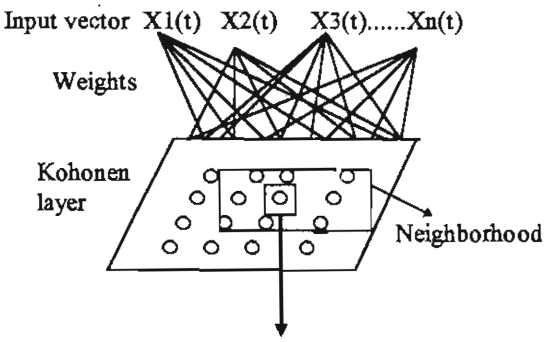

Fig. 1 Kohonen neural network

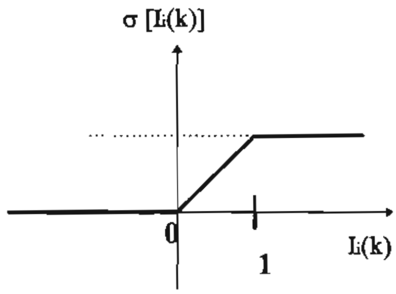

Fig. 2 Output function of Kohonen

Once the neural network is trained, the input pattern fires the output neuron closest to the input pattern. The weights between output neurons are changed by:

$$\Delta w_{ij}(k)=\alpha(k).(I_i(k).X_j(t)-O_i(k).w_{ij}(k)) \tag{13}$$

where α(k) is a decreasing function with learning step k.

$$0<\alpha(k)<1 \tag{14}$$

In the self organizing networks, there are several output neurons that respond to the input pattern. Among the output neurons, the neuron with the largest output becomes the winnered neuron defined as nw(k). The input and output of neurons in equation (13) are determined by the Euclidean norm, i.e. the distance between neurons such as

$$d_i=\|n_i-n_w(k)\| \tag{15}$$

where, $\|*\|$ is the Euclidean norm, and ni is the neuron i. If the following equation is satisfied,

$$d_i\le\gamma(k) \tag{16}$$

where γ(k) is the distance from nw(k) at learning step k, then we have

$$Ii(k) = 1, \quad Oi(k) = 1 \tag{17}$$

therefore, equation (13) becomes

$$\Delta w_{ij}(k) = \alpha(k)(X_j(t) - w_{ij}(k)) \tag{18}$$

Otherwise,

$$Ii(k) = 0, \quad Oi(k) = 0 \tag{19}$$

From equation (19), equation (13) becomes

$$\Delta wij(k) = 0 \tag{20}$$

Neurons around nw(k) satisfying equation (16) are called "topological neighborhood".

The following summarises an algorithm used in this paper for training the KNN:
Step 1: Set learning step k = 0 and initialize weights wij(0) between input and output.
Step 2: Set k = k+1.
Step 3: Present new input vectors to the network.
Step 4: Compute the distance to all neurons from an input vector di(k) as follows

$$d_i = \|X - wi\| = \sum_j (X_j(t) - w_{ij}(k))^2 \tag{21}$$

Step 5: Find the winning neuron nw(k) that has the closest distance, d*(k), to input pattern X(t), where d*(k) is given by

$$d^*(k) = \min(di), \quad i \, \varepsilon \text{ (Kohonen layer)} \tag{22}$$

Step 6: Find topological neighborhood around nw(k) using Eqn. (16).
Step 7: Update weight vectors of a winning neuron nw(k) and topological neighborhood as

$$wij(k) = wij(k) + \alpha(k)\,(Xj(t) - wij(k)) \tag{23}$$

Step 8: Iterate the procedure from step 2.

3.3 Input Information for KNN

One of the key issues for the application of ANN in power system for voltage stability monitoring and control is how to select a limited input variables, with salient features as the input information of the neural network. Studies and utility experiences indicate that voltage instability is mainly driven by heavily loading or by system contingencies. Therefore, the following variables are important for voltage instability and are used as input to the KNN. The input vector is given by

$$X = \left[P^T, Q^T, V^T, P_G^T, Q_G^T, V_G^T, I_C^T\right]^T \tag{24}$$

where P, Q, V of dimensions (nx1) and PG, QG, VG of dimensions (nGx1) are the vectors of real powers, reactive powers and voltage magnitudes at the n load buses and nG generating buses, respectively. The input subvector Ic is given by

$$I_C = \left[I_1, I_2, \ldots\ldots\ldots\ldots, I_C\right]^T \tag{25}$$

takes into account contingencies that may directly influence the voltage stability, for a given operating point.

4. TEST RESULTS

The proposed approach is tested on IEEE-30 bus system. The system includes six generation buses, 21 load buses and 41 transmission lines.

4.1 Training of KNN

To determine the input vector of the KNN, a load flow analysis of the system was performed. In the training phase, a large number of operating conditions related to voltage stability are considered, including:
(i) different loading conditions.
(ii) different generation/load patterns.
(iii) single contingency analysis.

For each operating point, the MSV method is utilized to find the voltage stability margin and to analyze the properties of clusters in the Kohonen output map. The number of neurons of the Kohonen layer depends on the application, and the actual number should be large enough to be capable of forming sufficient clusters of input vector. For the IEEE-30 bus system, tested in this paper, three variables are considered for each load/generation bus. In order to take into account generation and lines outage, 6 and 41 input variables are included, respectively. For this test system, bus 1 is a slack bus and that buses 6, 9, 22, 25, 27 and 28 are floating buses. Therefore, voltage, active and reactive power for these buses are omitted from the input vector. Thus, there are a total of 119 inputs which include 72 giving bus information and 47 giving single generator and line outage. The two-dimensional array of Kohonen layer consists of 60 x 60 output neurons. In other words the different operating conditions of the system are classified into 3600 patterns.

4.2 Interpretation of Results

After training, the neurons of the Kohonen network are clustered. The neurons of the same pattern belong to the same cluster. There are different types of clusters in the output map which represent different operating states of the system in terms of voltage stability. The first type of clusters groups all safe operating conditions created by load variation of 15% up to 18.5% from the base case, and in such cases no voltage stability problems exists. The second type of clusters represents the operating conditions in which the system faces severe voltage violation problems caused by load increase or contingencies. The third type of clusters represents the status of the system when the load is increased above 30 % from the base case.

To interpret the organization of the weight vectors, we note that, some of the neurons in Kohonen layer are associated with several input vectors, and some to none of the input vectors. However, the weight vectors for those neurons appear to represent feasible states of the power system, which can be understood as generalization from the learned vectors. The weight vectors themselves represent the weighted sum of a certain number of input vectors which form a cluster. The Euclidean distance between weight vector and input vector is the minimal distance between this input vector and any weight vector of the network. If we assume an voltage stability limit for each bus, the comparison of this limit to the corresponding weight vector component of neuron i indicates whether neuron i classifies system states that likely to violate this limit or not. When a test vector is applied into the trained KNN, one of the neurons in the Kohonen layer will be fired. The position of the fired neuron indicates the degree of voltage stability, on the other hand, weight vectors of the fired neuron associated with each load bus input can be used to identify the voltage stability margin at these buses.

Table 1 gives the voltage stability margin at selected load buses as calculated by the MSV method and the trained KNN method. The results show that, at certain operating state, the voltage stability margin at each bus is calculated with a good accuracy, helping system operators in monitoring voltage stability. Figure 3 shows the variation of system voltage stability margin as the system load increases. Test results have shown that the KNN-based approach can produce quite accurate estimation of voltage stability margins under diversified system operating conditions, except for very few of operating states very close to the collapse point. To test the ability of the proposed KNN in performing the voltage stability assessment function, a single-line outage contingency analysis was carried out. The assessment of each contingency involved a load flow analysis, necessary to form the set of inputs for the KNN. Table 2 illustrates the results of some selected cases for the values of minimum voltage stability index (VSImin), and its location bus, as calculated by MSV method and the proposed KNN method. Also, table 3 illustrates the ranking process for weak buses, based on voltage stability index , as the result of line outage from bus 8 to bus 28.

Table 1 Voltage stability margin at selected load buses for heavily loaded system.

Bus No	MSV	KNN
12	0.2715	0.2713
13	0.2684	0.2685
14	0.2355	0.2353
15	0.1972	0.1975
16	0.4444	0.4443
17	0.4235	0.4235
18	0.4136	0.4136
19	0.4179	0.418
20	0.3614	0.3612
21	0.3279	0.328
23	0.2756	0.2757
24	0.2637	0.2635
26	0.2349	0.2348
29	0.3979	0.3978
30	0.1608	0.1602

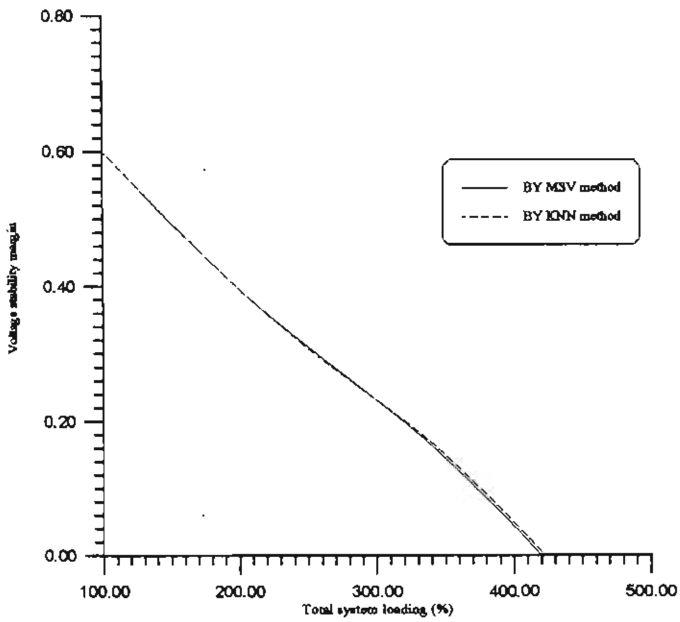

Fig. 3 Voltage stability margin change with total percentage system loading

Table 2 Results of Contingency analysis

Contingency	MSV method		KNN method	
Line outage	VSImin	Bus	VSImin	Bus
2 - 5	0.0776	5	0.0771	5
8 - 28	0.2969	30	0.2972	30
27 - 28	0.3175	30	0.3177	30
27 - 29	0.4754	29	0.4753	29
27 - 30	0.4567	30	0.4566	30

Table 3 Ranking process of weak buses with line outage from bus 8 to bus 28.

Rank	MSV	KNN
1	26	26
2	30	30
3	29	29
4	24	24
5	23	20

5. CONCLUSIONS

This paper presents the application of an artificial neural network of Kohonen for monitoring voltage security of electric power systems. The Kohonen model is based on the self-organization feature mapping technique that transforms input patterns into neurons on two dimensional grid. By using the power flow analysis and the minimum singular value method a

KNN is trained to give the expected values of voltage stability index at each load bus and also for the whole system. The generalisation capability of the KNN under various load and contingency conditions show that the approach can be applied on-line to practical systems to provide system operators with useful information about voltage security and control. Simulation results on IEEE 30-bus test system show that the proposed approach is promising in a sense that the mapping technique helps power system operators to monitor voltage security in power systems.

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