KOHONEN NEURAL NETWORK CLUSTERING FOR VOLTAGE CONTROL IN POWER SYSTEMS

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Abstrak

Pengklasteran sistem tenaga listrik sangat bermanfaat untuk tujuan pengendalian stabilitas tegangan. Bagaimanapun, metode-metode yang telah dikembangkan biasanya memiliki komputasi yang tidak efisien. Tulisan ini memaparkan teknik klaster bus baru menggunakan jaringan syaraf Kohonen untuk tujuan membentuk kelompok bus klaster pada sistem tenaga listrik dari sudut pandang kestabilan tegangan listrik. Dengan terbentuknya klaster bus ini maka pengaturan tegangan listrik pada jaringan listrik menjadi mudah dilakukan. Pada usulan algoritma Kohonen ini suatu sistem bus yang besar akan disekat-sekat menjadi kelompok bus kecil yang mempunyai koherensi V, θ, P dan Q. Jumlah maksimum klaster akan menjadi acuan berapa jumlah area kestabilan tegangan yang diperlukan untuk pengaturan. Teknik yang diusulkan ini diuji pada sistem IEEE 39 bus dengan mempertimbangkan dua kontingensi berupa penambahan beban dan putusnya talian menggunakan analisis keruntuhan tegangan. Hasil tes pembentukan klaster bus ini selanjutnya dibandingkan dengan algoritma Learning Vector Quantization (LVQ). Hasil penelitian menunjukkan bahwa teknik yang diusulkan menghasilkan empat klaster pembagian pada kontingensi penambahan beban dan tiga klaster pada kontingensi putus talian pada system IEEE 39 bus, sama seperti yang ditunjukkan oleh LVQ.

Kata kunci: kestabilan tegangan, klaster, Kohonen, learning vector quantization

Abstract

Clustering a power system is very useful for the purpose of voltage stability control. However, the methods have developed usually have computational inefficiency. This paper presents a new cluster bus technique using Kohonen neural network for the purpose of forming bus clusters in power systems from the voltage stability viewpoint. This cluster formation will simplify voltage control in power system. With this proposed Kohonen algorithm, a large bus system will be partitioned into a small bus groups that have a coherence V, θ, P and Q. The maximum number of area clusters will be formed need for voltage stability needed. The proposed technique was tested on IEEE 39 bus system by considering two contingency namely load increased and line outage by using voltage collapse analysis. This formation will be compared with the Learning Vector Quantization (LVQ) algorithm. The results showed the proposed technique produces four clusters on contingency load load increased and three clusters online outage contingency on IEEE 39 bus system as shown by the LVQ.

Keywords: clustering, Kohonen, learning vector quantization, voltage stability

1. INTRODUCTION

Voltage stability is concerned with the ability of the power systems to maintain acceptable voltages at all system buses under normal conditions as well as after being subjected to a disturbance. For the system to remain secure in real time situation, it is essential to monitor the system status with respect to load changes and contingencies and take preventive action every time a contingency drives the system towards insecure state [1]. Voltage instability phenomenon has been known to be caused by heavy loads where large amounts of real and reactive powers are transported over long transmission lines. It may occur at the operating loading condition when a system is subjected to a contingency. The probability

for a system to experience a voltage collapse resulting from the voltage instability condition is higher for weak areas or non-secure buses [2], [3]. Voltage instability incidence and hence power blackout can be avoided if identification of weak areas in a power network and voltage control are taken into account [2]-[4]. The need for fast control action so as to improve voltage stability calls for the formation of bus clusters or groups of buses in a power network. This is important because the information can be used for voltage control scheme in order to maintain power delivery to utility. The coherent bus clusters are formed in which the buses in a cluster are said to be coherent when the voltage and angle changes for these buses are the same for a particular contingency. Each cluster can therefore represent a group of coherent PV or PQ buses so as to form one sub-network of a large network [5]-[7]. By forming several sub-networks representing the entire power system, the size of the system can be reduced and therefore the computational efficiency of application program such as voltage control can be considerably improved. In this paper, the method for forming bus clusters is presented using a new clustering technique based on Kohonen neural network.

Many works have been carried out on bus clustering, for instance in voltage stability analysis where the sensitive lines in a system during stressed condition are identified and based on these lines the bus clusters are formed [2]. Clustering is also referred as a weak area partitioning which is determined based on the reduced load flow Jacobian determinant [6]. In this work, the weak areas are clustered by encircling the load and generator buses that are connected close to the critical bus. In [7], bus clusters are formed by utilizing the line stability factors for voltage stability analysis. A power network can be clustered into smaller networks containing buses that are closely connected [3], [8]. A group of load buses that have similar voltage and angle change are considered as electrically belonging to the same cluster. On the other hand, for load buses with voltages and angles not affected by load variations are considered as electrically distanced or weakly connected and therefore belong to different clusters [3], [8].

This paper presents the development of a new clustering technique using the Kohonen neural network for determining the bus clusters in power systems. The objective of the work is to form bus clusters in a power system based on the coherency of the buses. In the proposed technique, a disturbance is first created at a particular bus such as load increase or line outage. The coherent bus clusters are formed by considering values of voltage difference, angle difference, real and reactive power differences which are similar for buses within a cluster. In other words, the coherent buses that are grouped into a cluster are said to have similar voltage and angle changes as well as real and reactive power changes. Unsupervised learning method based on Kohonen neural network is also used to form the bus clusters by giving a good representation on the characteristic groups from the input data space [3]-[5], [9]. The proposed clustering technique was implemented on the IEEE 39-bus test system.

2. PROPOSED METHOD

The bus clusters are formed based on the coherent nature of buses in a smaller cluster by using the sensitivity information such as voltage magnitude and angle as well as real and reactive power differences. A bus that tolerates a higher increase in load is considered less sensitive as compared to a bus which tolerates a lower increase in load from its base load [10]. In order to create the cluster buses the Kohonen neural network will be proposed. The proposed method is described as follow.

2.1. Kohonen Neural Network

Kohenen network is an unsupervised neural network in which its input data with similar features are mapped to form clusters by competitive learning algorithm. The algorithm considers the Euclidean distance between two n-dimensional vectors which is measured by the similarity between input vectors. The distance of an input vector from each neuron i, D_i is given by,

$$D_i = \left\| W_{ij} - X \right\| = \sqrt{\sum_{j=1}^{n} \left(x_j - w_{ij} \right)^2} \qquad (1)$$

where X = $(x_1, x_2, \ldots x_n)^{\mathsf{T}}$ denotes an input vector
$w_{ij} = (w_{11}, w_{12}, \ldots w_{im})^{\mathsf{T}}$ denotes the weight vector of the i-th neuron

The Kohonen with a minimum distance is called as the winner. In other words, the winner's weight vector is closest to the input vector.

$$D_w = \min\{D_i\} \quad i \in \{1,2,\ldots,m\} \tag{2}$$

In the Kohonen algorithm, the concept of the winner-take-all units are related to the biological concept of grandmother cells because they are responsible for selecting one specific feature, for example, the feature presenting the stereotypical grandmother. However, this representation is not robust because when one unit is removed; all information concerning the corresponding class would be lost. For robust competitive learning, Kohonen proposed the self organizing training algorithm. Ideally neighboring neurons classify neighboring features and thus the loss in one neuron will result in a decrease of accuracy but not in a complete loss of information [11]. For each input vector only one such unit will respond, namely the unit characterized by the maximum output, respectively minimum distance, for this input vector x. During the training, the winner adjusts its weights to be closer to the values of data and the neighbours of the winner also adjust their weights to be closer to the same input data vector according to the following relation [12],

$$W_i = W_{ij} + \alpha(W_i - X) \quad i = \{1,2,\ldots,m\} \tag{3}$$

The units of the network are thus competing for selection. Only the weights of the winner will be adapted. The adjustment of the neighbouring neuron is instrumental in preserving the order of the input data. Thus, the winning neuron is the closest to the input value. After training, the weight vectors are self organizing and represent prototypes of classes of input vector [13]. The complete algorithm is described as follows:

(i)   t :=1; initialize w_{ij} randomly for i= 1,…,m ; j = 1,.., n,
       Initialize weight of bias $b_i = e^{\left[1-\ln(1/k)\right]}$,
       where *bi* is bias weight neuron-i and K is amount of class.
       Set learning rate and maximum epoch.
(ii)   Choose input vector x∈ X randomly in the training set.
(iii) Determine the neuron i such that its weight vector w is closest to the input vector.
       $D_w = \min\{D_i\} \quad i \in \{1,2,\ldots,m\}$ for all i
(iv)   Update the weight vector w_i, i=1, …, m;
       $W_i = W_{ij} + \alpha(W_i - X) \quad i = \{1,2,\ldots,m\}$
(v)   Update bias weight :
       $c(i) = (1-\alpha)e^{(1-\ln(b(i)))} + \alpha y(i)$ for the winner neuron
       $b(i) = e^{(1-\ln(c(i)))}$ for else
(vi)   Increment the time t:=t+1
(vii) Go to step (ii) until maximum epoch is reached.

2.2. Learning Vector Quantization
A supervised version of the Kohonen algorithm known as the learning vector quantization (LVQ) is also introduced by Kohonen [14]. In this algorithm, it is assumed that for each training vector x, the class is known. Using this knowledge, the weight vectors can be

moved, that is, the class prototypes move towards a correctly classified training vector and away from a wrongly classified one. The LVQ algorithm is described as follows:

(i) t :=1; initialize weight input variable-j to cluster-i w_{ij}
randomly for i= 1,…,m ; j = 1, … , n,
Set maximum epoch, Learning rate (α), Decrease learning rate ($dec\alpha$) and minimum learning rate (minα)

(ii) Input vector x$\in$ X randomly in the training set, and target class.

(iii) Initialize condition epoch=0

(iv) If (Epoch $\leq$ MaxEpoch) and ($\alpha \geq$ Minα)
  a. epoch=epoch +1
  b. for i = 1 to n

(1) determine j for $D_w = \min\{D_i\}$ $i \in \{1,2,...,m\}$ for all i

(2) update W_j

$$W_j = \begin{cases} W_j + \alpha(W_i - X) & \text{for } x \text{ correctly classified} \\ W_j - \alpha(W_i - X) & \text{for } x \text{ incorrectly classified} \end{cases}$$ (4)

(3) Decrease α with $\alpha = \alpha * dec\alpha$

Since only the nearest weight vector is changed, this step can be interpreted as an additional supervised fine-tuning of the feature map once the neighborhood order is decreased to zero. This fine-tuning is useful if the decision surfaces of the classification are known and the classes covering its boundary classify inputs inside as well as outside of the boundary. In this case, it may be advisable to fine tune the position of the weight vectors with an LVQ algorithm such that safe and unsafe operating points are classified by different neurons.

3. RESEARCH METHOD

In the proposed clustering technique, the first step is to determine the coherent bus clusters. A contingency is considered such as load increase at all bus and outage of a line. To determine the coherency of buses, the sensitivity information such as voltage difference, angle difference, real and reactive load power differences are calculated. Using such sensitivity information as inputs to the Kohonen neural network, the coherent buses are grouped together to form several bus clusters. The buses in a cluster are coherent if the voltage, angle, real power and reactive power differences for each bus within a cluster are the same when subjected to a disturbance [7]. The results of bus clusters formed by using the Kohonen neural network are compared with the LVQ algorithm. Figure 1 shows the flowchart of the procedure for formation of bus clusters technique by using Kohonen NN.

As an input data a set of data namely Voltage (V), phase angle (θ), Real Power (P) and Reactive Power (Q) at each bus in every contingency are taken from simulation results. Firstly, simulation running with an increasing all load bus by 25% in a step as contingency. The maximum cluster number determined by using coherency data (V, θ, P and Q) before voltage at a bus consider collapsed. This maximum cluster is then compared by using LVQ result. The test will be repeated by using other contingency such as line outages. A line from bus 3 to 4 will consider outages in order to get the maximum cluster number. Then maximum cluster for this contingency will be compare with LVQ result.

4. RESULTS AND DISCUSSION

To illustrate the effectiveness of the proposed method in forming the bus clusters, the coherency based clustering algorithm was applied to the IEEE 39-bus test system which consists of 17 load buses and 12 generator buses. Two contingencies were considered in the simulation of voltage collapse, namely, load increase at the load bus and line outage at a particular line.
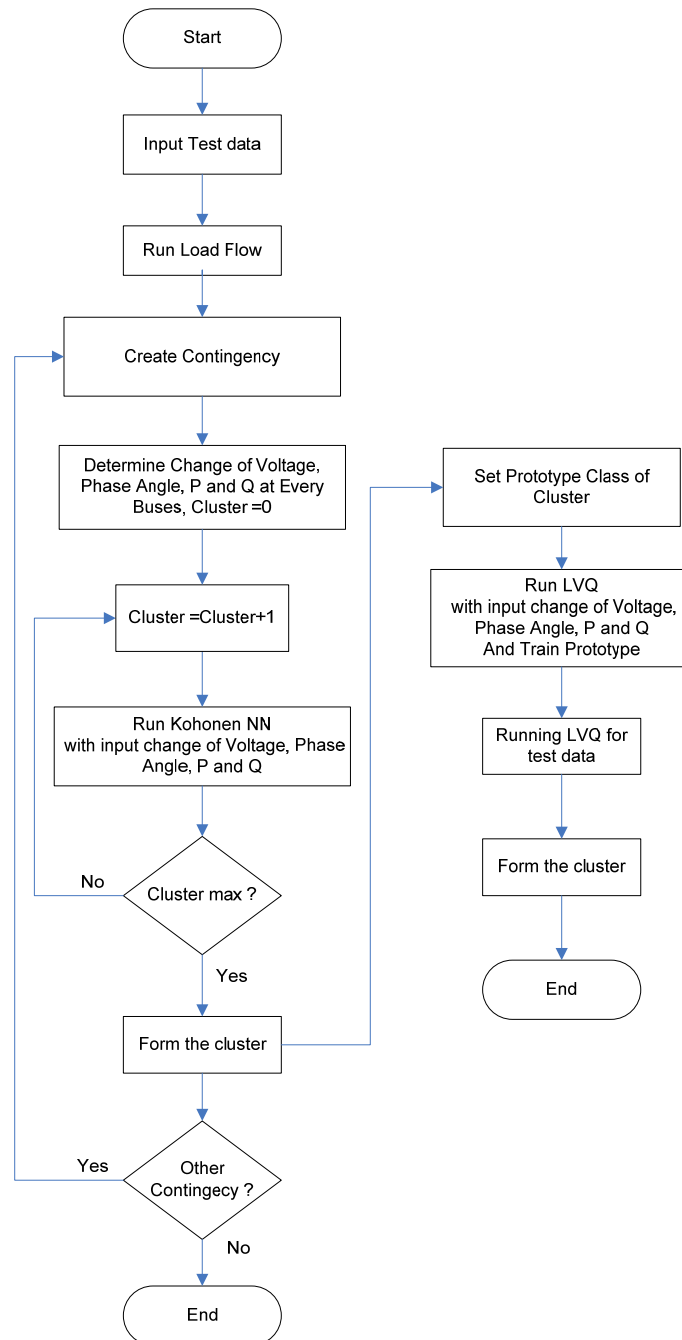
Figure 1. Procedure for the Formation of Bus Clusters Using Kohonen NN

In this case, for the load increase scenario, the loads at all the load buses were increased in steps of 25% p.u. MVA. All the loads are considered as voltage dependent loads. The simulation results are described as follows:

4.1. Formation of Bus Clusters Due to Load Increase

The results of clustering the 17 load buses and 12 generators buses of the 39 bus test system are shown in Table 1. The results show that the buses are grouped into 4 clusters in which all the buses in a cluster are said to be coherent. If the clusters are increased more than 4, it is noted that the performance of the Kohonen NN does not improve in which it still forms 4 clusters.

Table 1. Formation of bus clusters by using Kohonen-NN and LVQ in load increase case

Bus No	Number of Cluster		Type bus	Bus No	Number of Cluster		Type Bus
	Kohonen-NN	LVQ			Kohonen-NN	LVQ	
3	1	1	PQ	9	3	3	PQ
7	1	1	PQ	10	3	3	PQ
17	1	1	PQ	11	3	3	PQ
21	1	1	PQ	13	3	3	PQ
23	1	1	PQ	14	3	3	PQ
24	1	1	PQ	18	3	3	PQ
25	1	1	PQ	19	3	3	PQ
27	1	1	PQ	22	3	3	PQ
28	1	1	PQ	30	3	3	PV
29	1	1	PQ	31	3	3	PV
4	2	2	PQ	32	3	3	PV
8	2	2	PQ	33	3	3	PV
15	2	1	PQ	34	3	3	PV
16	2	1	PQ	35	3	3	PV
20	2	2	PQ	36	3	3	PV
39	2	4	PQ	37	3	3	PV
1	3	3	PQ	38	3	3	PV
2	3	3	PQ	12	4	3	PQ
5	3	3	PQ	26	4	1	PQ
6	3	3	PQ				

It can be seen that bus cluster number 3 consists of 21 coherent buses in one cluster. Both the Kohonen-NN and LVQ clustering techniques give similar results with regards to the number of clusters formed. The bus clusters formed for the 39 bus test system based on the Kohonen-NN is shown graphically as in Figure 2. The Kohonen-NN gives more freedom to determine the maximum number of clusters based on coherency of the buses rather than the LVQ in which the number of clusters are pre-determined depending on the representative buses that are selected.
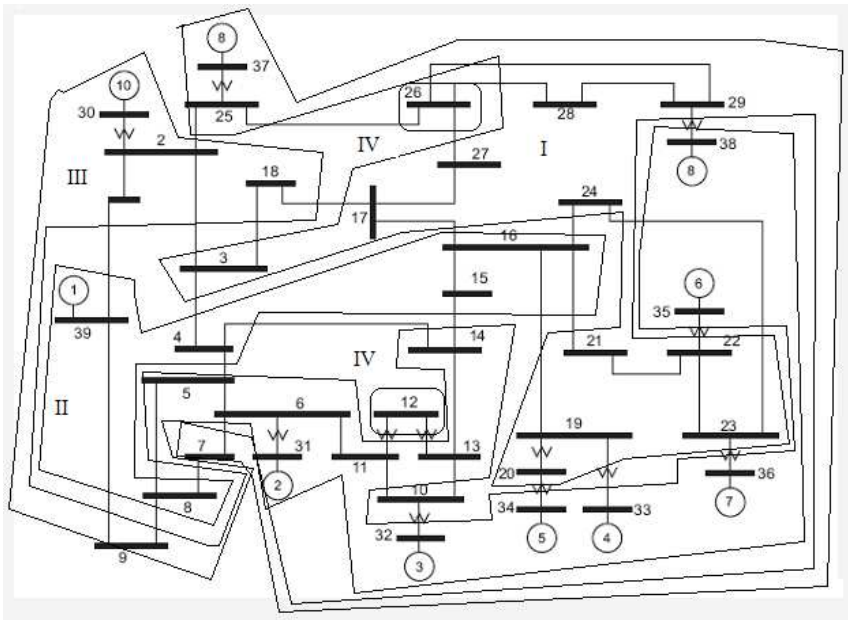

Figure 2 Bus Clusters formed Due to Load Increase

4.2. Formation of Bus Clusters Due to Line Outage
The results for the formation of bus clusters when a line outage of line between bus 3 and 4 is considered is shown in Table 2 and Figure 3. Results in Table 2 show that the buses in the 39-

bus test system are grouped into 3 coherent bus clusters due to the effect of a line outage of line between bus 3 and bus 4. By forming 3 bus clusters, the number of measurements can be reduced considerably to almost one third.

Table 2   Formation of bus clusters by using Kohonen-NN and LVQ line outage case

| Bus No | Number of Cluster | | Type bus | Bus No | Number of Cluster | | Type Bus |
	Kohonen-NN	LVQ			Kohonen-NN	LVQ	
6	1	1	PQ	37	2	2	PV
17	1	1	PQ	39	2	2	PV
23	1	1	PQ	10	3	3	PQ
24	1	1	PQ	11	3	3	PQ
26	1	1	PQ	13	3	3	PQ
27	1	1	PQ	14	3	3	PQ
28	1	1	PQ	15	3	3	PQ
29	1	2	PV	16	3	2	PQ
38	1	2	PQ	18	3	3	PQ
1	2	2	PQ	19	3	3	PQ
2	2	2	PQ	20	3	3	PQ
3	2	2	PQ	21	3	3	PQ
4	2	2	PQ	22	3	2	PQ
5	2	2	PQ	31	3	3	PV
7	2	2	PQ	32	3	3	PV
8	2	2	PQ	33	3	3	PV
9	2	2	PQ	34	3	3	PV
12	2	2	PQ	35	3	3	PV
25	2	2	PQ	36	3	3	PV
30	2	2	PV				
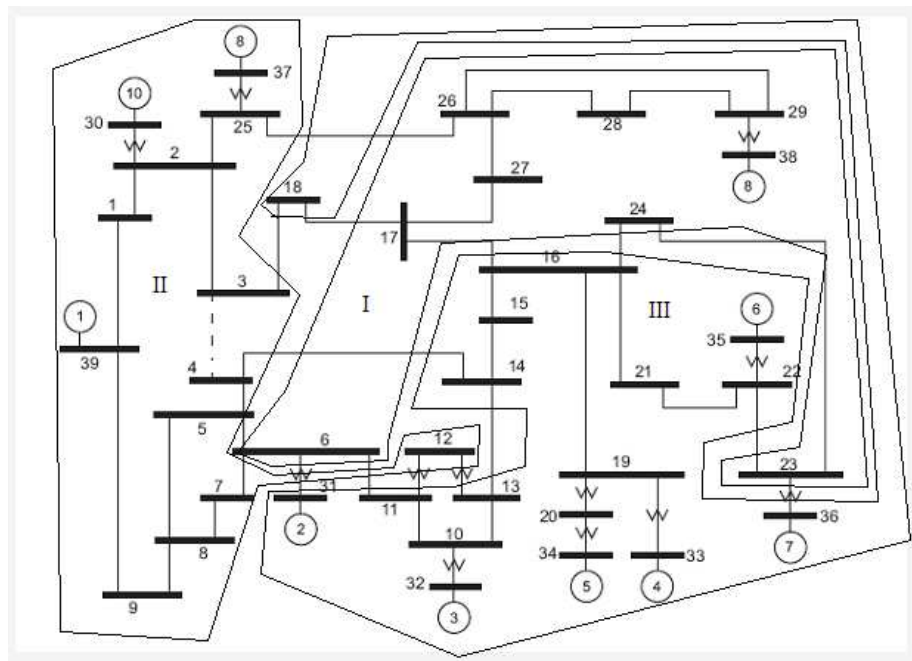
Figure 3. Bus Clusters Formed Due to Line Outage

5. CONCLUSIONS

Clustering a power system is very useful for the purpose of voltage stability control. By forming bus clusters the size of a power network is reduced and therefore the computational efficiency of application program such as voltage control can be considerably improved. The bus clusters are formed based on the coherent nature of buses in a cluster. To automate the process of forming the bus clusters, the Kohonen-NN which is based on an unsupervised training algorithm is proposed. The LVQ which is based on the supervised training algorithm is

also implemented to compare it with the Kohonen-NN. The results showed that both the Kohonen-NN and LVQ techniques give similar results with regards to number of bus clusters formed. The proposed technique results showed four clusters on contingency load increased and three clusters online outage contingency on IEEE 39 bus system as shown by the LVQ

REFERENCES
[1]. Pandit M, Srivastave L, Sharma JD. ANN Based Voltage Contingency Screening and Ranking using a Novel Feature Selection Technique, *IE(I) Journal-EL*, 2004:154-160
[2]. Musirin I, Rahman TKA. *Voltage Stability Based Weak Area Clustering Technique in Power System.* Proceedings of Power & Energy Conference (PECon). Kuala Lumpur. 2004: 235-240.
[3]. Nizam M. Clustering Based Self-Organizing NN Algorithm for Identification The Weak Area in Power System. *Jurnal Media Informatika*. 2007; 5(1): 31-39.
[4]. Modi PK, Singh SP, Sharma JD. Fuzzy neural network based voltage stability evaluation of power systems with SVC Source. *Applied Soft Computing*. 2008; 8(1): 657-665.
[5]. Shamsuddin SM, Zainal A, Yusof NY. Multilevel kohonen network learning for clustering problems. *Journal of Information and Communication Technology*. 2010; 8(7): 1-25.
[6]. Rahman TKA. A New Voltage Index and Its Application in Power System Control. Ph.D dissertation. Kuala Lumpur: University of Malaya; 1996.
[7]. Mohamed A, Jasmon GB. A New Clustering Technique for Power System Voltage Stability Analysis. *Journal of Electric Machines & Power Systems*. 1995; 23(2): 389-403.
[8]. De Souza ACZ, Quintana VH. *New Technique of Network Partitioning for Voltage Collapse Margin Calculations.* IEE Proceeding-C. 1994; 141(6): 630–636.
[9]. Pandit SL, Vijay S. *Identification and Ranking of Weak Buses using Modified Counterpropagation Neural Network.* Proceedings of IEEE Power India Conference. 2006.
[10]. El-Sharkawi, Niebur D. Artificial Neural Networks with Applications to Power System. Piscataway-New Jersy: Power Engineering Society. 1996: 28-38.
[11]. Kohenen T. Kohonen Formation of Topologically Correct Feature Maps, *Biologically Cybernetics.* 1982; 1(43): 59-69.
[12]. Moghadam MM, Khaloozadeh H. *Optimal Fuzzy Self-Organizing Structure For Voltage Security Margin Estimation.* Proceeding of 15th PSCC. Liege. 2005: session 30 No.6.
[13]. Niebur D, Germond AJ. Unsupervised Neural Net Classification of Power System Static Security States. *Int. Journal of Electrical Power and Energy System.* 1992; 14(2-3): 233-242.
[14]. Cotrell M, Fort J. A Model Retinotopy: A Self-Organizing Process. *Biol Cybernetics.* 1986; 2(53): 405-411.