# OPTIMAL FUZZY SELF-ORGANIZING STRUCTURE FOR VOLTAGE SECURITY MARGIN ESTIMATION

Mazyar Mirhoseini Moghaddam
Azad University of Lahijan, Lahijan, Iran
mmirhoseini@ yahoo.com

Hamid Khaloozadeh
K. N. Toosi University of Technology, Tehran, Iran
h_khaloozadeh@kntu.ac.ir

**Abstract: In recent years, research efforts have been focused to estimating voltage security margins. Voltage security margin shows how close the current operating of a power system is to a voltage collapse point. One main disadvantage of these techniques is that they require a large amount of computations, therefore they are not efficient for on-line use in power control centers. Therefore the intelligent networks classification techniques for systems that are illustrated by series of data are offered. In this paper, two methods are used to estimate voltage security margin. The first method is general fuzzy min-max neural network (GFMM NNs.) with on-line adaptation. The second method which we named it as "Fuzzy Self-Organizing Network," combines two structures of Kohonen and GFMM neural network then by using Akaike criterion the optimal values of the proposed network parameters are determined. The data set needed for training this structure is obtained from the minimum singular value of the power flow Jacobian matrix. These methods are applied on the IEEE 30-bus system with 2000 simulated data randomly generated from different operating conditions. Finally, the results compared with the three-layer feed forward neural network as the most common used neural networks. The results clearly show the advantage and high efficiency of the proposed structure.**

***Key words: kohonen neural network, general fuzzy Min-Max neural network, akaike information criteria, power systems, voltage security margin estimation***

## 1 INTRODUCTION

The assessment of security in a power system is an important problem in operation it that effect on electric energy generation, transmission and distribution quality. Many research efforts have been devoted to voltage security estimation that show how close the current operating point of power system is to voltage collapse point as assessment of voltage security. Tranuchit proposed the minimum singular value of the Jacobian of the load flow equation as a voltage security criteria and static control solution to deal with it [1]. Chang proposed two methods for identifying weak buses. The first method was based on the right singular vector, corresponding to a minimum singular value of the power flow Jacobian matrix that indicates sensitive voltages. The second method was based on the voltage collapse proximity indicator that the weakest node in the network was corresponding to the maximum value this indicator [2]. Macarov a new method that named $\Delta-$method. In this method by using load flow equation has been shown that the set of all of the possible values correspond to voltage stability limit is indirection of a straight line in system variables space (buses voltage) [3]. One main disadvantage of the above mentioned techniques is that they require large computation, therefore, they are not appropriate tools to be used as on-line in control centers, since advance warning signals are required for operators to steer a system away from a developing voltage collapse whenever possible.

To overcome these problems, an artificial intelligence (AI) networks is offered to established in base of computation indicators for voltage security margin estimation (VSME). Neural networks were the first structures that are justified in this field, since they can be constructed off-line from a given training set and then be used on-line in control centers. Basically, a feed forward multiplayer neural network with sufficient hidden nodes has been proven to be universal approximator [4-6]. Hui was from the first persons that used from neural network for voltage security monitoring, prediction and control. In this method is used from multilayer perceptron structure and back-propagation algorithm for training [7].

Another approach to VSME is to formulate VSME as a classification problem. These methods are depended on a too amount of data that obtain from power system. These methods increase training phase efficient. Classification problems can be solved either exclusively or nonexclusively. An exclusively or crisp classification is a partition of the set of objects that each object belong to exactly one class. Song used this method to determine voltage security margin. He used self-organizing neural network that consists of Kohonen network and back-propagation network to power system voltage stability assessment [8]. A nonexclusively or overlapping classification can assign an object to several classes. Fuzzy classification is a type of nonexclusive classification in which a pattern is assigned a degree of belongingness to each class in a partition. That is, the decision boundaries of the classes are vague. Neuro-fuzzy structures are a type of nonexclusive classification in which prepares expression of acquaintance strictly in fuzzy logic with strength of learning in neural networks. Maranino used neurofuzzy approach of adaptive network based fuzzy inference system (ANFIS) for determining fuzzy security distance to voltage collapse point [9]. In this approach consider a measure in a percent rate of the security level degradation with respect to the voltage collapse risk. There is a main disadvantage in above mentioned approaches. In these methods there is no any way to determine optimal value of input parameters dimension.

Using nonexclusively classification in neural network increases the precision of classification problem. In this paper, we use an approach of nonexclusively classification for VSME which has been named fuzzy self-organizing. In fact, this method is the hybrid of two structures of Kohonen neural network and general fuzzy min-max (GFMM) neural network [12]. The optimal method for structure selection is based on Akaike Information Criteria (AIC). Using this criterion to derive the optimal values of parameters, which are affecting in decision and operating fastness of algorithm. This neuro-fuzzy network is used for classification of data to quantize the voltage stability margin into five levels based on the magnitude of the minimum singular value of the power flow Jacobian matrix. This paper is organized as follows. The first introduced fuzzy self-organizing algorithm briefly, then, the proposed scheme for VSME is introduced and simulated on the IEEE 30-bus is done to illustrate its performance and introduce Akaike criteria for this problem determines optimal value of parameters by using it. Finally, a summary and conclusion are illustrated.

## 2 FUZZY SELF-ORGANIZING NETWORK

### *2.1 Kohonen Neural Network*

Kohonen network is an unsupervised neural network. With this network, input data with similar feature are mapped to continue cluster by competitive learning algorithm. The Euclidean distance between two n-dimensional vectors can measure the similarity between input vectors. The distance of an input vector from each neuron i, $D_i$, can be calculated by using of equation 1.

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

Where $X = (x_1, x_2, ..., x_n)^T$ denotes an input vector; $W_i = (w_{i1}, w_{i2}, ..., w_{im})^T$ denotes the weight vector of the $i$-th neuron.

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

$$D_w = \min\{D_i\} \quad i \in \{1,2,...,m\} \qquad (2)$$

During training, the winner adjusts its weights to be closer to the values of the 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.

$$W_i = W_i + \alpha(X - W_i) \quad i \in \{1,2,...,m\} \qquad (3)$$

The adjustment of neighbouring neuron is instrumental in preserving the order of the input data. Thus the winning neuron is, in a measurable way, the closest to the input value and thus represent the input value. After training, the weight vectors are self-organizing and represent prototypes of classes of input vectors. (See references [10], [11])

### *2.2 GFMM Description*

GFMM neural network for clustering and classification [12] that illustrated by Gabrys is a generalization of and extension to the fuzzy min-max neural networks developed by Simpson [14,15]. The main changes in GFMM constitute the combination of unsupervised and supervised learning, associated with problems of data clustering and classification respectively, within a single learning algorithm and extension of the input data from a single point in n-dimensional pattern space to input patterns given as lower and upper limits for each dimension-hyperbox in n-dimension pattern space.

This method builds decision boundaries by creating subsets of pattern space. The basic idea of this method is to represent groups of input patterns using hyperbox fuzzy sets. A hyperbox fuzzy set is a combination of a hyperbox covering a part of n-dimensional pattern space and associated with it membership function. A hyperbox is completely defined by its min point and its max point and change size of each dimension from 0 to 1, then the first stage is map of data from $R^n$ to $I^n$. A membership function acts as a distance measure with input patterns having a full membership if they are fully contained within a hyperbox and the degree of membership decreasing with the increase of distance from the hyperbox. By extension input pattern space from n-dimension to 2n-dimension, GFMM allows processing both fuzzy (hyperboxes in pattern space) and crisp (points in pattern space) input patterns. This means that the uncertainty associated with input patterns, represented by confidence limits, can be processed explicitly.

The GFMM is represented by a tree layer feedforward neural network in Figure.1. It consists of *2n* input layer nodes, *m* second layer nodes representing hyperbox fuzzy sets and *p+1* output layer nodes representing classes.

Each assumed input data $X_h = \left[X_h^l \quad X_h^u\right]$ is the $h$-th input data in a form of lower, $X_h^l = \left(x_{h1}^l, x_{h2}^l, ..., x_{hn}^l\right)$, and upper, $X_h^u = \left(x_{h1}^u, x_{h2}^u, ..., x_{hn}^u\right)$, limits vectors contained within the n-dimensional unit cub $I^n$.

The j-th hyperbox fuzzy set, $B_j$, is defined as follows:

$$B_j = \{V_j, W_j, b_j(X_h, V_j, W_j)\} \qquad (4)$$

for all $j = 1,2,...,m$, where $V_j = (v_{j1}, v_{j2}, ..., v_{jn})$ is the min point for the $j$-th hyperbox, $W_j = (w_{j1}, w_{j2}, ..., w_{jn})$ is the max point for the $j$-th hyperbox, and the membership function for the *j*-th hyperbox is:

$$b_j(X_h, V_j, W_j) = \min_{i=1,2,\ldots,n}(\min([1-f(x_{hi}^u - w_{ji}, \gamma_i)], \ldots$$
$$[1-f(v_{ji} - x_{hi}^l, \gamma_i)])) \qquad (5)$$

where:

$$f(x,\gamma) = \begin{cases} 1 & if \quad x\gamma > 1 \\ x\gamma & if \quad 0 \le x\gamma \le 1 \\ 0 & if \quad x\gamma < 0 \end{cases}$$ - two parameter ramp threshold function; $\gamma = [\gamma_1, \gamma_2, \ldots, \gamma_n]$- sensitivity parameters governing how fast the membership values decrease; and $0 \le b_j \le 1$.

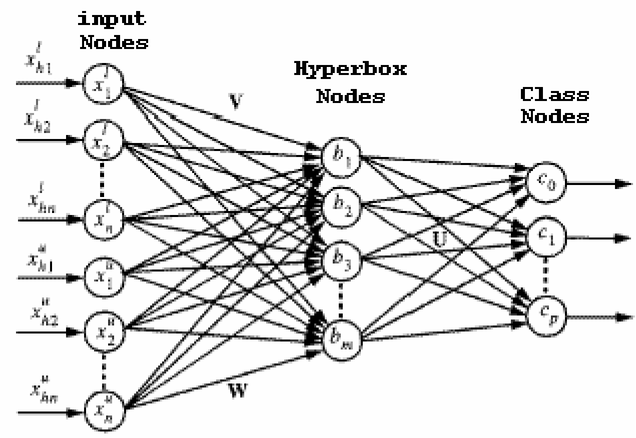



**Figure 1:** GFMM Neural Network for Clustering and Classification

Hyperbox fuzzy sets from the second layer are aggregated using the aggregation formula (6) in order to generate an input which represents the degree to which the input pattern $X_h$ fits within the class k. the transfer function for each of the third layer nodes it defined as:

$$C_k = \max_{j=1}^{m} b_j u_{jk} \qquad (6)$$

For each of the *p+1* third layer nodes. Node $c_\circ$ represents all unlabelled hyperboxes from the second layer. Matrix *U* represents connections between the hyperbox and class layers of the network and the values of *U* are assigned as follows:

$$u_{jk} = \begin{cases} 1 & \text{if } B_j \text{ is a hyperbox for class } C_k \\ 0 & \text{otherwise} \end{cases} \qquad (7)$$

Weight matrixes of *W*, *V* and *U* are adjusted by on-line training algorithm in GFMM. The on-line learning for GFMM neural network consists of creating and expanding/contracting hyperboxes in a pattern space. The learning process begins by selecting an input pattern and finding the closest hyperbox to that pattern that can expand (if necessary) to include the pattern. If a hyperbox cannot be found that meets the expansion criteria, a new hyperbox is formed and added to the system. This growth process allows exiting clusters/classes to be refined over time, and it allows new cluster/classes to be added without retraining. One of the undesirable effects of hyperbox expansion is overlapping hyperboxes. Hyperboxes belong to the same class are allowed to overlap while hyperboxes of belong to different classes are not allowed to overlap because These hyperboxes overlap cause ambiguity and create possibility of one pattern fully belonging to two or more different cluster/classes. A contraction process is utilized to eliminate any undesired hyperbox overlaps.

The maximum size of the hyperbox ($\theta$) is most important part of GFMM algorithm that is specified by user and adjusted in train algorithm. A large value of $\theta$ can cause too many misclassification, especially when there are complex, overlapping classes. On the other hand, when $\theta$ is small, many unnecessary hyperboxes may be created, especially for concentrated stand-alone groups of data which normally would form one class. But of course small $\theta$ helps to resolve overlapping classes. These problems have been addressed by introducing an adaptive maximum size of the hyperbox. The idea is to start training the network with large $\theta$ and decrease it (if necessary) in subsequent presentations of the data. The training in this algorithm is completed when after presentation of all input pattern there have been no misclassification for the training data. This, however, may lead to memorization of individual data patterns (overfitting) and deterioration in recognition performance for an independent testing data set. In such case, it used from the minimum user-specified value of the parameter $\theta$ such as stop condition that is selected according to minimum misclassification.

### *2.3 Structure of Fuzzy Self-Organizing Network*

Separation of deciding region of GFMM neural network such as most of neural networks has a form based on Euclidean norm. In case of which regions of input data are separated by a nonlinear strictly indicator, It is possible that overlap these regions each other based on Euclidean norm index, then for recognizing of regions of nonlinear of data and training of them completely. It is necessary that generate a lot of hyperboxes. This operation increases number of hyperboxes that include a single data and deterioration in recognition performance for an independent the testing data set. For increasing efficient of training phase and keeping suitable efficient in test phase, it is used from complex structure of fuzzy self-organizing that is compound two Kohonen and GFMM neural network. With Kohonen network, input data with similar feature are mapped to contiguous clusters, and then centers of these clusters are mapped to desire classes by GFMM neural network. The determined algorithm increases efficiency of the training set and the testing set strictly that reflect effect of Kohonen network in optimization of mapping.

## 3 CASE STUDY

The IEEE 30-bus system is used to test the effectiveness of GFMM network's for VSME. This system contains two generators on buses 1 and 2 and three synchronous condensers on buses 5, 11 and 13. It is used 1500 patterns and 500 patterns in the training set and the testing set, respectively. These patterns are generated from an expensive power flow by considering random load changes (light load to critical load) under normal distribution, effects of under load tap changers (ULTC's), reactive power limits on generators and various contingencies. We used from buses 30, 26, 29, 25, 27, 24, 23, 19, 18, 20, 21 and 22 based on weak bus ranking of the test system under heavy load condition. The identification of weak buses is based on the right singular vector from base load flow [2]. The weakest bus would imply the largest change in voltage magnitudes; therefore, the system buses are arranged in order of weakness. We quantized the voltage stability margin into five levels based on the magnitude of the minimum singular value of the power flow Jacobian matrix. The five voltage security levels are as follows:

Class1 (very dangerous level) $0 \le \delta_n < 0.1$

Class2 (dangerous level) $0.1 \le \delta_n < 0.195$

Class3 (alert level) $0.195 \le \delta_n < 0.36$

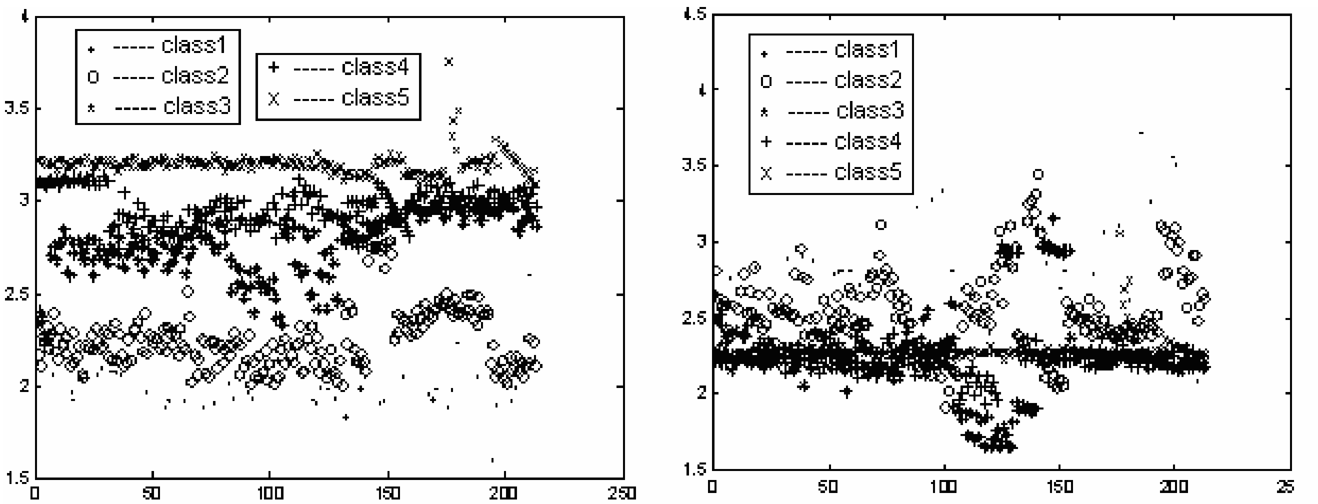
Class4 (security level) $0.36 \le \delta_n < 0.45$

Class5 (very security level) $\delta_n \ge 0.45$

where $\delta_n$ is the minimum singular value. Of curse, the determination of the range of the minimum singular value depends heavily on the specific power system under operation. On possible way to determine the appropriate ranges of $\delta_n$ for each security level is to extensively conduct simulations off-line for the study system under various operating conditions to statistically determine appropriate ranges. Each training pattern is then labeled to be one of the five levels.

Such as above mentioned, input data determine based on information of voltage of weak buses. In this base, there are two input structures. In the first case, it is only used information of voltage magnitude of weak buses but in second case is added information of voltage phase to voltage magnitude of weak buses. Since GFMM algorithm has a region form such as Euclidean norm, with using Figure.2, it is specified that is strength of discrimination of regions in the first case is better than the second case in this algorithm (in Figure2. is only used information of ten weak buses). It is effect to be used information of voltage magnitude of weak buses such as input data for increasing precision of classification very much.

The simulation has performed by MATLAB software. GFMM neural network was the first algorithm that is used. Since minimum singular value is strictly nonlinear and GFMM neural network establish based on Euclidean norm your reign, then for determining precision of training of 100% this algorithm require to generate many hyperboxes. This operation lead to memorization of individual data patterns (overfitting) and therefore, deterioration in recognition performance for an independent testing data set. This training process obtains in $\theta = 0.009$. For resolving this problem, it used from on-line adaptive process on magnitude of $\theta$ parameter. With using this method, the average of recognition rates of the training set and the testing set are 90.5% and 82.4%, respectively. In this case, number of hyperboxes and training time decrease strictly and magnitude of $\theta$ parameter becomes 0.015 (see Table 1).




(a) The first case data, 10 dimension (Descrimination of data is large)

(b) The second case data, 20 dimension (Descrimination of data is small)

**Figure 2:** Comparison Decrement of Data Regions that has determined Based on Singular Value Index and Separated with Euclidean Norm.

| Network Type | Maximum Magnitude of Hyperbox ( $\theta$ ) | Number of Hyperboxes | Efficiency of Training Phase | Efficiency of Testing Phase | Time in Training Phase (second) |
|---|---|---|---|---|---|
| GFMM | 0.009 | 960 | 100% | 65% | 113 |
| GFMM with On-Line Adaptive | 0.015 | 340 | 90.5% | 82.3% | 25 |

**Table 1:** Comparison of GFMM Algorithm under Training of 100% by GFMM with On-Line Adaptive of Magnitude of $\theta$ (Input Data dimension equal 10)

| Network Type | Maximum Magnitude of Hyperbox ( $\theta$ ) | Number of Hyperboxes | Efficiency of Training Phase | Efficiency of Testing Phase | Time in Training Phase (second) |
|---|---|---|---|---|---|
| Fuzzy Self-Organizing (Proposed Method) | 0.0124 | 138 | 97.3% | 91.8% | 186 |

**Table 2:** Fuzzy Self-Organizing Network with 144 Clusters

For increasing efficient in training and testing phase, it is offered to compound above network with Kohonen network that named fuzzy self-organizing network. In this new way, the first input data patterns with similar feature are mapped to contiguous clusters, and then GFMM neural network maps the output of Kohonen network to desire outputs. In this way, robust mapping can be learned through which input features are extracted and hence the efficiency of GFMM has been increased. With using this algorithm, the average of recognition rates of the training set and the testing set increase to be 97.3% and 91.8%, respectively. The Kohonen network that used in this algorithm has $12 \times 12$ Kohonen layer and magnitude of $\theta$ parameter becomes 0.011 (see Table 2).

### *3.1 Optimal structure of the Fuzzy Self-Organizing using Akaike Criteria*

Increase of model order that is equal of increase of number of parameters lead to large computation time, then it is not proper for on-line computation. It is used Using Akaike criteria to compromise between model order and computation time. This criterion is illustrated by Akaike in 1974. The base of this criterion is based on log-likelihood function [13] and for issue algorithm is illustrated as follows:

$$C_i^{'} = N_{train} \ln V_{train,i} + N_{test} \ln V_{test,i} + 2 p_i \qquad (8)$$

where $V_{train,i}$ and $N_{test}$ denote testing error and number of testing pattern for *i*th structure, respectively and $p_i$ denotes input parameters. According to above criterion, the model is optimal (trade off between order (accurate) and computation time) if its $C_i^{'}$ represents the smallest criteria magnitude. The proposed Fuzzy self-organizing structure has two selective parameters that are, input data dimension and the number of cluster centers in Kohonen network. In the first case, by freezing input data dimension (for example ten), it is considered the effect of change of number of cluster centers such as input parameter ( $p_i$ ). According to the Table 3, it is shown that the optimal selection of the number of cluster centers is 144 in the Kohonen network In this case, the Akaike criterion is the least. When we change the input data dimensions, we obtain similar results.

In the second case, the number of cluster centers fixed to 144 and we change the input data dimension from 8 t0 11 ( $p_i$ shows input data dimension). According to the Table 4, the Akaike criterion to be minimum for the input data dimension equal to 9.

| Model Number | Training Error | Testing Error | Number of Training Pattern | Number of Testing Pattern | Number of Cluster Centers | Akaike Test Criteria |
|---|---|---|---|---|---|---|
| 1 | 9.1% | 11.6% | 1500 | 500 | 81 | -4510.426 |
| 2 | 8.6% | 10.3% | 1500 | 500 | 100 | -4616.625 |
| 3 | 7.2% | 9.4% | 1500 | 500 | 121 | -4886.134 |
| 4 | 5.9% | 8.2% | 1500 | 500 | 144 | -5206.845 |
| 5 | 5.7% | 8.3% | 1500 | 500 | 169 | -5203.513 |
| 6 | 5.8% | 8.2% | 1500 | 500 | 196 | -5129.486 |
| 7 | 5.6% | 8.2% | 1500 | 500 | 225 | -5124.123 |

**Table 3:** Using of Akaike Method in Optimal Determining Number of Kohonen Cluster Centers

In the second case, it is assumed that is constant number of cluster centers equal to 144, and change input data dimension from 8 t0 11 ( $p_i$ show input data dimension). According to Table 4, it obtains the least of Akaike criteria for input data dimension equal to 9. It shows that is optimal value of this algorithm in precision and time computation under this input data dimension.

| Model Number | Training Error | Testing Error | Number of Training Pattern | Number of Testing Pattern | Input Data Dimension | Akaike Test Criteria |
|---|---|---|---|---|---|---|
| 1 | 6.5% | 9.1% | 1500 | 500 | 8 | -5282.46 |
| 2 | 5.4% | 7.8% | 1500 | 500 | 9 | -5635.68 |
| 3 | 5.9% | 8.2% | 1500 | 500 | 10 | -5475.84 |
| 4 | 6.2% | 8.1% | 1500 | 500 | 11 | -5405.58 |

**Table 4:** Using of Akaike Method in Determining Input Data Dimension

| Network Type | Maximum Magnitude of Hyperbox ( $\theta$ ) | Number of Hyperboxes | Input Data Dimension | Efficiency of Training Phase | Efficiency of Testing Phase | Time in Training Phase (second) |
|---|---|---|---|---|---|---|
| Fuzzy Self-organizing | 0.0124 | 138 | 10 | 94.1% | 91.8% | 186 |
| Fuzzy Self-organizing | 0.0145 | 116 | 9 | 94.6% | 92.2% | 105 |

**Table 5:** Comparison of Self-Organizing Network under Two Input Data Dimension Given Dimension (10) and Offered by Akaike Criteria Dimension (9)

For better comparison, it is showed information of fuzzy self-organizing structure in input data dimension equal to 9 (determined from Akaike criteria) and 10 according to Table 5, it can be seen that the results from Akaike criteria are better.

The multilayer perceptron (MLP) neural network is the most common used neural network that is used for voltage stability and voltage security estimation. In this research by using the same training set and testing set. We also used the backpropagation algorithm to train a three-layer neural network with 20 nodes in hidden layer and five nodes in output layer (number of classes). After 20000 iterations, the average true recognition rates are 91.9% and 83.1% for the training set and the testing set, respectively. The results of the comparison between the performance of the proposed fuzzy self-organizing structure and the three-layer feed forward neural network are given in the Table 6.

## 4 CONCLUSION

In this paper a nonexclusively classification method has proposed for voltage security margin estimation (VSME). For testing this algorithm, we used the IEEE 30-bus system as a benchmark that is a stressed standard system. The extensive testing performed on the IEEE 30-bus system under various operation conditions. We used two structures to estimate voltage security margin, general fuzzy min-max neural network and a proposed structure named fuzzy self-organizing network. Fuzzy self-organizing structure tested with the data set generated randomly from a load flow. The simulation results has confirmed the using of Kohonen network in fuzzy self-organizing structure has a very important role in optimization of system mapping and cause to increasing of efficiency in the training set and the testing set. In this paper, also we use the Akaike information criterion to select the best model order of the two networks. Finally, the results compared with the three-layer feed forward neural network as the most common used neural networks. The results clearly show the advantage of the proposed structure.

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| Network Type | Pattern | **Voltage Security Level** | | | | |
|---|---|---|---|---|---|---|
| | | Very Secure | Secure | Alert | Dangerous | Very Dangerous |
| Fuzzy Self-Organizing (Offered Method) | Training Set | 98.3% | 97.4% | 96.5% | 97.1% | 97.1% |
| | Testing Set | 94.1% | 92.6% | 91.8% | 92.6% | 91.4% |
| MLP | Training Set | 92.9% | 92.8% | 91.3% | 91.7% | 92.1% |
| | Testing Set | 83.5% | 84.8% | 82.3% | 81.5% | 81.8% |

**Table 6:** Comparison of Classification Performance of The Fuzzy Self-Organizing Network and The Trained Backpropagation Network