Static Security Assessment of Power System Using Self Organizing Neural Network

P. Britto Corthis and K. Shanti Swarup

***Abstract* - A Neural Network aided solution to the problem of static security assessment of a model power system is proposed. This paper utilizes the artificial neural net of Kohonen's Self Organizing Feature Map (SOFM) technique that transforms input patterns into neurons on the two dimensional grid to classify the secure / insecure status of the power system. The SOFM uses the line flows under different component cases as inputs and perform self-organization to obtain the cluster of the components based on their loading limits. The output of the SOFM provides information about the violation of the constraints from which the operating state of the power system can be identified as the result of which the system can be classified as secure or insecure. The above method of security assessment was successfully tested for a model 3-generator, 6 bus system and latter extended to an IEEE 14 bus and 30 bus systems respectively.**

***Index Terms*- Clustering, Power System, Security Assessment and SOFM**

I. INTRODUCTION

Power system security can be defined to remain secure without serious consequences to any one of a pre-selected list of credible disturbances or contingencies. Security Assessment (SA) is the analysis performed to determine whether, and to what extent, a power system is reasonably safe from serious interference to its operation. In other words power system security assessment is the process of determining if the power system is in a secure or alert (insecure) state, the secure state implies the load is satisfied and no limit violation will occur under present operating conditions and in the presence of unforeseen contingencies (i.e., outages of one or several lines, transformers or generators) [1].
The alert (or emergency) state implies that some limits are violated and / or the load demand cannot be met and corrective actions must be taken in order to bring the power system back to the secure state. Figure 1 shows the different operating states of the power system, which are classified as secure and insecure.

II. STATIC SECURITY ASSESSMENT

One of the main aspects of power system security is static security. Static security is defined as the ability of the system to reach a state within the specified secure region following a contingency. The standard approach to the security assessment problem is to perform the static security analysis followed by dynamic security analysis. The static security analysis evaluates the post contingent steady state of the system neglecting the transient behavior and any other time dependent variations due to the changes in load generation conditions. On the other the dynamic security analysis evaluates the time dependent transition from the pre-contingent to the post contingent state. Most of the Energy Management Systems perform only the static security analysis and hence focus of this paper is on static security assessment.

III. CONVENTIONAL TECHNIQUES

In conventional practice security assessment is obtained by

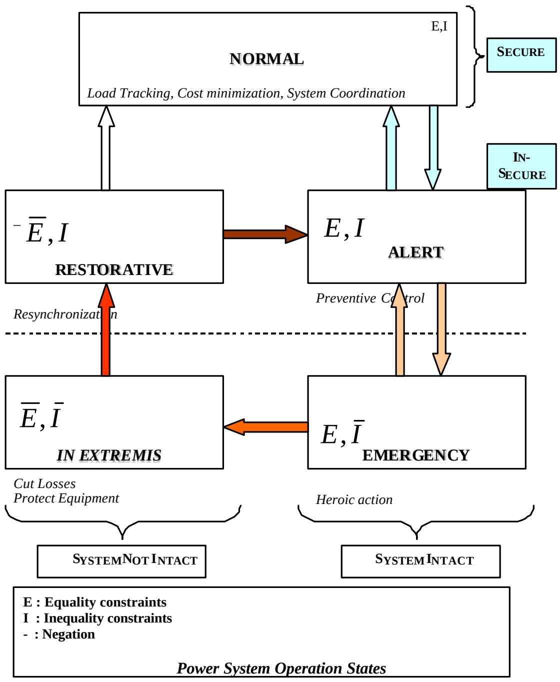

Fig. 1. Power System Operating States

analytically modeling the network and solving load flow equation repeatedly for all the prescribed outages, one contingency at a time. These analytical techniques are usually time consuming and therefore not always suitable for real time applications. Also these methods suffer from the problem of misclassification or / and false alarm. Misclassification arises when an active contingency is classified as critical. With recent advancements in

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information processing and learning techniques, ANN based methods for security assessment is a viable alternative.

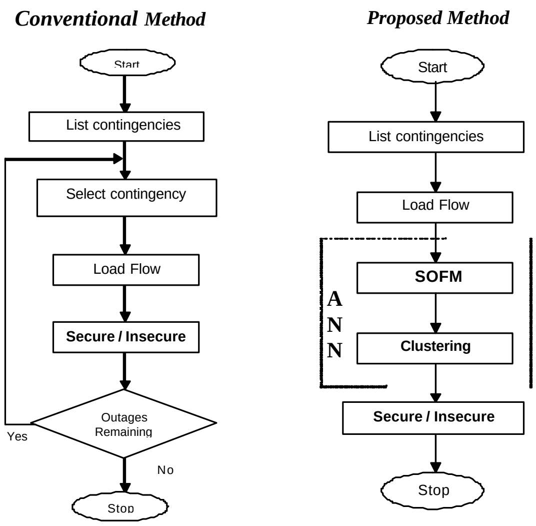

Fig. 2 Comparison between Conventional and Proposed method.

IV. Application Of ANN To Static Security

According to the literature, several ANN approaches have been proposed as alternative methods for security assessment in power system operations. The neural network methodology is applied in areas where conventional techniques have not achieved the desired speed and accuracy. One such area is the classification of system security status. Once the neural network is properly trained, it can interpolate patterns using a limited amount of input data. Since the neural networks are quick in response time and can be easily adapted, they become excellent for on line application [2]. Figure 2 shows the comparison between the conventional and proposed ANN method for security assessment. It can be observed that the iterative computational burden can be eliminated in the ANN approach. In the Self Organizing Feature Map (SOFM), an unsupervised learning technique, proposed by Kohonen[3,], each neuron has one weight vector, which represents the center of a class of operating states. This weight vector is interpreted as a typical operating state, which in this application is given by the line flows. The operating space is presented on the map by secure and insecure regions

V. Algorithm For Classification using SOFM

In the classification phase, the network maps a vector with unknown features to the cluster where its closet neighbors have been mapped to. The algorithm [4] is:

1. Present the input vector x.
2. Select the neuron *c* with the weight vector closest to the input vector.

$$\| w_c(t_{max}) - a \| = \min \| w_{ij}(t_{max}) - a \|$$

VI. Implementation Aspects

Figure.3 illustrates the structure of the six-bus eleven-line system. For 11 lines the system state is defined by 11 complex respectively 22 real components, the 11 active and reactive line power flows. These input vectors were obtained by off –line load flow simulations. Number of neurons depends on number of contingencies taken. Here 14 number of single line are taken into consideration. Number of generator outages = (3), Number of line outages = (11), Base case = (1) Total number of Neurons =15. To represent in a square matrix, a 4 x 4 matrix is assumed and therefore 16 neurons are taken to represent the given power network.

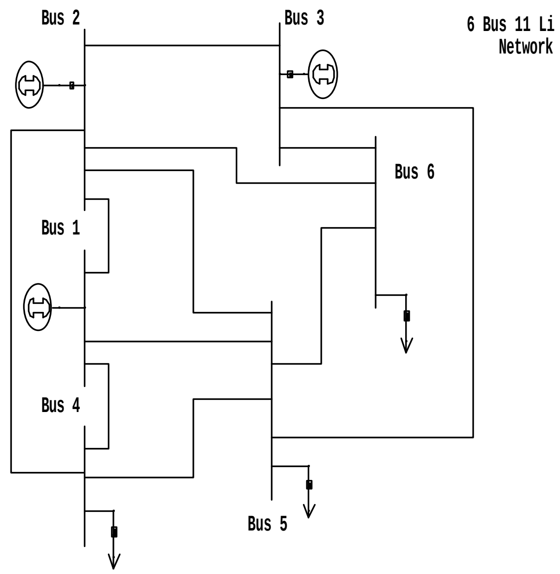

Fig 3. The six-bus eleven-line system.

VII. Simulation

A simulator for the Kohonen learning algorithm was developed in MATLAB[5]. All parameters can be defined and changed interactively: the size of input vector and of the Kohonen network, the neighborhood function and their decrease with the learning steps. Vectors are drawn randomly from the set of input training vectors and are presented several times as inputs to a two dimensional Kohonen network of size of 4 x 4. Neighborhood and learning rate decreases exponentially with the number of training steps as shown in the figure 4. The adaptation of the weight vectors with respect to the learning step can also be observed. After around 20000 steps of unsupervised learning, the network is already organized. i.e., the weight vectors do not change significantly. Weight vectors whose norm is represented by a straight line correspond to those neurons which are never chosen as the nearest weight vector for any training vector and which therefore do not change any more once the neighborhood order function is smaller than 1.

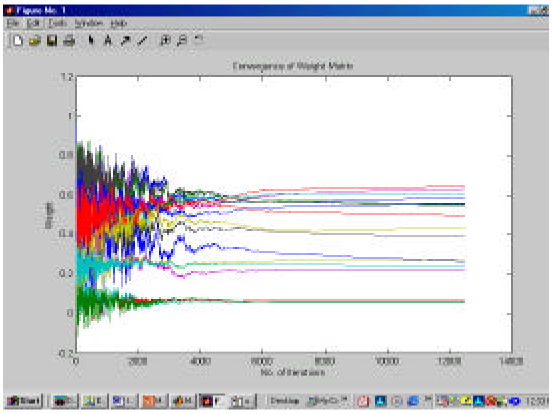

Fig. 4. The adaptation of the weight vectors

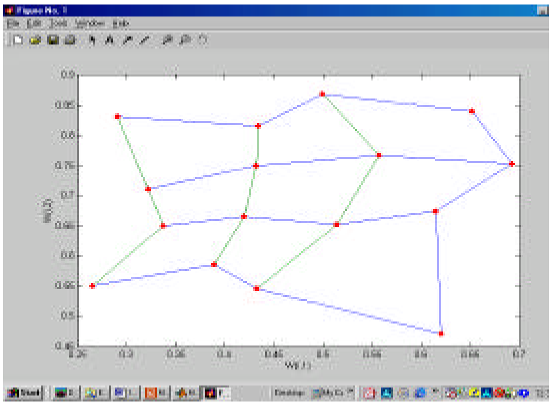

Fig 5. Self-Organization of the neurons

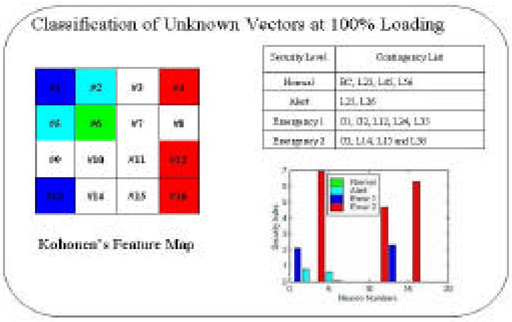

Fig. 6. Security Assessment Result for 100% loading

The figure 5 plots the self-organization of the neurons, where the neurons are located at the x and y component of its weight vector. The structure of the grid represents the uniform distribution of the input vectors. It is evident that the classification is not perfect in this case and a more regular pattern can be obtained for larger training sets and more slowly decreasing neighborhood function.

Classification of Static Security States

In the present work, the power system static security index is being proposed which classifies the power system states

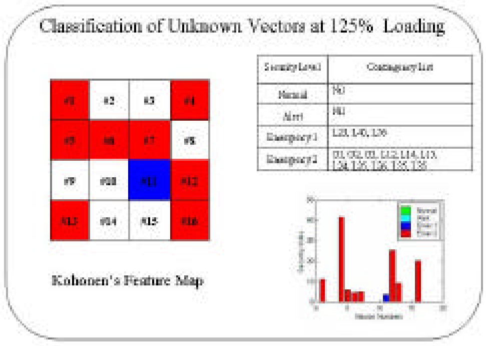

Fig.7. Security Assessment Result for 120% loading

whether it belongs to secure or insecure conditions and in-turn in which operating state it is, whether Normal, Alert, Emergency or in Network Splitting states. This is calculated by calling an output neuron where the estimated index is assigned. After an output neuron on the grid responds to a input pattern, the output calls the estimated index or performance index which is calculated as follows.

$$\text{Estimation Index, } EI_{MW} = \sum_{i=1}^{NL} \left(\frac{Wi}{2n}\right) * \left(\frac{P_L}{P_L^{\lim}}\right)^{2n}$$

where,

P_L = MW flow of line l, $P_L^{\max}$ = MW capacity of line l, NL = Number of lines of the system, W_i = Real non negative weighting factor (=1), N=Exponent of penalty function (=2)

2) Power System Static Security Levels and Its Security Index

In order to quantify the concept of secure and insecure operating states, four security levels have been determined which goes as Normal, Alert, Emergency 1 and Emergency 2. For these operating states the values of the security index are also given.

VIII. Simulation Results

Simulation results are obtained by the proposed scheme for different power system networks to assess the security level of the network. The proposed method is trained and tested on a 6 bus 11 line system shown in figure 3.

1) Classification of Known Training vectors

The neural network is trained using the database obtained from 100 % loading and the same is tested for classification of the loading patterns. The neural network test results consist of the classification of training patterns and the classification results for 15 training vectors.

The operating states of the neurons in the Kohonen Map are also presented in the results. From the cluster map the states of the power system can be identified easily.

2) *Classification of Unknown Vectors*

In order to generate vectors, which have not been trained, load of the base case were uniformly changed by 10% for lower loads and 25% increase for higher loads. Thus the proposed system is tested successfully for 70%, 125% and 150% loading.

Figures 6 and 7 show the Security Assessment Results obtained the SOFM for 100% and 125% loading respectively. It can be observed from Figure 6 for 100 % loading that the neuron 6 (#6) consisting of Base Case (BC), Line 23 outage (L23), Line 45 outage (L45) and Line 56 outage (L56) correspond to the normal state. The Alert State consists of the line outages L25 and L26 are distributed in neuron #2 and neuron #5. Similarly the Emergency State I consist of the outages of G1, G2, L12, L24 and L35 are represented by neuron #1 and neuron #13 respectively.

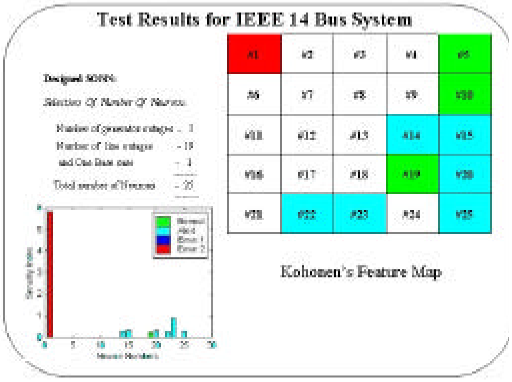

Fig. 8 Simulation Results for IEEE 14 Bus System

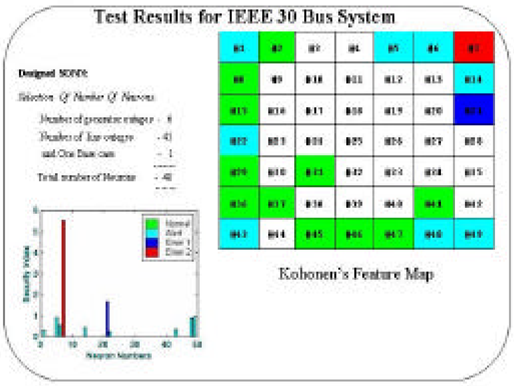

Fig. 9 Simulation Results for IEEE 30 Bus System

In the case of 125 % loading in figure 7, it can be observed that all the outages are in the Emergency I and Emergency II classes. Thus it can be concluded that with increase in

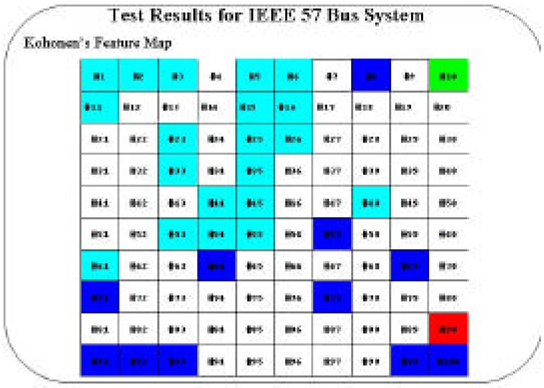

Fig. 10. Simulation Results for IEEE 57 Bus System

loading level all on the outages are clustered together and grouped into two classes of Emergency I and Emergency II respectively. In other words, the ANN approach can cluster the outages classify them according to the severity level with reference to the operating states of the power system. Figures 8, 9 and 10 show the simulation results obtained by the SOFM for the IEEE 14, 30 and 57 Bus Systems respectively.

IX. Conclusion

An NN-based static security assessment technique for a model power system is proposed. This work demonstrates the feasibility of classification of load patterns for power system static security assessment using Kohonen self-organizing feature map. The most important aspect of this network is its generalization property. Using 15 different line loading patterns for training, the network successfully classifies the unknown loading patterns. This powerful and versatile feature is especially useful for power system operation as an aid in training the operator in alert, emergency and restorative region identification and control.

X. References

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