

DYNAMIC AND STATIC SECURITY ASSESSMENT OF POWER SYSTEMS USING ARTIFICIAL NEURAL NETWORKS

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What follows is a summary of some of the authors' work on two types of security problems. In this work we used a layered perceptron with two training algorithms, a projection algorithm and an error backpropagation algorithm. The projection algorithm is based on the least squares approximation technique and the error backpropagation on the steepest descent technique.

1. Dynamic Security

Preliminary results were obtained from studies of the dynamic security of a 9 buses, 3 generators, and 14 transmission lines test system. Our first study analyzed the relationship between system stability and the output power of generator 3, the excitation of generator 3, the apparent power of load 8, and the availability of lines 9 and 10. The results were reported in [1]. Some of these results are shown in Figures 1 and 2. Basically, the accuracy of classification and the ability of the ANN to generalize were very good. However, we encountered difficulties in extending the results to larger systems due to properties of the projection algorithm. First, the number of hidden nodes must be at least as large as the number of training data points. Second, as the number of hidden nodes grew, the projection algorithm became unstable due to the problem of inverting an ill-conditioned matrix.

Our second examination of the dynamic security of this system used the error backpropagation training algorithm [2]. While this approach requires fewer nodes in the ANN, the training time is longer because it is iterative. This second study examined the security of the system with respect to the outputs P3 and Q3 of generator 3, the apparent power output S2 of generator 2, and the status of line 10. The ANN used had 4 input nodes, three representing

the quantities P3, Q3, and S2 and 1 for a constant bias input. The hidden layer had 10 nodes and the output had one node.

Two types of training sets were used, each of 1000 points chosen from allowed domain in the three dimensional P3 x Q3 x S2 space. One set was chosen at random over this domain using a uniform distribution. The other training set was selected to emphasize the security region boundaries. Each training set was used separately to train an ANN. In both cases, convergence required a few hundred iterations through the set as shown in Figure 3. To assess the classification accuracy of each trained ANN, we performed an exhaustive query and Figure 4 shows the performance curves.

For both cases the classification accuracy is seen to be very good. The additional accuracy that appears to be achieved by the boundary enhancing training set is probably not important. Rather, the significance of this result is that the ANN is able to give a good representation of the security boundary for a complex relationship, information that can help the dispatcher operate near the boundary with more confidence than is available at present.

2. Static Security

This section provides a brief review of the work reported in [3]. The test system was composed of 8 buses, 4 generators, and 14 transmission lines. The goal was to represent the security relationship involving the loads at buses 6 and 8 and transmission line number 4.

The ANN chosen had 3 input neurons, one for each of P6, Q6 and S8, and one constant value, or bias input neuron. There was one hidden layer with 10 neurons and one output neuron. With line 4 operating, the network was trained to monitor the values of P6, Q6 and S8 and to indicate when constraints would be violated if line 4 were to fail. That is, line 4 was the only element in the contingency list.

Training was accomplished with the error backpropagation algorithm and two different training sets. The first set was a two dimensional case where S8 was fixed at 100% of its nominal value. Two thousand training points were selected randomly in the P6, Q6 plane. Figures 5 and 6 indicates the relationship between the true and predicted security region. About 2% of the 6561 points over which the ANN was tested were misclassified. The false secure and false insecure indications were about equal in number.

The second training set explored all 3 input variables. The variable S8 was allowed to have the discrete values of 0%, 50% and 100% of nominal load and P6 and Q6 were again

selected randomly for each of these S8 values. A total of 1469 training points was used. When tested, the ANN was found to generalize smoothly between the fixed values of S8 used in training as shown in Figures 7 and 8. In both cases, the performance of the ANN was judged very good for the complex relationships being classified.

3. The Current Challenge: Solving Full Scale Problems

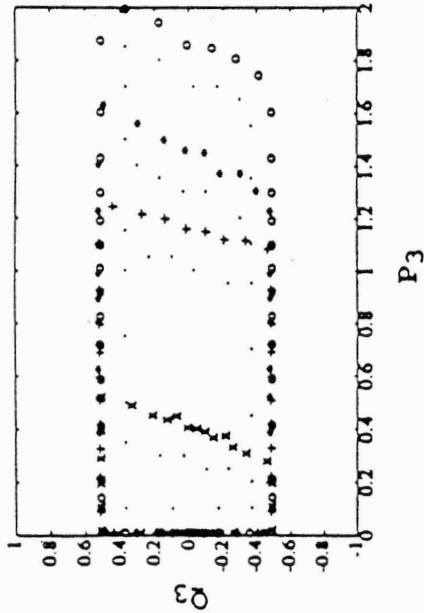
The basic challenge we see at present for developing useful tools is one of scale. Power systems are typically considered "large scale systems." Hence, an ANN approach must ultimately accommodate this problem of scale in some manner.

The problems that we think will need to be faced are to determine:

- o how large an ANN is required and what its architecture must be,
- o how much data is required for training and if that training can be accomplished in reasonable time,
- o whether the training data (probably from off-line studies) can be generated with reasonable effort,
- o a method for testing the trained ANN to measure its classification accuracy and develop the confidence of the dispatcher, if warranted, and
- o how to update the ANN so it continues to be current.

4. References

- [1] M. E. Aggoune, et al., "Preliminary Results on Using Artificial Neural Networks for Security Assessment." PICA Conference, pp. 252-258, May 1989.
- [2] M. A. El-Sharkawi, et al., "Dynamic Security Assessment of Power Systems Using Back Error Propagation Artificial Neural Networks." Second Symposium on Expert Systems Application to Power Systems, pp. 366-370, July 1989.
- [3] M. E. Aggoune, et al., "Artificial Neural Networks for Power System Static Security Assessment." IEEE Proceedings of the International Symposium on Circuits and Systems, Vol. 1, pp. 490-494, May 1989.



(x) $K_A=110\%$ and $D_B=0\%$, (*) $K_A=90\%$ and $D_B=0\%$
 (+) $K_A=110\%$ and $D_B=200\%$, (o) $K_A=90\%$ and $D_B=200\%$
 Figure 1. Training data

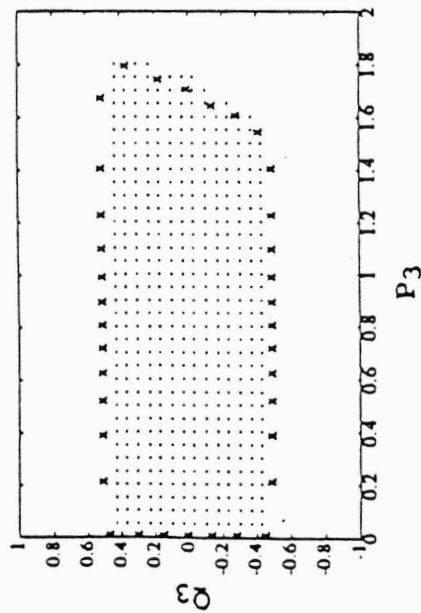


Figure 2. Test results at $K_A=100\%$, $D_B=200\%$

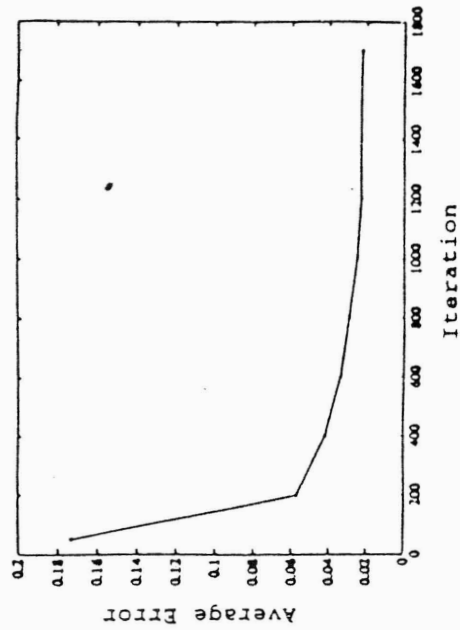
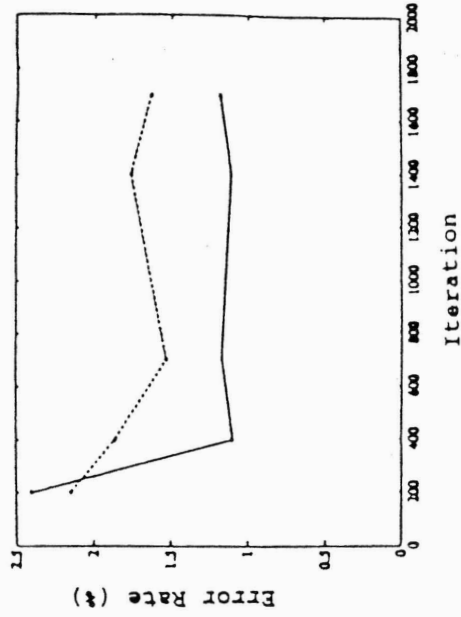


Figure 3. Learning curve



(.) ANN trained with random data
 (-) ANN trained with selected data
 Figure 4. Testing data

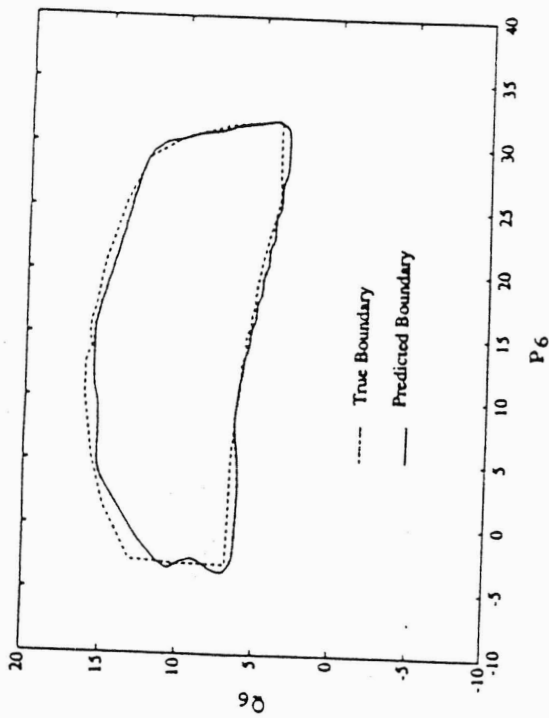


Figure 5. Error Backpropagation classifier ($S_g=100t$)

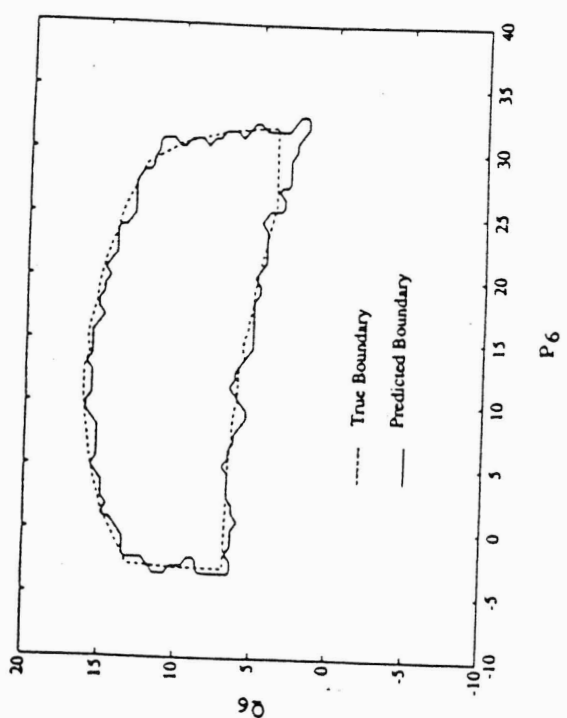


Figure 6. Nearest Neighbor classifier ($S_g=100t$)

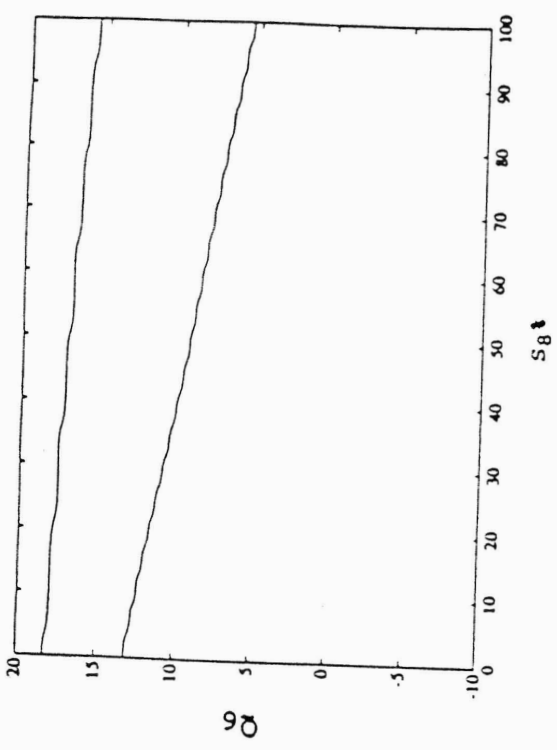


Figure 7. Error Backpropagation ($P_6=15 \text{ MW}$)

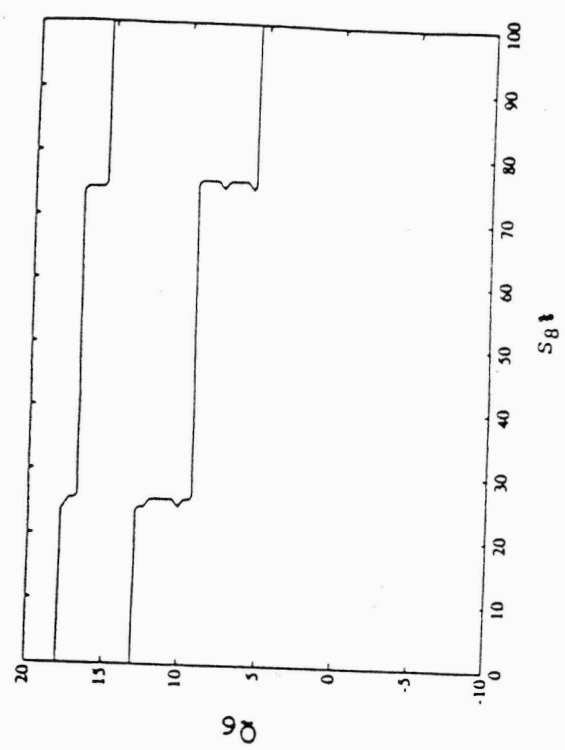


Figure 8. Nearest Neighbor ($P_6=15 \text{ MW}$)