POTENTIAL OF ARTIFICIAL NEURAL NETWORKS IN POWER SYSTEM OPERATION

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Abstract

Recent experience suggests that artificial neural networks (ANN's) may be particularly appropriate for assisting dispatchers in operating electric power systems. Dispatchers often need to make rapid decisions to maintain satisfactory operation when the system is threatened with possible disturbances. This paper discusses the potential applicability of ANN's to electric power systems with emphasis on aiding dispatchers with decision making, particularly with decisions relating to power system security. Examples illustrate how ANN's can alert dispatchers to security threats due to possible constraint violations, unstable dynamics and uncertain loads. The paper also reviews the problems that must be overcome before an ANN dispatcher's aid is realizable.

1. Introduction

Numerous researchers have explored ways in which artificial neural networks (ANN's) may apply to the electric power industry. Those applications which interest us most are focused on electric power system operation. In this paper we review the current literature applying ANN's specifically to operational problems and argue that there may be an exceptionally good match between the problem of power system operation and the capabilities of ANN's. One important class of problems is that of power system "security" but we believe other applicable operations problems exist as well.

In the next section we discuss the power system security problem in more detail and argue that it is a classification problem for which ANN's may be suitable. That section is followed by a review of literature discussing recent ANN applications. The rest of this paper is devoted to reporting the results of three small-scale applications by the authors and their co-workers. The final section of the paper discusses what we believe to be the fundamental challenge to this research area: the need to build ANN tools that can be applied to full-scale power systems.

2. Review of the Power System Security Problem

Operating an electric power system network involves on-line control to maintain economic operation while avoiding disruption of service to customers. The term economic operation relates to the fact that a utility attempts to minimize its cost of energy generation and transmission. This minimization is subject to constraints intended to assure reliable service. The basic equality constraints are that the total real and reactive generated powers must meet the total demand plus losses. Inequality constraints must also be imposed on the system to ensure secure operation. The basic inequality constraints are that all bus voltages must be bounded, all line currents must not exceed the respective thermal limits, and all generator power outputs must be limited.

The function of maintaining economic operation during "normal" conditions is automatic without intervention by the dispatcher. However, in some types of "abnormal" operation the dispatcher is expected to react. A common example occurs when all variables are within allowable ranges but there is a credible threat of violations. Here the system is said to be "insecure." An event which is disruptive enough to cause preventive action and is reasonably likely is called a "contingency."

We can think of the system as being represented by a large set of key variables. At any time, the system operating "state" is a point in the high dimensional space of these variables [1]. Insecurity problems occur in the region containing the "alert" states. When the dispatcher is concerned about "static" security and the system is in one of these alert states, the equality and inequality constraints are met but would not be met if some specific contingency occurs [2]. Consequently, the dispatcher may be willing to abandon pure economic operation for the sake of greater security.

The other form of security, "dynamic" security, is not concerned with the constraint equations but with stability [2]. After a contingency, system variables such as frequency and voltage will oscillate, no matter how small the disturbance. If the system is stable, the oscillations will decay. However, if the system is unstable, they will grow until equipment, probably a generator, switches off automatically. A system is called secure if all contingencies would yield stable oscillations.

The contingency analysis of a single operating state requires much off-line calculation involving power flow [3], economic dispatch [4], and stability [5] analysis. In using analysis for guidance, the dispatcher faces two basic problems. First, the operator must determine which analyzed state is "closest" to the present system operating state so that the analyzed state can be used for guidance. Second, the dispatcher must be alerted when conditions exist that cause insecurities.

It is our position in this paper that the dispatcher clearly needs a tool to assist with these two problems. This tool must monitor the system state and identify when it falls within the insecurity region for some contingency. This tool can refer to off-line studies but it must generalize from those individual studies. Hence, we need a "classifier". That is, the current state

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must be compared to the collection of reference states to determine whether it should be classified as "secure" or "insecure."

3. Historical Perspective

General reviews of the history of classifiers are readily available [6-8]. In this section we will review applications of classifiers to power systems. The initial approaches used pattern recognition but, more recently, applications of ANN's have been an active area of study. The idea of using pattern recognition in power systems was first suggested by Dy Liacco in 1968 [9]. This suggestion was followed by a wave of enthusiasm as power system engineers expected that pattern recognition would fulfill the need for an on-line aid [10-14]. Unfortunately, no tool based on pattern recognition has yet achieved operational status. This lack of implementation is probably due in part to the fact that the effort to develop the training cases was very large, the classification accuracy was disappointing and the scope of the application often too narrow. However, this work must be judged part of the foundation upon which any successful on-line applications of ANN classifiers will be built.

Artificial neural networks have demonstrated the ability to properly classify complex relationships. This ability has been demonstrated in speech recognition and signal processing [15-17], and power systems [18-27]. In all these cases, the relationships classified by the ANN's are highly nonlinear and often result from large mathematical models. The major benefit is that once trained, the ANN can classify new data much faster than would be possible by solving this model.

Neural network research reached power systems at the end of the 1980's due mainly to the contribution of Sobajic and Pao [18]. This paper was followed by numerous additional applications of ANN's, many of which are reviewed below. We first review the papers specifically about power system security and then discuss those concerning other issues.

D.J. Sobajic and Y.H. Pao (1989) [18] used a three layered artificial neural network to estimate the critical clearing time for a three phase short circuit. In this study the error backpropagation algorithm was used to update the networks' parameters. The test system was composed of four generators, seven lines, and six buses.

R. Fischl, et. al (1989) [19] used a three layer neural network to screen contingencies to identify those which could lead to an insecure state. In this study the error backpropagation algorithm was used to update the network's parameters. The test system chosen was composed of 6 buses, 9 lines, and 3 generators. The main contributions of this paper were (1) the appropriate choice of the inputs to the neural network and (2) the investigation of the learning capability of the network.

N.I. Santoso, and O.T. Tan (1989) [20] used a group of neural networks to control capacitors installed on a 30 bus distribution system. The model chosen for the networks was based on error backpropagation. The main contributions of this paper were: (1) the use of multi-neural networks in the same power system and (2) the choice of inputs to the neural networks.

H. Mori, and S. Tsuzuki (1989) [21] used a Hopfield model based neural network to determine the network topological observability of a test system. In this study, the test system was composed of 5 buses and 7 transmission lines. The main contributions of this paper were: (1) the first application of the Hopfield model to power system network observability and (2) the appropriate choice of the inputs to the neural network.

More recently many other applications were suggested in the power system field. Among the contributors are: Mathur et. al. (1989) [22], Matsuda and Akimoto (1989) [23], and Uhrig (1989) [24]. Mathur et. al. suggested using artificial neural networks for many problems in the utility industry and provided a checklist for ANN applications. Their discussion emphasized coal-fired generating plant control. Matsuda and Akimoto used a Hopfield model ANN to solve the economic power dispatch problem. Uhrig provided an overview of the operation, and characteristics of artificial neural networks and discussed some of their potential applications to nuclear power plants.

4. Results of Preliminary Research on ANN Applications

The previous sections have argued that ANN's may be useful for on-line security assessment because they have the correct basic properties:

1. They can be trained with the off-line data used to understand power system operation.

2. They can be queried rapidly on-line when the dispatcher needs help.

3. They can generalize from the cases that were studied and, hence, respond to cases that were not.

What follows is a review of the authors' work on three types of security problems. In this work we used a layered perceptron [25] (figure 1) with two training algorithms, a projection algorithm [26] and an error backpropagation algorithm [25]. The projection algorithm is based on the least squares approximation technique and the error backpropagation on the steepest descent technique. Once the ANN has been trained to classify adequately, it is ready to be applied on-line, that is, installed in the power system EMS.

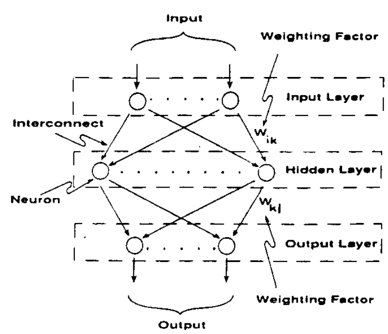

Figure 1. A layered Artificial Neural Network

4.1 Dynamic Security

Dynamic security assessment consists of determining whether or not the system can reach a new steady operating state following a disturbance. Stability can be checked by examining the eigenvalues of the system model linearized about the new operating state.

Preliminary results were obtained from studies of the dynamic security of the test system of figure 2. Our first study analyzed the relationship between system stability and the output power of generator 3, the excitation of generator 3 and the availability of lines 9 and 10. The results were reported in [27]. 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.

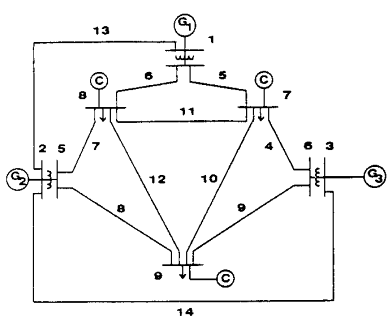

Figure 2. Dynamic security test system

Our second examination of the dynamic security of this system used the error backpropagation training algorithm [28]. 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, P_3 and Q_3, of generator 3, the apparent power output, S_2, of generator 2, and the status of line 10. The ANN used had 4 input nodes, three representing the quantities P_3, Q_3, and S_2 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 $P_3 \times Q_3 \times S_2$ 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.

To assess the classification accuracy of each trained ANN, we performed an exhaustive query of two different slices in the 3 dimensional domain of inputs. For the first case, we fixed S_2 = 0.8 per unit. Figures 3 and 4 show the results for both training sets where the solid curve represents the true security boundary and the dotted or broken curve represents the classification of the ANN. The second case was chosen to examine the generalization ability in a small region around a critical portion of the boundary when Q_3 was fixed at 0.3. 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.

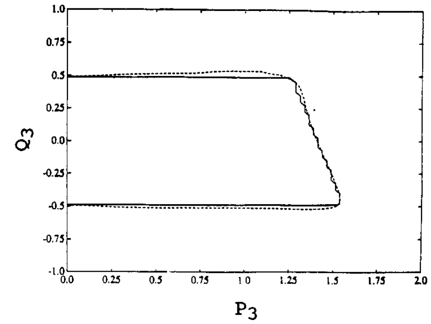

Figure 3. Security contour obtained using random data

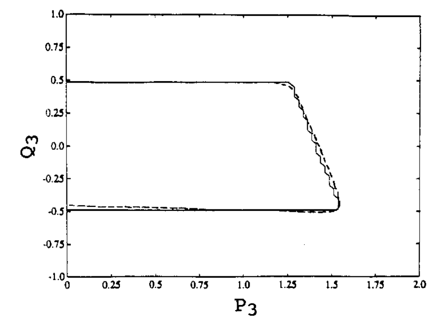

Figure 4. Security contour obtained using interval halving data

4.2 Static Security

This section provides a brief review of the work reported in [29]. The problem was to monitor the network and assure that the constraints were met even if a disturbance in the contingency list occurred. After training, the ANN should indicate the security status by the value of its output node. The test system was that of figure 5 consisting of 8 buses, 14 lines and 4 generators. 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 P_6, Q_6 and S_8, 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 P_6, Q_6 and S_8 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.

To represent system operation in the "normal" mode, each training point must represent economic operation. Specifically, for a given load, an optimal power flow must be solved to determine the minimum cost pattern of generation. Then, with those values for each generator output, line 4 is removed from the network and a power flow solution determines if any constraints are violated. If not, the point is in the secure region, else it is an insecure operating point. This procedure was used to determine the input values and status of each of the training points.

Training was accomplished with the error backpropagation algorithm and two different training sets. The first set was a two dimensional case where S_8 was fixed at 100% of its nominal value. Two thousand training points were selected randomly in the P_6, Q_6 plane. Figure 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 S_8 was allowed to have the discrete values of 0%, 50% and 100% of nominal load and P_6 and Q_6 were again selected randomly for each of these S_8 values. A total of 1469 training points was used. When tested, the ANN was found to generalize smoothly between the fixed values of S_8 used in training. In both cases, the performance of the ANN was judged very good for the complex relationships being classified.

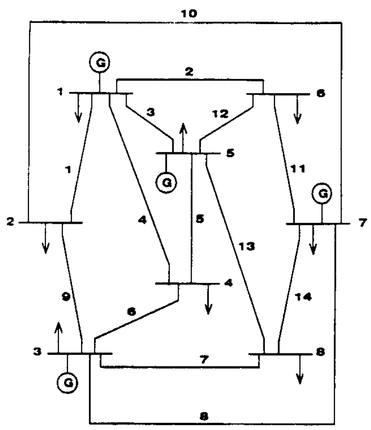

Figure 5. Static security test system

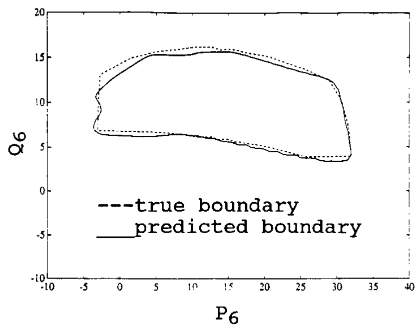

Figure 6. True and predicted security boundaries

4.3 Load Forecasting

In addition to the contingencies which are emphasized in the previous security issues, another major source of uncertainty facing power system dispatchers is the future system load. Near term forecasts of a few days are needed to plan which generation units should be committed for use at a particular time, a concern of "operations planners."

To explore one such forecast, we used data provided by the Puget Sound Power and Light Co. to train ANN's to predict (1) the total load and peak load one day ahead using temperature information, and (2) the load with different lead times from 1 hour ahead up to 24 hours ahead [30].

For the total load forecast, the errors ranged from a low of 0.03% to a high of 5.64% and averaged 1.68%. For the peak load forecast, the errors ranged from a low of 0.13% to a high of 6.64% and averaged 2.04% over the 30 test days.

Figure 7 shows the curves for the actual load at time k and the one hour ahead prediction for time k for a typical day. The average hourly error for this day was 1.41%. The three hour ahead prediction was so similar it could not be distinguished from the one hour prediction if plotted on the same graph. For one 5 day test set, which was roughly nominal of all test sets, the average error was 1.39% for the one hour ahead prediction and 1.84% for the three hour ahead prediction

From our brief experience, we conclude that load forecasting is another role that ANN's might perform in power system operations. The forecasts that we have obtained in these early experiments are at least as good as those currently used by the Puget Sound Power and Light Co. Further investigation is required to determine the reliability of such forecasts and the actual use that engineers and dispatchers may make of them.

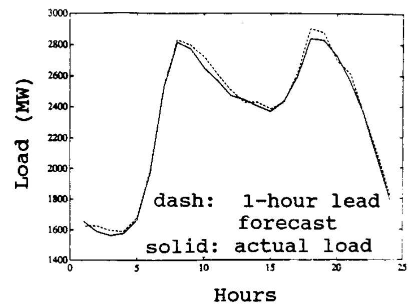

Figure 7. 1 hour lead forecasted load

5. 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 relationship between system size and ANN size is not clear to us. Certainly that relationship must depend on the function the ANN is to perform. However, it does seem likely that an ANN for a useful on-line function on a full-scale system will need to be large. Perhaps it will need to be much larger than those used as examples in section 4. The problems that we think will need to be faced are to determine:

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

The immediate challenge then to developing useful on-line dispatcher aids with ANN's is two fold:

1. identify applications which are of suitable scale for current ANN technology and
2. develop the ANN technology until it is capable of application to larger scale problems.

One possible solution to the large scale problem may be the parallel application of many ANN's, each focused on one very narrow, local subproblem (security issue). If this large collection of ANN's can be managed by a supervisory layer of software, then large scale problems may be manageable without "order of magnitude" advances in ANN technology. Development in ANN technology needs to focus on (1) knowing the relationships between the ANN size and the power system scale, and (2) developing fast training algorithms.

6. Acknowledgements

The authors are grateful to the National Science Foundation and the Washington Technology Center for their support of this work. They also wish to recognize the significant contributions of Milan Casey Brace of the Puget Sound Power and Light Co. and D. Park, Les Atlas and David Cohn of the University of Washington.

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