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Power System Security Boundary Enhancement Using Evolutionary-Based Query Learning

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Abstract

This paper presents a new method for enhancing the accuracy of partially trained multilayer perceptron neural networks in specific operating regions. The technique is an extension of previously published query learning algorithms and uses an evolutionary-based boundary marking algorithm to evenly spread points on a contour of interest - in this case the power system security boundary. These points are then presented to an *oracle* (*i.e.* simulator) for validation. Any points that are discovered to have excessive error are then added to the neural network training data and the network is retrained. This technique has advantage over existing training methods because it produces training data in regions that are poorly learned and thus can be used to improve the accuracy of the neural network in these specific regions. An example of the proposed algorithm is applied to the IEEE 17 generator test system.

1. Introduction

The modern trend towards deregulation is altering the manner in which electric power systems are operated. In the past, electric utilities were able to justify improvements in system infrastructure based solely on security considerations. In a deregulated environment this is no longer the case. Economic pressure tends to delay construction of new facilities. Therefore, utilities are being forced to operate their systems closer to their security boundaries. This demands the industry to develop better methods of quantifying the real-time security status of their systems.

Several researchers have investigated the use of neural networks as a means to predict security status of large electric power systems [1-3]. Neural networks provide a mapping $f(\mathbf{x})=S$, where $f(\cdot)$ is the network function, $\mathbf{x}$ is a vector of network inputs and S is the corresponding security status of the power system. Neural networks offer several advantages over traditional security assessment methods including faster execution times and the ability to model the entire power system in a compact and efficient form.

McCalley *et al.* proposed the idea of using neural networks as a means of creating nomograms customized to the current operating status of the power system [4]. Nomograms are usually 2-dimensional plots showing the relationship of system control variables to the security of the system.

In [4], a multilayer perceptron neural network was trained to learn the security status of a power system given a set of precontingency operating variables. Nomograms were then created by fixing a subset of the network input variables and adjusting the remaining variables to find the set of points

$$\mathbf{X} = \{\mathbf{z} : f(\mathbf{z}, \mathbf{y}) = S\}$$

where

$$\mathbf{z} = \text{the subset of varied parameters}$$
$$\mathbf{y} = \text{the subset of fixed paramters}$$

Repeated application of a simple one-dimensional root finding technique was proposed to generate two-dimensional nomograms. An example of a typical nomogram is shown in Figure 1.

Jensen *et al.* [5] proposed a similar idea using an inversion of a trained neural network to extract information relative to the operation of the system. A gradient based neural network is used for the inversion algorithm to extract power system operating information such as the location of the security boundary to a given operating state. This information is used to either avoid insecurity or to regain security once lost.

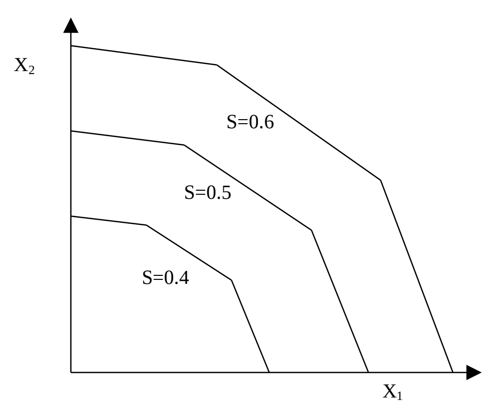

Figure 1 Nomogram for two parameters showing three security levels

Both of the above applications are based on searching the functional relationship of a trained neural network. Therefore, the accuracy of the neural network is critical to their performance. It is especially important that the neural network be accurate in operating regions of interest such as near the security boundary.

This paper presents a new evolutionary-based query learning algorithm whereby the accuracy of a partially trained neural network can be increased. Moreover, the proposed algorithm is particularly well suited to quantifying and improving performance in specific regions of interest, such as security boundaries. The system is based on a boundary marking technique originally proposed by Reed and Marks [6] which makes use of an evolutionary algorithm to spread points evenly on a contour of interest. These points are then verified via simulations thus quantifying the accuracy of the security boundary. Areas of inaccuracy can then be improved by augmenting the training data base and retraining the neural network.

Section 2 of this paper deals with issues involved in training neural networks for power system dynamic security assessment including; data gathering, training and validation. Section 3 introduces the concept of evolutionary algorithms and the proposed query learning technique of this paper. Section 4 describes the application of this technique to the creation of nomograms and the location of critical operating regions using the IEEE 17 generator transient stability test system as a case study. Finally, conclusions are presented in section 5.

2. NN's for DSA

Neural networks have demonstrated the ability to approximate complex nonlinear systems when presented with a representative sample of training data. Several researchers have reported remarkable results when applying the multilayer perceptron neural network to the power system security assessment problem [1-3]. Typically, traditional methods such as time domain simulations [7] or energy function methods [8] are used to generate a database of training data. This database includes examples of all power system operating scenarios of interest described by a set of selected power system features as well as their resulting security measure. The neural network then adapts itself to the training database and produces an approximation to the security assessment problem in the form an equation $f(\mathbf{x})=S$, where f is the neural network function, $\mathbf{x}$ is the vector of power system features and S is the resulting security index. Examples of commonly used security indices include energy functions and critical clearing times [7,9].

A key advantage of using neural networks is the ability to extract operating information after training via neural network inversion techniques [10-12]. Neural network inversion is the process of finding an input vector that produces a desired output response for a trained neural network. For example, consider a neural network trained to predict the security S of a power system given a vector of system features $\mathbf{x}$. By clamping the output value S to the marginally secure state, say $S=0.5$, where $S=1.0$ is secure and $S=0.0$ is insecure, and inverting the network, a marginally secure state $\mathbf{x'}$ can be found in the input space. This state then describes a region of the power system operating space where insecurity is likely to occur. It should be noted that since the neural network is typically a many-to-one mapping, the inversion is generally not to a unique point, but rather to some contour in the input space.

In this paper we used the IEEE 17 generator transient stability test system as a case study. We used the EPRI energy margin software package called DIRECT [13] to create the training database for the neural network. Software was written to automate the data gathering process by repeatedly running the DIRECT software to calculate the system energy margin for a single fault under many different prefault operating states. The database consists of a set of prefault system features, in this case generator settings and system load, and the corresponding system energy margin. The DIRECT software determines the energy margin, which is related to the security of the system, by assigning a positive energy margin to secure states and a negative energy margin to insecure states. The magnitude of the energy margin indicates the degree of stability or instability.

A software package called QwikNet [14] to design and test the neural network was used. QwikNet is a remarkable windows based neural network simulation package that allows experimentation with many different network topologies and training algorithms. After training, the neural network function, $f(\mathbf{x})=S$, can be written to a file in a convenient C programming language format that can easily be incorporated into the inversion software.

3. Evolutionary-Based Query Learning Algorithm

Query learning [15-16] is a method that can be used to enhance the performance of partially trained neural networks. Query learning is based on the notion of asking a partially trained network to respond to questions. These questions are also presented to an oracle which always responds with the correct answer. The response of the neural network is then compared to that of the oracle and checked for accuracy. Areas that are poorly learned by the neural network can be thus identified. Training data is then generated in these areas and the network is retrained to improve its performance.

The query learning procedure proposed in this paper is an extension of previously proposed methods. The principle difference is that instead of locating and then querying individual points, our algorithm works with a population of solutions, thus offering the ability to query entire areas of interest. This algorithm also seeks to evenly distribute the points across the area. Evenly distributing the points is important because a global view of the security boundary in multiple dimensions is provided thus allowing the entire boundary to be queried and potentially improved. After the points are spread, they are simulated via the energy margin simulator and their true security index is determined. If all the points are within tolerance the algorithm stops. Otherwise, the points with unacceptably large errors are added to the training database and the neural network is retrained

In the evolutionary boundary marking algorithm, all reproduction is asexual, *i.e.* no mating or crossover takes place. Offspring are produced as perturbations of single parents. This concentrates the search in the area close to the security boundary and speeds convergence. The algorithm seeks to minimize a fitness function, F, of the following form;

$$F = \left| f(\mathbf{x}) - S \right| + \frac{1}{D_{avg}}$$

where,

f	is the neural network function,
$\mathbf{x}$	is the current point,
S	is the security boundary, and
D_{avg}	average distance to the nearest neighbors

The evolutionary algorithm is randomly initialized with N points and then proceeds as follows.

1. The population is sorted based on fitness, F.
2. The M points with the lowest fitness scores are deleted.
3. Replacements are generated for each deleted point:
   (a) M parents are selected proportional to fitness from the remaining points.
   (b) New offspring are created as perturbations of the selected parents, $\mathbf{x}_{new} = \mathbf{x}_{parent} + \mathbf{n}$, where $\mathbf{n} \sim N(0, s)$.
   (c) Feasibility constraints are enforced on the new offspring via the solution of a standard power flow.
4. Repeat until convergence.

By successively deleting points with poor fitness values and replacing them with perturbations of points with high fitness, the population tends to spread evenly across the solution contour. Typical values used in this paper are N=100, M=20, m=3 and s =0.05.

Figure 2 shows histograms of the initial and final population distributions. It can be seen that the final population has converged to the security boundary and is evenly spread across the boundary. These points are then added to the training database and the network is retrained. Several iterations of query learning may be required produce acceptable results.

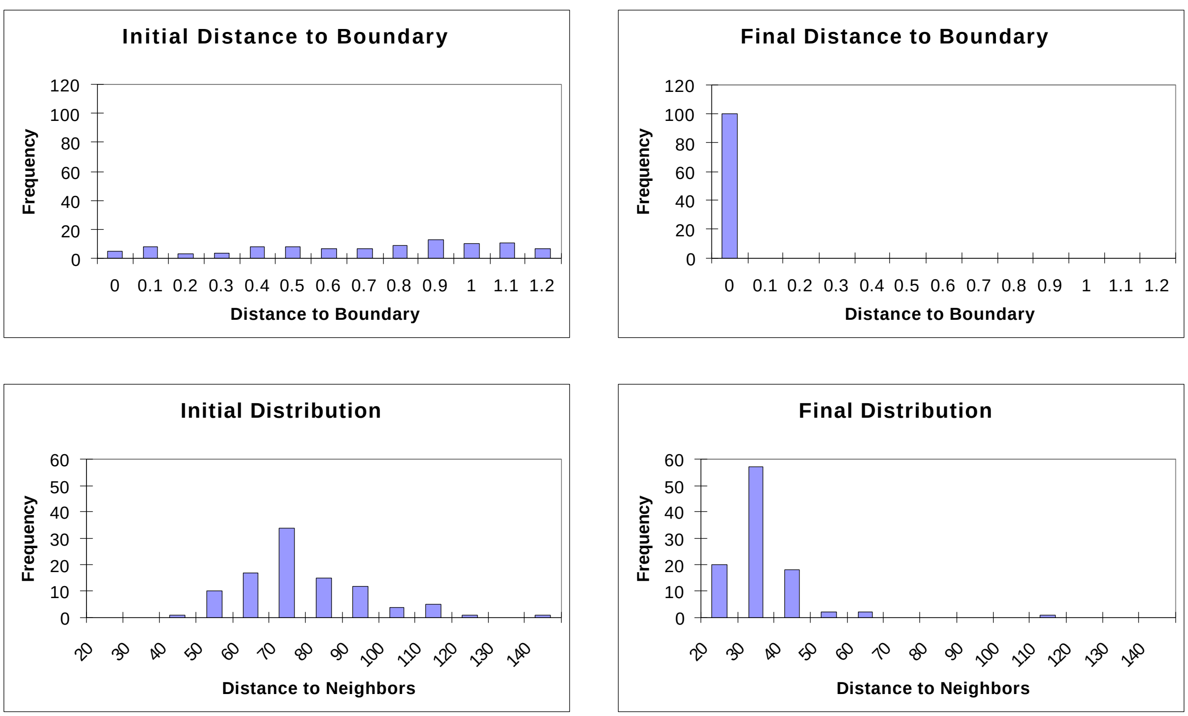

Figure 2 Histograms of the initial population and final population of the boundary marking algorithm

4. Case Study – IEEE 17 Generator System

The IEEE 17 generator transient stability test system [17] is used to illustrate the performance of the proposed algorithm. This system consists of 17 generators and 162 buses. The EPRI energy margin software DIRECT is used to determine the energy margin of the system in response to a single three phase fault. Twelve system features are selected to represent the system for neural network training. These include the real and reactive powers of the 5 generators closest to the fault location and the total system real and reactive load level. A training database of 436 samples was created for initial training of the neural network by randomly perturbing generation settings and system load levels and then simulating each case on the energy margin software. The initial RMS neural network testing error was 0.113 corresponding to a test database that was not used for training.

The proposed query learning algorithm was then used to generate additional training samples near the security boundary. These points are simulated on the DIRECT energy margin simulation software and the points with large errors are added to the training data file. The final training database consisted of 1177 training samples and the final RMS test error was reduced to 0.062.

Nomograms were then created from the initial and the enhanced neural networks based on the method proposed in [4]. These nomograms show the relationship between two generator power outputs and the security boundary. The two nomograms are shown in Figure 3 along with the true nomogram which was created by repeatedly querying the simulator. It should be noted that the nomogram of the simulator as shown in Figure 3 required smoothing by fitting a 2nd order polynomial to the raw data. The smoothing operation is required due to the approximations and assumptions made by the simulation software. The RMS error for the initial nomogram is 48.53 while the enhanced neural network nomogram is 10.11. This experiment proves the viability of the proposed technique in increasing the accuracy of a partially trained neural network near the security boundary.

5. Conclusions

This paper presents an enhanced query learning algorithm that effectively locates regions of interest and distributes neural network training data in these regions. The process is used to enhance the accuracy of partially trained neural networks in specific operating regions. The proposed technique is applied to the problem of generating power system operating nomograms from neural networks. Results show a nearly 5 fold improvement in RMS error when applied to the IEEE 17 generator test system.

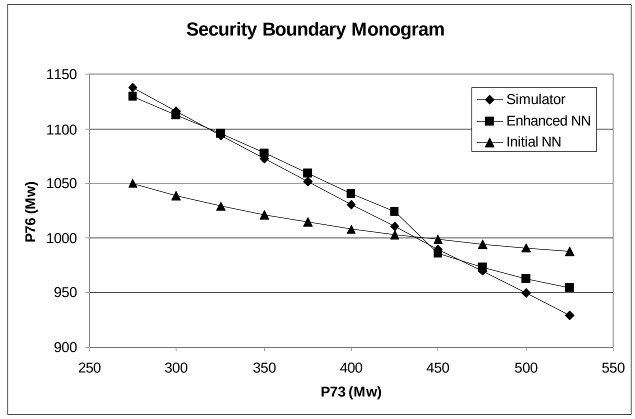

Figure 3 Nomogram of P73 vs. P76

6. Acknowledgement

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