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Intelligent Techniques for Power Systems Vulnerability Assessment

Mohamed A. El-Sharkawi

Computational Intelligence Applications (CIA) Laborartory, Department of Electrical Engineering, University of Washington, Seattle, WA 98195-2500, http:// cialab.ee.Washington.edu.

التقنيات الذكية لتقييم هشاشة نظم القوى الكهربائية

محمد الشرقاوي

خلاصة : تولي شركات إنتاج الكهرباء نظم القوى أعلى الأوليات حيث تعتبر القوى الكهربائية من مسائل الأمن القومي ويهتم نظام تقييم الهشاشة بقدرة نظم القوى الكهربائية على توفير الخدمة في حالات الطوارئ . تعرض هذه الورقة طريقة يتم بها تقييم هشاشة نظم القوى بشكل مباشر من دون أن تقطع الخدمة وذلك باستخدام التقنيات الذكية.

ABSTRACT: With power grids considered national security matters, the reliable operation of the system is of top priority to utilities. This concern is amplified by the utility's deregulation, which increases the system's openness while simultaneously decreasing the applied degree of control. Vulnerability Assessment (VA) deals with the power system's ability to continue to provide service in case of an unforeseen catastrophic contingency. Such contingencies may include unauthorized tripping, breaks in communication links, sabotage or intrusion by external agents, human errors, natural calamities and faults. These contingencies could lead to a disruption of service to part or all of the system. The service disruption is known as outage or blackout. The paper outlines an approach by which feature extraction and boundary tracking can be implemented to achieve on line vulnerability assessment.

KEYWORDS: Intelligent techniques, Vulnerability assessment, Power systems

1. Introduction

Because the trend towards deregulation is altering the manner in which electric power systems are operated, accurate vulnerability assessment is becoming vital. In the past, regulated electric utilities were able to justify improvements in system operation or infrastructure based solely on crude methods for security assessments. In a deregulated environment this is no longer the case. Economic pressure tends to delay construction of new facilities forcing utilities to operate their systems closer to their security boundaries. This, in turn, demands the industry to develop better methods of quantifying real-time VA.

The approach to power system VA involves the examination of system performance based on all postulated and credible system contingencies. Such analysis allows for a means to evaluate both system performance and system reliability while meeting current and future demands. The goal is to determine if the severely disturbed system will remain in synchronization following a disturbance. If any generator loses synchronism, its protection devices will quickly remove it from the network resulting in another disturbance to the power system, which, in turn, can lead to removal of another generator. This is called a cascading outage and can lead to severe consequences such as blackouts. If the analysis indicates vulnerable or insecure operation, corrective actions must be taken to steer the system to a more viable operation, thus preventing outages should the contingency occur. A power system is said to be dynamically secure or invulnerable if it can withstand all postulated credible contingencies without violating any of the dynamic system constraints. If there is at least one contingency for which the system constraints are violated, the system is said to be vulnerable or insecure.

2. Conventional Methods for Vulnerability Assessment and their Challenges

Accurate VA requires simulating all postulated contingencies. This is very time-consuming and prohibitive process. Clearly, such analysis for large-scale power systems is not only the concern of system planning and design groups, but also of operating engineers. The operating engineer will have a greater responsibility in system VA analysis, and in this case, the analysis will have to be repeatedly performed. Therefore, approximate but faster methods have been developed by utilities assuming a restrictive set of operating and topological conditions. Utilities found it necessary to a select small subset of the most critical information. These cases are usually selected based on expert knowledge of the particular system. Most of these methods are crude and can work for the operating conditions far from the border of vulnerability. Near the boundary, which is likely to be the operating space for deregulated utilities, these methods are unacceptable.

Among these assessment methods are time domain simulations, direct stability, and hybrid methods. Time domain methods require the solution of a set of non-linear algebraic and differential equations describing the power system. This method is computationally prohibitive which limits its usefulness to few off-line studies. Time domain methods also fail to offer any information about the relative security of a particular case.

Direct stability or energy function methods seek to describe the system by an energy function (Atthay, T., *et al.*, 1979, Bose, A., 1984, El-kady M, *et. al.*, 1988, Stanton, F., *et. al.*, 1981 and 1987, Chiang, H., *et. al.*, 1994, 1995 and 1989, Maria, *et. al.*, 1990, Tong, J., *et. al.*, 1993, Vaahedi, E., *et. al.*, 1996). These methods are less computationally demanding than time domain methods, but are less accurate. Direct methods are usually limited to very short-term stability studies due to the simplistic models used. Hybrid methods (Vaahedi, E., *et. al*, 1996 and Mansour, Y., *et. al.*, July, 1997, 1995, and May, 1997) are a combination of time domain simulations and transient energy function methods. This hybrid method determines the system critical energy by integrating the system equations in the time domain, thus calculating the exact system trajectory. Hybrids offer no speed increase over time domain methods, but do offer one key advantage: the ability to determine the relative stability of a particular operating case. The hybrid method does not suffer from the approximations and modeling limitations of the direct methods, making it appealing when high accuracy is desired.

3. Role of Intelligent Systems

Pattern classifiers, such as neural networks, have great potential for achieving fast and accurate security evaluation (Kumar, B., *et. al.,* 1991, Jensen, C., *et. al.*, 1999, El-Sharkawi, 1996, M., Bonissone, P., *et. al.*, 2001). The pattern classification concepts to power system engineering problems appear to be more feasible with the decline in the cost of computer memory and faster clock speeds. The primary objective of a pattern recognition technique is to monitor the power system performance and store the relevant data along with the consequent processed information in the computer memory. Once the stored data constitute a sufficient representation of the different operating conditions of the power system, a classifier can be used to recognize the VA status of the current operating patterns. This requires the data to be of sufficient size and highly correlated with the class. The ultimate objective is that the pattern classifier system should have the ability to classify any given new pattern or new operating condition into its appropriate class without the need to perform extensive contingency evaluations. It is worth mentioning that the pattern classifier does not require restrictive system topology or operational constraints as with conventional methods.

4. Challenges to Intelligent Systems

Thus far, the work on intelligent systems for VA, including neural networks (Kumar, B., *et. al.,* 1991, Jensen, C., *et. al*., 1999, El-Sharkawi, 1996, M., Bonissone, P., *et. al*., 2001) are based on at least one of the following processes:

1. Reducing the operating space to a subspace of a manageable size. This is implemented by ignoring large portions of system operation.
2. Use extensive off-line simulations to hopefully cover the operating space of the system.

The first process cannot be implemented without severely sacrificing the accuracy of the assessment technique beyond the training subspace. The second is also unrealistic process because the size and operating space of the power system is immense. For example, the VA of a power system requires extensive information on such variables as:

- Pre-disturbance network topology.
- Pre-disturbance load/generation conditions.
- Dynamic machine data.
- Post-disturbance control actions.
- Type and duration of disturbance.
- Operating conditions

With the above list, an unlimited number of data can exist for a given power system. Moreover, some variables in the data vector may likely have a weak correlation with the VA status. The curse of dimensionality states that, as a rule of thumb, the required cardinality of the training set for accurate training increases exponentially with the input dimension. Attempts to identify correlations or reductions of the data vector (El-Sharkawi, 1996) requires approximation to the system dynamics under restrictive conditions. If the correlation among elements in the input vector and the VA status is weak, the classifier will try to force a mapping that is unlikely to result in worthwhile information. In fact, such weak correlation can stray the classifier to an undesirable region with high testing errors.

Therefore, the key to the success of the classifier is the effective feature extraction/selection. Learning patterns based on data will succeed, given the right features to the classifier. It is a strong conviction that feature extraction/selection is the key to the success of VA, and cannot be considered an "art" anymore. Glorioso states, "Feature extraction is the least understood and most difficult part of pattern recognition problems."

5. Proposed Approach

An alternate approach to matching data and machine, applicable in many important scenarios, occurs when training data can be obtained on demand at a cost. The matching of data to machine can be performed dynamically. A partially trained neural network can communicate with the data source, called an *oracle*, to resolve ambiguities in the operation of the machine. The oracle then, at a cost, is able to correct these areas of uncertainty by generating clarifying training data (Jensen, C., *et. al*., 1999).

The procedure in Figure 1 is a candidate for application of a dynamically trained machine to the problem of power system VA. The first step is the creation of a preliminary training data set. A common approach is to simulate the system in response to a few disturbances and then collect a set of pre-disturbed system variables along with their corresponding VA index. For a realistic size power system, it is expected that

1. the number of variables of each data vector will be very large;
2. the collected data are sparse in the operating space; and
3. information near the VA border is likely to be unavailable.

In the algorithm of Figure 1, three basic operations are suggested:

1. feature extraction, selection andconstruction to reduce the dimensionality of the data vector;
2. query based learning to identify areas in the operating space that are essential to the VA where the initial data contains no or little information; and
3. boundary tracking to identify the nearest viable operating point on the border of the class thereby identify the VA margin.

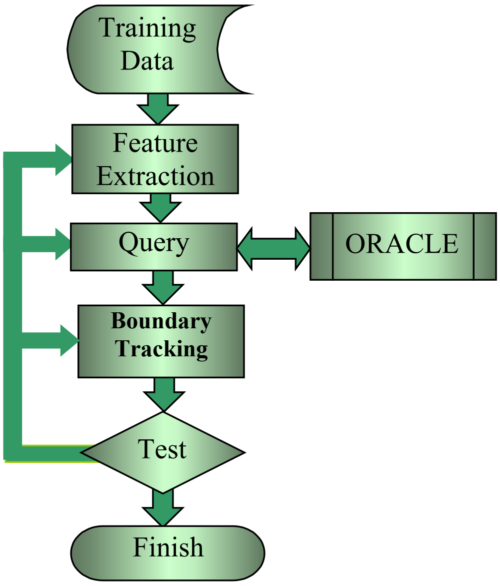

Figure 1: General VA algorithm.

6. Feature Extraction

Feature reduction, selection and construction are techniques used to massage data into a form more conducive to training. Feature selection, important when cost is associated with the acquisition of features, has, as its goal, choosing the best subset of features able to effectively perform accurate classification or regression. Reducing the cardinality of the feature set by combining two or more features into a single composite feature is the goal of feature reduction. Feature construction involves combining features to generate composite features. The goal is to synthesize an augmented feature space conducive to classification or regression. This occurs, for example, in support vector machines.

A popular, though flexibly limited, procedure for feature reduction is through the use of autoencoder networks (Reed, R.D., *et. al*., 1999). In the most fundamental architecture, the input features from a training data set are presented sequentially as both the input and output. If the network converges, the representation at the bottleneck hidden layer is a feature dimensional reduction of the original data.

Support vector machines (SVMs) (Vapnik, 1998) map feature data into a high dimensional feature space via a nonlinear mapping, wherein linear classification/regression is performed. Data is therefore molded into a form appropriate for a linear machine that occurs in the high dimensional (feature) space. Doing so corresponds to nonlinear classification/regression in the low dimensional (original) input space.

7. Query Learning

In query learning, neural network inversion can be used to identify points that, according to the network, lie near a decision surface. These points represent regions in the input space where the neural network is unsure of the proper classification. The inverted points are then presented to an oracle to determine their correct classification. The inverted points along with their classifications are then added to the training set and the network is retrained to a more accurate representation. This way, the initial neural network is trained by a relatively sparse data set while inversion guides the query to generate data in the areas where information is missing and needed. This results in a much leaner, and therefore less expensive, data set distributed where it is needed - along the functional operating space.

Inversion is also an important tool for understanding the functional mapping encoded in a neural network. Specifically, inversion of a neural network highlights characteristics of the input space important to a given output vector. Thus, through inversion, a network codebook vector describing the important input characteristics for a particular output class can be generated.

8. Vulnerability Boundary

Due to the complexity of the power system, it is not possible to determine the dynamic security border analytically. Boundary tracking is a name given to the process of inverting a trained neural network by using gradient information or any directed search to track along specific contours in order to locate new areas of interest (Bounissone, P., *et. al*., 2001). Figure 2 shows the concept. Given a search point, $\mathbf{x}_0$, boundary tracking can be used to find the point $\hat{\mathbf{x}}_0$ that is closest to $\mathbf{x}_0$ and lies on the surface $f(\mathbf{x}) = c$, where c is the value of the VA boundary. This point must also satisfy the operational constraint of the system. The process begins by generating random points around the search point and projecting them onto the surface, $f(\mathbf{x}) = c$, by neural network inversion. Gradient information, a genetic algorithm, or even particle swarm optimization can then be used to step down the surface until the point closest to the search point that satisfies all constraints is located. By identifying the boundary point, a VA margin is computed. The VA margin is a major concern in the everyday operation of the modern deregulated electric power system. Information about the location of the nearest insecure operating state is valuable in that it outlines operating strategies that should be avoided. In the event of a loss of system security, it defines the nearest stable operating state.

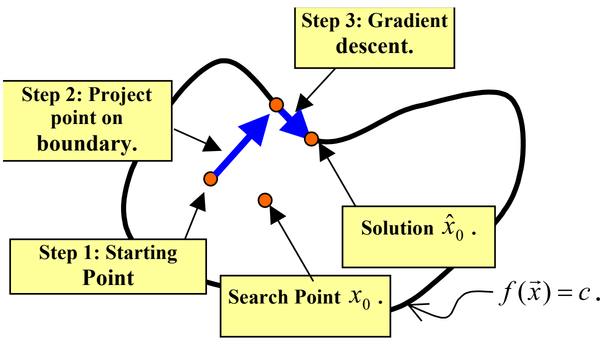

Figure 2. Illustration of boundary tracking wherein training data is dynamically generated in regions only of interest in the classification process.

The overall neural network mapping with the above structure contains information relating the input (feature) space to the output (security) space. The main goal is to query this mapping and extract useful information for the everyday operation of the power system. Ideally, the proposed system will be able to answer questions such as:

- What is the nearest unstable operating point?
- What is the most stable operating configuration?
- Given recent trajectory, when is instability likely to occur?

This information could then be used by the system operator as a tool in the everyday operation of the power system in a secure manner.

An alternative method to the inversion of the neural network is to use a search technique to place as many points on the border as needed to achieve the desired interpolation accuracy among them. This process requires the use of a fast VA technique and a rapid optimization search algorithm. The NN can be used as a fast VA tool, and the Particle Swarm Optimization (PSO) can be used as the search technique.

PSO is a novel optimization technique developed by Russell Eberhart (Eberhart, R., 1995). It is a multi-agent search technique that traces its evolution to the emergent motion of a flock of birds searching for food. It uses a number of agents (particles) that constitute a swarm. Each agent (particle) traverses the search space looking for the global minimum (or maximum). The goal of the PSO is to find the operating points that lies on the border under selected conditions (El-Sharkwai, *et. al*., 2000).

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