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On-line Estimation of Power System Security Limits

K. Tomsovic A. Sittithumwat J. Tong
School of Electrical Engineering and Computer Science
Washington State University
Pullman, WA 99165

Abstract

This paper proposes a fast pattern matching technique using Artificial Neural Networks that takes advantage of the off-line studies to accurately estimate security limits on-line. The precise methodology of operation planners is followed to establish the limits used to train the networks. A hierarchical design combining margin estimators for different security criteria and operating conditions is developed. Here this framework is applied to dynamic security.

1. Introduction

In the deregulated environment, determining the system operational limits has become increasingly important. In current practice, operational planners employ detailed power system studies to find the maximum allowable loadings in particular areas and the associated transfers across key interfaces. Reliability standards require that the system withstand any credible contingency and furthermore, must be operated with some security margin to allow operators the possibility of responding to events. Under this approach, the system ratings tend to be conservative, as studies are based on highly stressed conditions and incomplete, as the studies cannot analyze all combinations of loading and equipment out-of-service. This paper proposes a fast pattern matching technique using Artificial Neural Networks (ANNs) that takes advantage of the off-line studies to accurately estimate security limits on-line.

Generally speaking, each operational planning study must look at static, dynamic and voltage security concerns. For a given loading condition and the status of any significant equipment out-of-service, response to all credible and major contingencies is investigated. The loading or other key system parameter (KSP) is varied to determine the proximity, or margin, to a security problem. For example in voltage security assessment, one may employ P-V and/or V-Q curves [1] with the distance to the nose representing the margin. The allowable margins and associate reliability criteria are based on the regional council guidelines, e.g., [2]. Margins for each scenario can be determined and documented in look-up tables or nomograms. The operator will then base the real time decisions on this information. Look-up tables have the obvious drawback of inflexibility and are prone to errors, as operators must search for the relevant scenario in the tables. Nomograms on the other hand provide slightly greater flexibility as they depict trade-offs in operating conditions, for example between some loading condition and a transfer across a key interface. Still, nomograms fail to fully capture all the information contained in the off-line studies and moreover lack the ability to manage more varied situations. Note this practical approach differs significantly from much of the on-line security literature. Those approaches focus on contingency screening and fast methods for calculating the security. While in practice, the security limits are tabulated off-line as described above.

In recent years, there have been several ANNs based methods introduced for finding security limits [e.g., 3-4]. The essential idea is to select a set of representative features, say line flows, loads, generator limits and so on, and train the ANN on simulation data so that one can estimate the security margin. The ANN is expected to interpolate or generalize to similar unstudied cases. The problem with much of this previous work is that researchers have focused on generic power system models that ignore the practical difficulties in determining these limits. Our earlier work has shown that accurate estimates can be obtained for voltage security on practical systems, specifically, the WSCC system [5], only by developing very narrowly focused estimators. For example, different ANNs need to be trained based on specific major equipment outages and security criteria.

In this paper, this early framework is extended to other security considerations. A hierarchical design combining margin estimators for different security criteria and operating conditions is developed. A voting mechanism is introduced that combines individual ANN estimates. Each ANN is designed using statistical criteria that ensure optimal performance [6]. Numerical examples show the viability of the approach.

2. Background

2.1 Operational Planning and Reliability Policies

System security depends on the cooperation of different interconnected entities to coordinate operation of the system. The primary method to ensure this coordination in practice is to establish precise guidelines for the allowable effects neighboring systems may have upon each other. These guidelines are based on both field experience and extensive operational studies. Different performance levels are used depending on the type of disturbance. For example under WSCC guidelines, allowable post transient voltage deviation is 5% for a single generator outage and 10% for the outage of two generators. Thus, each reliability criteria depends on the type of disturbance. The disturbance should not violate constraints on:

- loading within emergency equipment ratings,
- transient voltage dip both in percentage deviation and in time duration,
- minimum transient frequency,
- post transient voltage deviation,
- positive damping, i.e., stability.

Operation planners generally address these criteria through detailed time domain simulation studies for different loading conditions and all major contingencies. In addition, there may be further requirements on running system studies. In the WSCC, this includes using both the P-V method (MW margin) and V-Q method (MVar margin) to determine an adequate voltage security margin. System operators, to greater or lesser degree depending on the utility, tend to rely heavily on the limits identified by operational planners and make relatively limited use of on-line security tools.

For on-line static security analysis, modern computational speeds allow load flow studies of a large number of contingencies in near real-time. Such software is a standard component of the energy management system (EMS), although it should be noted that this software usually does not directly compute a security margin. On-line dynamic security has focused on using fast methods to quickly determine system stability including both time-domain simulation for transient stability indices and various energy function based methods. This in sharp contrast to the comprehensive, detailed and time-consuming studies employed in operational planning. Voltage security has been based primarily on static or pseudo-dynamic methods.

2.2 Remarks

In order to bridge the gap between the practical procedures employed to determine power system interface limits and the various proposed methods for on-line security, we note the following should be considered:

- Operational planning methods cannot identify all possible operating conditions that may arise and are generally too slow to repeat on-line when unstudied system conditions arise.
- Operators do not have full access to all the detailed assumptions that might have been used in an off-line study. Further, they only have access to the conclusions of a study, i.e., the actual transfer limit and limiting outage, and not all the underlying case studies that might have been performed.
- Many of the proposed on-line security methods are fast methods to determine security but are not as effective at determining a practical operating limit, say, the transfer between systems.
- The various proposed on-line security methods work well under certain conditions but will fail at other times that may not be well-understood.
- Most of the on-line security methods do not base assessment on the detailed reliability requirements employed by the various regional councils.
- Practical system security assessment always has a certain degree of system specific considerations that do not lend themselves to more formal analysis.

In the following, a framework is introduced to address these concerns and to take advantage of the benefits of both approaches.

3. Real-time Security Framework

3.1 Proposed Security Analysis Approach

The primary method to take better advantage of the off-line operational studies is to form a type of associative memory. That is, each of the studies cases is recorded in terms of the system conditions and the estimated security margin.

Our earlier studies have shown the following [5]:

- Simple linear regression models cannot accurately estimate the security margin.
- Feedforward ANNs have the best understood design criteria and for this type of estimation problem display the most favorable performance.
- No single estimator appears to be workable across a variety of security indices or widely different network topologies regardless of the number of study cases.
- A family of smaller ANNs with different network parameters whose estimates are combined through a voting mechanism will perform better than a single large ANN.

We propose then several layers to the on-line estimation of security limits. At the highest level, the current state and major equipment outages are used to identify the appropriate set of margin estimators. This is depicted in Fig. 1. The set of estimators includes different estimators for different topologies, this means not necessarily a separate estimator for each outage scenario but say an estimator which represents the base case, a wide range of operating conditions and includes the possibility of one or possibly two major

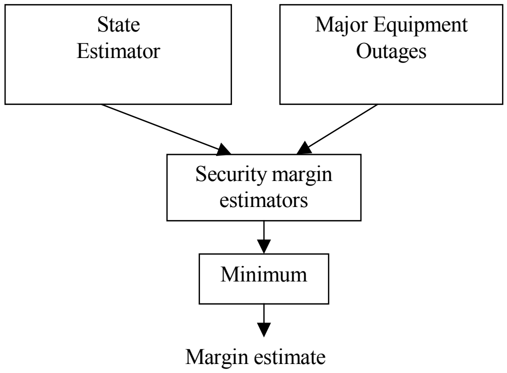

Fig. 1 Overall security margin estimation

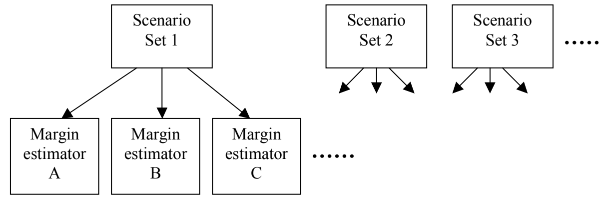

Fig. 2 Hierarchical structure of security margin estimators

equipment outages. This is in addition to the fact that the margin itself includes consideration of all contingencies. This is emphasized graphically in Fig. 2. At the lowest level, a family of ANNs is used to estimate the security margin for a specific security criterion and operating condition. The structure of an estimator for a given set of operating conditions and a specific security criterion is shown in Fig. 3.

3.2 Operating Planning Studies

For each of the system performance criteria identified in section 2.1, the limits of the power system operation are established. This may be total load in an area, interface transfer limit or some other KSP. Starting from a base case, a set of relevant system variables is recorded and a full analysis of all major contingencies performed. The KSP is incremented and the analysis repeated until the limits of the system is identified. Thus for each performance criterion, there is a large set of studies that establish the operating limit and a correspondingly large set of variables describing the operating conditions.

3.3 Estimator Design

A feedforward ANN based on the Levenberg-Marquardt algorithm is used [6]. There are five primary considerations in design of the neural networks.

3.3.1 Feature selection. Selected features should be based on engineering knowledge and statistical correlation coefficients between the seleted features and the computed security margins computed from security studies. These will typically be variables such as: real and reactive power flow, reactive power reserve, voltage levels, and so on. A large set of features can be selected and then reduced based on the correlation coefficients.

3.3.2 Principal component analysis. Principal component analysis (PCA) assesses the independence of the features in the selected feature set. This is in essence finding an orthogonal set of features to present to the estimator, improving both training time and accuracy. For example the P-V margin estimator for the WSCC system [5], the 106 system variables were reduced to 46 for training.

3.3.3 Hidden layers. Generally, multiple hidden layers will improve the approximation process and thus, two hidden layers are needed when finding estimates for larger systems with more complicated non-linearities.

3.3.4 ANN nodes and voting scheme. The number of nodes in the hidden layers significantly impact the performance. In the Bayesian framework of MacKay [7], the parameters are then estimated using statistical techniques. Here, several ANNs with parameters near the determined optima are trained. The estimates from these networks can be combined using a voting scheme. For example, one effective method is to disregard the lowest and largest margin estimates from such a set of networks and then average the remaining estimates.

3.3.5 Splitting training data for estimation and validation. A statistical theory of the overfitting phenomenon that may occur with ANNs is presented in [8]. If N is the size of the training set and W is the number of free parameters in the network with $N<W$, the optimum split of the training data between estimation and validation subsets is given by

$$r_{opt} = 1 - \frac{\sqrt{2W-1}-1}{2(W-1)} \qquad (1)$$

where is r_{opt} is the fraction to be used for training.

4. Numerical Examples

The proposed methodology has also been successfully applied to estimate the transfer limits on the WSCC system using a static method, P-V curves, to determine voltage security limits [5]. Here the examples are presented for dynamic events that satisfy the WSCC disturbance criteria for performance level A [2]. The performance of is demonstrated here using the New England 39-bus system. The system has been modified to represent a system with different zones and critical interfaces. Figure 4 shows a load center of buses 17,18 and 27 with three tie lines 3-18, 16-17 and 26-27. The total system loading for the base case is 6150.5 MW and 1658.90 Mvar . The flow

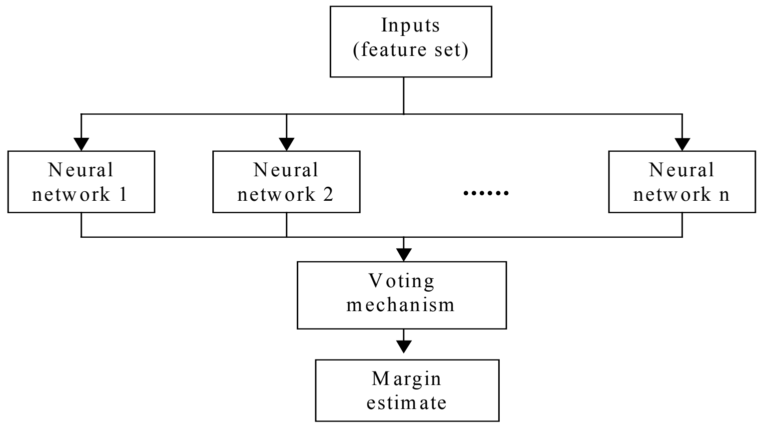

Fig. 3 Individual estimators with voting mechanism

across the interface of this load center is the parameter of interest here. Since this is a rather small system, satisfactory performance is obtained here using a simplified estimator of only one ANN.

To determine the security limits, detailed time domain studies are for each contingency under increasingly heavily loaded conditions. The transfer is incremented in 400 MW blocks and the point at which a performance criterion fails for a given contingency determines the transfer limit. This rather rough estimate of the transfer limit serves for demonstration purposes here but obviously would requirement more refinement for a practical system. Real and reactive power flows in the network are used to form the initial feature set. A line outage is represented by an arbitrarily large line flow in that line.

4.1 Voltage Instability

The first performance criteria considered is voltage stability as seen by the post-disturbance voltage response. The

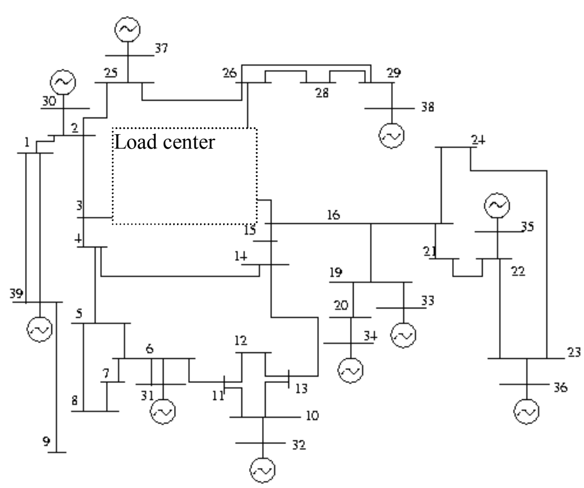

Fig. 4 New England 39 bus system

maximum voltage dip at any bus following a contingency cannot exceed 25% and a more than 20% dip cannot last for more than 20 cycles. The post-transient voltage dip should not exceed 5%. Finally, there must be positive damping. Note this obviously may overlap with the angle instability criteria.

The designed ANN has a single hidden layer with 10 hidden nodes. There are 131 test cases of which 20% are used for testing. The overall performance is shown in Table 1 and indicates very low percentage errors. Notice also that the combination of PCA and correlation greatly reduces the number of needed features. Figure 5 plots these estimates for the test data.

4.2 Angle Instability

The second performance criteria considered is angular stability. The minimum transient frequency dip at any bus following a contingency cannot exceed 59.6Hz for more than 6 cycles. Again, the system must have positive damping.

The ANN has a single hidden layer with 15 hidden nodes. Again there are 131 test cases of which 20% are used for testing. The overall performance is shown in Table 2 and again there very low percentage errors are seen. Figure 6 plots these estimates for the test data.

5. Discussion

This paper proposes an involved framework employing ANNs to estimate on-line security estimates. The primary advantage of the approach is in taking advantage of the numerous detailed off-line studies performed during operations planning. At the same time, it does create an added burden on planners to perform more extensive studies. In previous work, it was established that this methodology will work for practical systems for static security. This work demonstrates the initial stages on estimates for dynamic security. While the results appear promising, the difficulty in implementing these

Table 1 Errors in estimate of voltage security limits

Max error (MW / %)	Min error (MW / %)	Mean error (MW / %)	Standard Deviation (MW)	Features after PCA	Features after correlation
1.0012 / 0.093%	0.0062 / 0.0015%	0.3549 / 0.031%	0.186	30	4

Table 2 Errors in estimate of angular security limits

Max error (MW / %)	Min error (MW / %)	Mean error (MW / %)	Standard Deviation (MW)	Features after PCA	Features after correlation
1.9799 / 0.25%	0.0650 / 0.0041%	0.4096 / 0.060%	0.602	32	6

approaches lies in applications for large systems. Larger systems not only contain more complicated non-linearities but also numerous system specific constraints that make application more difficult. Application to the WSCC system is on-going.

Future efforts will also investigate the use of energy function methods and transient stability indices. While these methods have limitations that prevent establishing security limits definitively, by virtue of computational speed they would allow a more extensive set of studies to be carried out for training the ANNs.

Acknowledgments

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References

[1] C. W. Taylor, *Power System Voltage Stability*, McGraw-Hill, 1994, New York.

[2] Western Systems Coordinating Council, *Reliability Criteria*, Aug. 1998.

[3] A.A. EI-Keib and X. Ma, "Application of Artificial Neural Networks in Voltage Stability Assessment," *IEEE Transactions on Power System*, Vol. 10, No.4, Nov. 1995, pp. 1890-1896.

[4] S. Chauhan and M.P. Dava, "Kohonen Neural Network Classifier for Voltage Collapse Margin Estimation," *Electric Machines and Power Systems*, Vol. 25, no. 6, July 1997, pp. 607-619.

[5] L. Chen, K. Tomsovic, A. Bose and R. Stuart, "Estimating Reactive Margin for Determining Transfer Limits," submitted to *IEEE Transactions on Power Systems*.

[6] S. Haykin, *Neural Networks, a Comprehensive Foundation*, 2nd Edition, Prentice Hall, 1999, New Jersey.

[7] D.J.C. MacKay, "Bayesian Interpolation," *Neural Computation*, Vol. 4, No. 3, 1992, pp. 415-447.

[8] S. Amari, N. Murata, K.-R. Muller, M. Finke, and H. Yang, "Statistical Theory of Overtraining - Is Cross-validation Asymptotically Effective?" *Advances in Neural Information Processing Systems*, Vol. 8, Cambridge, MA: MIT Press, 1996, pp. 176-182.

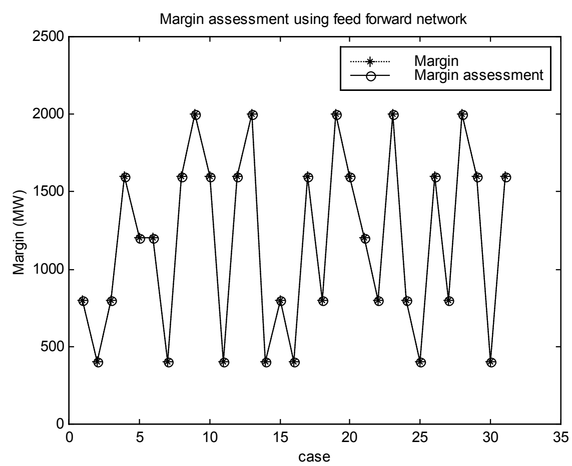

Fig. 5 Margin estimate for voltage stability

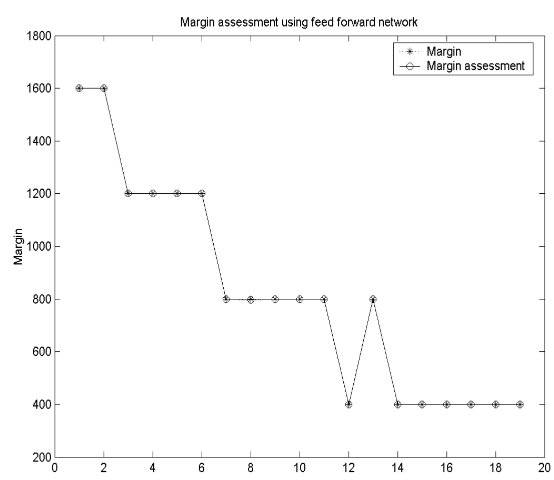

Fig. 6 Margin estimate for angle stability