Estimating the Active Power Transfer Margin for Transient Voltage Stability

J. Tong and K. Tomsovic

Abstract-- **On-line security analysis is one of the important functions for modern power system control centers. It is well known that voltage magnitudes alone are poor indicators of voltage stability or security. Voltages can be near normal with generators, synchronous condensers, and SVCs near current limiting levels resulting in a possible voltage collapse. For on-line application, a pattern matching or interpolation method rather than analytic approaches may be most appropriate. In this paper, an ANN is used to estimate the active power transfer margins for transient voltage stability. The method is applied to a small system, the New England 39 bus system, and a large system, the WSCC system. The numerical results show that the ANN can give accurate and satisfactory estimation for the active power transfer margins.**

Index Terms-- **Artificial neural networks, Power system dynamic stability, Stability criteria, Voltage stability margin**

I. Introduction

THE power system will operate closer to the limit points in the deregulated environment. With operating conditions becoming more and more stressful, voltage security is often the main restriction on power transfers. The transfer capacity of an existing transmission network needs to be increased without major investments but also without compromising the security of the power system.

More efficient use of the transmission network has already led to a situation in which many power systems are operated more frequently, and for longer, close to their voltage stability limits. A power system stressed by heavy loading has a substantially different response to a disturbance from that of a non-stressed system. The potential size and effect of disturbances has also increased. When a power system is operated close to a stability limit, a relatively small disturbance may cause a serious system outage. In addition, larger areas of the interconnected system may be affected by a disturbance.

Voltage security usually means the ability of the power system to maintain acceptable voltages at all buses under normal operating conditions and after a disturbance [1]. However, no voltage collapse after a change in the system condition does not mean the system is voltage stable, there are also requirements considering the transient voltage stability such as the maximum voltage dip and the time duration of the voltage fall below a certain level after the disturbance. For example, the Western Systems Coordinating Council (WSCC) has issued detailed requirements for transient voltage stability under different operation levels [2] in Western North America.

On-line security analysis is one of the important functions for modern power system control centers. It is well known that voltage magnitudes alone are poor indicators of voltage stability or security. Voltages can be near normal with generators, synchronous condensers, and SVCs near current limiting levels resulting in a possible voltage collapse. For on-line application, a pattern matching or interpolation method rather than analytic approaches may be most appropriate. Among these techniques, artificial neural networks (ANNs) are one of the most promising methods [3] because ANNs have excellent generalization capabilities, superior noise rejection, and fast execution (most of the calculations occur during the initial off-line training). In this paper, an ANN is used to estimate the active power transfer margins for transient voltage stability. The method is applied to a small system, the New England 39 bus system, and a large system, the WSCC system. The numerical results show that the ANN can give accurate and satisfactory estimation for the active power transfer margins.

II. Voltage Margin and Stability Criteria

A. Voltage Margin

As regards voltage security assessment, the initial efforts focused on a special measurement, computable on-line, that would have indicated the distance to potential collapse. Many of these indicators have been proposed, such as voltage drops, losses evolution, or indices based on sensitivity computations. But these kinds of indicators have limits. They are poorly predictive because they cannot take the system non-linearity into account. Hence, they may have very normal values, until they sharply, and suddenly, increase, just before a collapse occurs.

The margin with respect to voltage collapse is now admitted to be the preferred indicator. Voltage stability margin is a measure of the available transfer capacity, net transfer capacity or total transfer capacity. The margin is the

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difference or a ratio between operation and voltage collapse points based on the Key System Parameter (KSP), i.e., loading, line flow, and so on, and accounts for a pattern of load increase or generation loss. As a concept for system operators, margin is a straightforward and easily understood index and thus, widely accepted.

The way to compute voltage stability margin is not unique. Many methods have been proposed such as minimum singular value [6], point of collapse method [7], continuation power flow [8], and optimization method [9]. These methods, although quite accurate in some aspects, are not computationally efficient for real-time applications. Recently, the applications of ANNs have drawn great attention in power system on-line applications [10-12]. In this paper, ANNs are used to estimate active power transfer margins for dynamic voltage security.

B. *Voltage Stability Criteria*

According to the definitions by WSCC, the transient voltage stability criteria include several aspects. The 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.

In the WSCC, voltage stability criteria are expected to apply equally to studies of interfaces and load areas. Interfaces include major WSCC paths, tie lines with neighboring systems, and critical paths within a system. The WSCC voltage stability criteria are specified in terms of real and reactive power margins. The margin for *N-0* (base case) conditions must be greater than the margin for Performance Level A to allow for unforeseen increases in load or interface flows without remedial action schemes that would be activated during contingency conditions but not during normal conditions.

III. Proposed Method

A. *Generation of Training Data*

To determine the transient voltage stability transfer limits, a load-flow must first be executed for a given topology to have a satisfactory steady-state case. IPFLOW is the load flow software used in our studies. This steady-state case is then applied to initialize the network for the transient-stability simulation program. ETMSP (Extended Transient/Midterm Stability Program) is used here [4]. When the simulation is completed, transient voltage stability criteria are applied to the extracted results from ETMSP. If the performance is adequate then the loading will be changed so that the power transfer on the interested interface will increase, and the load-flow will be modified accordingly. This is repeated till the highest acceptable transfer level for an interface is found. In general, to find the security limit, the process must be repeated for different contingency types and locations until the most constraining (i.e., lowest) transfer limit has been identified. Note that it is impossible to pre-study all possible contingencies because the assessment processes are very time-consuming, and the analysis of every degraded topology is a problem of combinatorial dimensions. In this paper, the three-phase faults on lines are the major contingencies to be studied. But we should note that it is easy to study other kinds of contingencies by using the same methodology.

B. *Type of the ANN*

Among all kinds of networks, the most widely used are multi-layer feed-forward neural networks that are capable of representing non-linear functional mappings between inputs and outputs. These networks can be trained with a powerful and computationally efficient method called error back-propagation. The feed-forward neural network with one hidden layer is chosen as the network model, and the Bayesian Regulation method is used for training.

C. *Feature Selection*

Selected features should be based on engineering knowledge and statistical correlation coefficients between the selected features and the 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. In this paper, we only choose the real and reactive power flow on lines as the feature set.

The dimension of the pattern vector may be very large. The process of finding the most significant variables, eliminating redundancy and reducing the dimension of the pattern vector is called feature selection. A large set of features can be selected and then carefully reduced based on the correlation coefficients and principle component analysis.

Feature extraction is often an important pre-processing step, as selected features must characterize properly a variety of power systems operating conditions. When the number of inputs is large, but the number of training examples is relatively small, it may result in poor generalization performance. A number of different methods, most based on statistical approaches, are available for feature extraction. The statistical approaches applied in the study are correlation coefficients and principal component analysis.

Principal component analysis (PCA), also called Karhunen-Loeve expansion, assesses the independence of the features in the selected feature set [5]. PCA works by performing a coordinate transform of the measurement space into an ordered set of outputs that captures most of the variance in the first few variables, or principle components. The assumption is made that large variances relate to some kind of structure in the data and are therefore retained. The remaining components can effectively be discarded with little loss of accuracy, thus effecting a dimensionality reduction

After PCA, the correlation coefficients are used to choose those features that are more correlated to the outputs. The correlation coefficients for each input features with respect to the outputs (voltage security margin) are calculated. Those features that are less correlated to the outputs are eliminated.

IV. Numerical Results

To illustrate the proposed approach two systems are analyzed. To begin, the New England 39 bus system is used to provide some insight into the limitations of the method and then a modified approach is applied to a practical model of the WSCC system.

A. The New England 39 Bus System

The New England 39 system is divided into two zones, one load center of only the load buses 17, 18, and 27 with three tie lines 3-18, 16-17, and 26-27 as shown in Fig. 1. The other zone contains all other load and generation buses. The focus of study here is the power flow at the interface of this load center. Here, the study applies only the WSCC disturbance criteria for performance level A [2], which considers only three phase faults with normal clearing.

The security margin is calculated by increasing the active power of the load center incrementally over the base case until there is a violation of the transient voltage stability criteria. The total system loading for the base case is 6150.5 MW and 1658.9 MVar. The flow across the interface of this load center is the parameter of interest here. The entire data set consists of 579 samples, with 20% for testing and 30% for validation. The training and testing data are obtained from transient stability studies using IPFLOW and ETMSP. Contingencies considered are three-phase faults on each line. For each load level, there are 31 cases, representing one base case and the 30 (n-1) contingencies.

There are 96 total features. After PCA, 30 features are left which are further reduced to 15 features using the correlation coefficients. Thus, the total number of features is reduced from 96 to 15 for a reduction rate of around 84.4%. The designed ANN has a single hidden layer with 10 hidden nodes. The overall performance is shown in Table 1 indicating very low percentage errors.

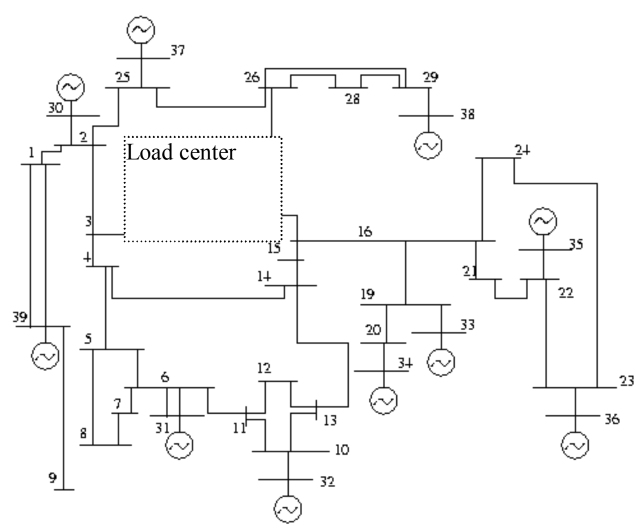
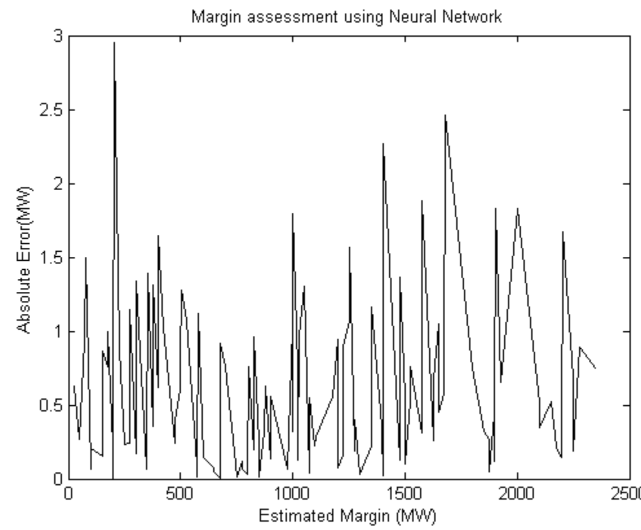


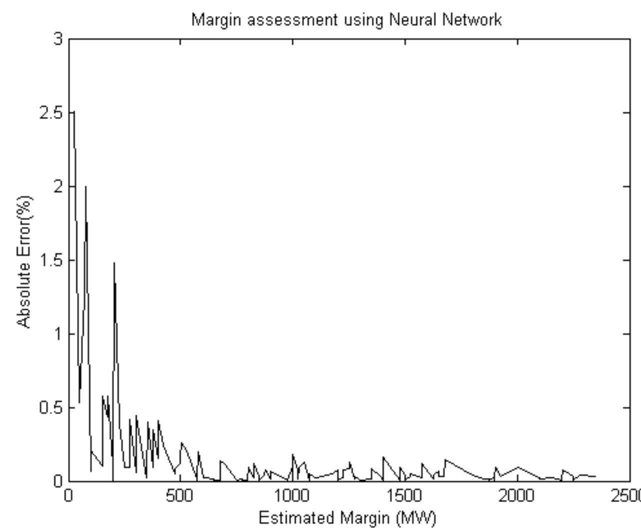
Fig. 1. New England 39 bus system

Table 1 Errors from ANN estimate of transient voltage security limits for 39 bus system

Max Error (MW / %)	Min Error (MW / %)	Mean Error (MW / %)	Standard Deviation (MW)	MSE (MW^2)
1.84 / 2.76	0.0011 / 0.0002	0.31 / 0.097	0.43	0.20



(a) MW error



(b) Percentage error

Fig. 1. Voltage security margin estimates for 39 bus system.

The results shown in Table 1 indicate more than sufficient accuracy using a very small network. Fig. 1 plots the errors versus the magnitude of the voltage security margin. The errors are generally lower where the margin tends also to be larger and so there are no misclassifications of security.

B. The WSCC System

The Western Systems Coordinating Council (WSCC) region encompasses a vast area of nearly 1.8 million square miles. It is the largest and most diverse of the ten regional reliability councils of the North American Electric Reliability Council (NERC). It encompasses all or part of fourteen western states, two Canadian provinces and portions of northern Mexico. The WSCC divides into four geographic subregions: California, Northwest, Arizona-New Mexico-

Southern Nevada, and Rocky Mountain. About sixty percent of the WSCC load is located in the coastal regions. On the other hand, a significant portion of the generation that serves these load centers is located inland, so power transmission over long distances is needed. As a result, significant portions of the WSCC network are stability limited. The primary interface of interest in this study is the California-Oregon Intertie (COI). The COI consists of: the two Malin-Round Mt. 500kV transmission lines, referred to as the Pacific AC Intertie, and the Captain Jack-Olinda 500kV line, referred to as the COTP.

The summer load condition is studied here. In summer, the power transfer direction is from north to south. To find the COI margin, generation in the Northwest area is scaled up while increasing loads in the California region by various step sizes until any violation to the transient voltage stability criteria is observed. The minimum step size is 25 MW.

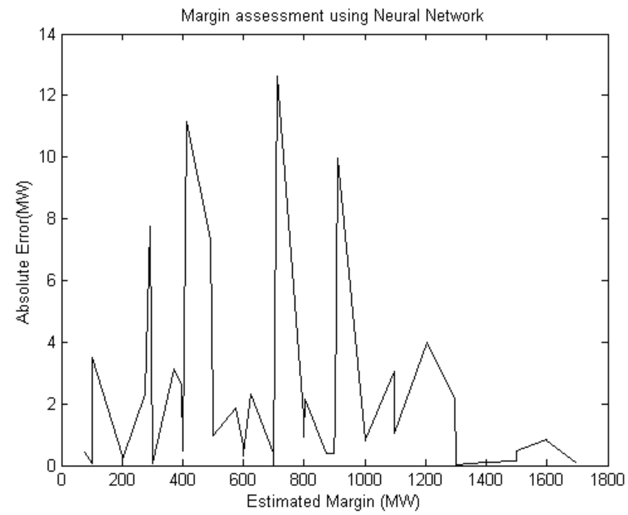
For the transient voltage margin, a three-phase fault on each 500kV line is studied. The fault duration is 0.15 second (9 cycles), which is longer than normal clearing but facilitates the analysis here. The system is simulated for 50 seconds following the fault. After the fault is cleared, the transient voltage reliability criteria for all 500kV buses are checked for any violation. If there is a violation, the system is considered transient voltage unstable. The entire data set consists of 361 samples, with 20% for testing and 30% for validation.

There are 252 total features representing line flows on the 500 kV system. After PCA, 20 features are left and 15 features are left after reduction using the correlation coefficients. Thus, total number of features is reduced from 252 to 15; or a reduction rate of about 94.0%. The designed ANN has a single hidden layer with 35 hidden nodes. Here, to improve the performance of the estimation, a voting scheme is used. The ANNs are trained in sets. Each set contains three independent ANNs. The three ANNs are trained independently but with the same training data. For the output of the ANNs, the largest and the smallest estimations are eliminated and the remaining estimate is chosen as the final estimation of the margin. Fifty such sets are trained and the best set is retained. The numerical results are shown in Table 2. And Fig. 2 shows plot of the errors versus the magnitude of the voltage security margin.

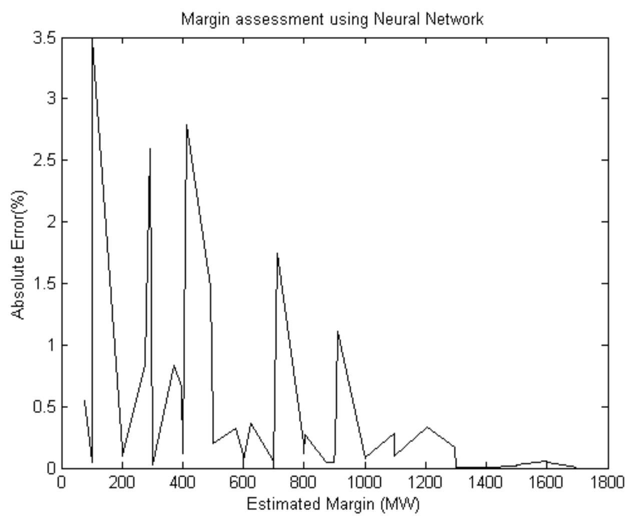
The numerical results of the WSCC system show that the method is also suitable for large and complex systems. However, with the increased system complexity, the performance of the ANN does degrade. Here, increasing the size of the ANNs and using a voting scheme improved the performance. This is not surprising since the size of the ANNs must match the complexity and non-linearity of the system, to yield satisfactory performance.

Table 2 Errors from ANN estimate of transient voltage security limits for WSCC bus system

Max Error (MW / %)	Min Error (MW / %)	Mean Error (MW / %)	Standard Deviation (MW)	MSE (MW^2)
12.64 / 3.48	0.024 / 0.0027	1.84 / 0.39	3.30	10.80



(a) MW error



(b) Percentage error

Fig. 2. Voltage security margin for WSCC system

Currently, there is no widely accepted method to decide the appropriate size of the ANN for a particular problem and instead one may be tuned by trial-and-error and experience. Compared to the New England the system, the largest error in percentage increases slightly from 2.76% to 3.48% but it is still well within tolerable limits. The mean error in percentage, which is a reasonable indication of the overall performance, is 0.39%. The most important criteria remains the correct classification of the security. Here, there were no misclassifications.

V. Conclusion and Future Works

In this paper, a method using a margin to estimate the voltage stability is proposed. The method uses artificial neural networks to estimate the security margins based on detailed off-line studies. Since the studies are carried out a priori, the estimates can be found essentially instantaneously and is suitable for online security analysis. From the numerical results on the WSCC, it is shown that the method is suitable for larger networks, regardless of size.

The effectiveness of the method, of course, depends largely on the credibility of the data. Data, i.e., training sets, must be representative of the different states of the power system since neural networks are designed for interpolation not extrapolation. That condition appears to be satisfied for the specific conditions of assessing voltage stability, since all three-phase faults on all 500kV lines are studied. In practice, the stability criteria may vary among systems; however, since the studies and the training of the neural networks is performed offline, this should not be a limiting factor.

The work of this paper proposes a new way for online security margin estimation. The same method can be applied to other security areas such as static voltage security and dynamic security. Different set of neural networks can be developed to cover great variety of operation conditions and different security criteria.

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Biographies

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