ANN-Based Technique for Predicting Voltage Collapse in Power Systems

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Abstract
Voltage stability problems have been one of the major concerns for electric utilities as a result of heavy loading of power system. This paper reports on an investigation on the application of Artificial Neural Networks (ANN) in voltage stability assessment using the energy function technique. A multi-layer feed-forward ANN with error back-propagation learning algorithm is proposed for calculation of Voltage Stability Margins (VSM). Extensive testing of the proposed ANN-based approach indicates its validity for determination of power system voltage collapse. Simulation results on two test systems are reported in the paper.

1. Introduction
Voltage control and stability problems are now receiving special attention in many systems. Also, voltage problems are a source of concern in highly developed networks as a result of heavier loading. The phenomenon of voltage collapse has been observed in many countries and has been analyzed extensively in recent years. Most of the incidents of voltage collapse are believed to be related to heavily stressed power systems where large amounts of real and reactive power are transported over long Extra High Voltage (EHV) transmission lines while appropriate reactive power sources are not available to maintain normal voltage profiles at receiving end buses. In some cases, however, voltage profiles show no abnormality prior to undergoing voltage collapse because of load variations. Operators may observe no advance warning signals until sudden significant changes in voltage magnitude result in actions of protective equipment to crash the network. Therefore, a tool which can provide timely evaluation of voltage stability of the system under diversified operating conditions would be very useful [1,2]. Maintaining an adequate margin from voltage instability limits is a major concern because many utilities are loading their bulk transmission networks to their maximum possible capability without increasing transmission capability. In many cases, while the system may reach a vulnerable state through an equipment outage or earlier contingency, the immediate cause of voltage instability is not a large disturbance to the system. Rather, the system operating point gradually changes over a period of minutes to hours from a state of relative security to one where collapse occurs. Thus the longer time frame of the problem allows manual operator intervention in addition to automatic control actions. Voltage instability problems are liable to occur in systems where voltage magnitudes decline below acceptable levels. Furthermore, near the point of collapse voltage variations can
be extremely sensitive to changes in load, so knowledge of voltage level only at current operating point may not be sufficient to predict the onset of stability problem. To take the most effective preventive control actions, an accurate, easily computable indicator of the proximity of the system to voltage collapse is needed [3,4].

In recent years, voltage instability has been responsible for several major network collapses [5] such as:

- Florida system disturbance of December 28, 1982.
- Northern Belgium system disturbance of August 4, 1982.
- Swedish system disturbance of December 27, 1983.
- Egyptian electrical system blackout of April 24, 1990.
- Israel blackout of June 8, 1995.
- Western United State blackout of August 10, 1996.

As a consequence, the terms “voltage instability” and “voltage collapse” are appearing more frequently in the literature and in discussions of system planning and operation.

Many approaches have been used for power system voltage stability assessment, e.g., power flow Jacobian matrix technique [6], total active and reactive power losses technique [7], singular value decomposition method [8], multiple load flow solution technique [9], energy function methods [3, 10-12], and recently Artificial Neural Networks (ANN) [6,7, 13-16].

This paper reports on an investigation on the application of ANN in voltage stability assessment using the energy function technique. A multi-layer feed-forward ANN with error back-propagation learning algorithm is proposed for calculation of Voltage Stability Margins (VSM). Simulation results on two test systems are reported in the paper.

2. Low and High Voltage Solutions

The high and low voltage power flow solutions may be, physically, explained by considering the two-bus system with lossless transmission line shown in Fig. (1) [10].

![Fig. (1) Two-bus system](image)

Fig. (2) shows a plot of $\alpha - V$ relations for different loading condition.

![Fig. (2) - Power balance constraints](image)

It is observed that the constant “P” and constant “Q” curves have typically two intersections, each corresponding to a power flow solution. One of them is referred as “High Voltage Solution” (HVS) and the other is referred as “Low Voltage Solution” (LVS). As shown, LVS’s are distinguished by their relative low values of voltage magnitudes. As shown, for $P = 2.0$, $Q = 0.5$, the two solutions are given by points “A” and “B”. Increasing $P$ to 3.0 and
Q to 1.0, the two solutions are given by points “C” and “D”. For further increase (P = 4.0, Q = 2.14), there will be no intersection between the two corresponding curves, i.e. there is no solution at all. In this case, the load flow Jacobian matrix is singular. Between cases 2 and 3, there is a case where the two curves are tangent to each other (HVS and LVS are the same) which represents the collapse point.

3. The Energy Function Technique

The energy function technique is dependent on defining a scalar energy function, which is dependent on system state. This energy function may be a vector integration of real and reactive power mismatch equations between two power flow solutions that are called high voltage solution and low voltage solution. This integration yields a closed form expression and can be formally shown to be a Lyapunov function. The energy function has the property that the operable solution defines a local minimum of this energy. Formally, the energy function is said to be positive definite about the operating point; intuitively, one may think of the operating point occupying the bottom of an “energy well”. A key step in such energy based stability studies is to identify those Unstable Equilibrium Points (UEP’s) that form saddle points on the boundary of the energy well.

To understand the use of such energy analysis in voltage stability studies, it is important to recognize that the instantaneous state of the system does not sit precisely at the Stable Equilibrium Point (SEP) predicted by the power flow. The system state is continuously being perturbed by small, random changes in time varying loads. These random changes perturb the system state away from equilibrium position, and can be viewed as introducing a small amount of energy into the system. This energy is normally dissipated in system damping, so that at a secure operating point, where the energy well is relatively deep, their effect are negligible. However, as the state of the power system changes with time, there is a corresponding change in the shape of the energy well, along with the energy measures associated with the boundary saddle point low voltage solutions. As the system evolves towards an operating point vulnerable to voltage collapse, the depth of the energy well decreases. Eventually, a point is reached where the disturbance energy is sufficient for the state to escape from this well, with a resultant voltage collapse. The depth of the energy well can provide an excellent indicator of the system vulnerability to voltage collapse. The height of the easiest path of escape out of the energy well; i.e. the energy necessary to exit through the lowest saddle point or closest UEP can be measured by calculating the energy difference between the appropriate low voltage solution and the current state, and serves as security measure that will be used to indicate relative vulnerability to voltage problems. As the system moves closer to the point of collapse, the energy difference decreases in almost a linear manner with system changes.

The energy function for voltage stability assessment as derived in [17] is expressed by:

\[
V(\omega, \alpha, \beta) = \sum_{j=1}^{n} Y_{ij} V_i V_j \sin(\beta_{ij} - \alpha_j + \alpha_i) - \sum_{j=1}^{n} Y_{ij} V_i V_j \sin(\beta_{ij} - \alpha_j + \alpha_i^*) - P_i(\alpha_i - \alpha_i^*) + Q_i \ln \frac{V_i}{V_i^o} + \frac{1}{2} B_{ii}(V_i^2 - V_i^o^2) + G_{ii}(V_i^2\alpha_i - V_i^o^2\alpha_i^*)
\]

\(\omega\) is the system speed deviation and it is equal to zero at steady state condition. \(V_i\) is the voltage magnitude at bus i at unstable equilibrium point. \(V_i^o\) = voltage magnitude at bus i at stable equilibrium point. \(V_j\) is the voltage magnitude at bus j at unstable equilibrium point. \(Y_{ij} \angle \beta_{ij}\) represents admittance of transmission line connecting bus i and bus j. \(P_i\) reactive power at bus i. \(Q_i\) active power at bus i.
\[
\alpha_i = \delta_{\text{ref}} - \delta_i
\]

\[
\delta_{\text{ref}} = \text{phase angle at slack bus.}
\]

\[
\delta_i = \text{phase angle at bus } i.
\]

\[
B_{ii} = \text{self susceptance at bus } i.
\]

\[
G_{ii} = \text{self conductance at bus } i.
\]

\(i\) is an indicator for the load bus under study.

\(n\) is the number of buses.

The previous expression is a general expression for obtaining an energy measure for a multi-machine power system considering all system parameters.

Numerical testing has shown that these energy measures tend to change in a manner proportional to the change in the voltage security of a particular area of the system. E.g. if the system loads were increased, the energy measures would tend to decrease, with one of them going to zero at the point where the high voltage solution coalesces with the low voltage solution. This point corresponds to the point of collapse, and is characterized by singularity of the power flow Jacobian.

4. Artificial Neural Networks

Artificial Neural Networks (ANN), represent a recent technology (that applicable in many disciplines) that try to mimic the biological brain as a mathematical model.

For more perceiving, the neural network can be viewed as three-stage system as shown in Fig. (3) below:

Fig. (3) - Block diagram for ANN

As shown above, central to the system is the brain represented by the neural network, which continually receives information, perceive it, and makes appropriate decisions. To sets of arrows, those pointing from left to right, indicate the forward transmission of information-learning signals through the system. The arrows pointing from right to left, signify the presence of feed-back in the system. The receptors convert the input data from the human body or the surrounding environment into electrical impulses that convey information to the neural net (brain). The effectors convert electrical impulses generated by the neural network into responses as the system outputs. Further details of ANN methods, and the various enhancements which have been used here, can be found in the extensive literature on the subject, e.g. in [18].

5. Application of ANN for determination of VSM using Energy Function

In this section, the application of ANN will be performed, first, on a 4-Gen, 11-bus test system. A one-line diagram for the system is shown in Fig. (4), and the system characteristics are given in [19]. Then the proposed approach is applied also to an 11-Gen, 55-bus actual system which is a reduced version of BRUCE system of Ontario Hydro, Canada. This system includes the state of Ontario (Canada) and upper New York area (USA). This system consists of 11 generator buses and 44 load buses [20]. The bus numbers mentioned in the results are the actual numbers of the actual system.

Fig. (4) - 4-Gen-11bus test system

For this purpose, samples of the data (loading conditions in p.u. and corresponding energy margins in p.u.) obtained using the energy function technique are chosen to be training data inputs and training data outputs of the ANN respectively. Then applying the rest of the data (loading conditions in p.u.) as a query data inputs and running the ANN to obtain
the query data outputs and comparing this query outputs with the results obtained using the energy function technique. These ANNs are trained and tested using Neural-Desk package [21]. The input variables to the ANNs are the magnitude of the active power at the load buses, while the output is the value of VSM obtained from the energy function technique. Number of input variables for ANN2 is 36 because there are 8 zero load buses in the second system. Table (1) shows the details of the construction and control parameters of the proposed ANNs. After extensive trials, it has been found that the proper design of the two ANNs used in this paper consists of three layers; an input layer having 3 input neurons for ANN1 and 36 neurons for ANN2, a hidden layer of 6 neurons in ANN1 and 30 neurons in ANN2, and an output layer of one neuron (VSM).

Table (1) - Construction and Control parameters of the proposed ANNs

<table>
<thead>
<tr>
<th>ANN Item</th>
<th>4-Gen, 11-Bus</th>
<th>11-Gen, 55-Bus</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of inputs</td>
<td>3</td>
<td>36</td>
</tr>
<tr>
<td>Number of hidden layers</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Number of neurons per hidden layer</td>
<td>6</td>
<td>30</td>
</tr>
<tr>
<td>Training algorithm</td>
<td>Back propagation</td>
<td>Back propagation</td>
</tr>
<tr>
<td>Average error value</td>
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<td>0.010</td>
</tr>
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<td>Momentum constant</td>
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<td>0.99</td>
</tr>
<tr>
<td>Learning Rate</td>
<td>0.01</td>
<td>0.0005</td>
</tr>
</tbody>
</table>

Fig. (5) – Fig (11) show the results of applying the ANN proposed approach to the two systems mentioned previously compared with the results obtained with the energy function technique. All the figures are drawn with MVA base = 100.

The ANN output results in Fig. (3) to Fig. (9) are matching with those obtained using the energy function technique with an accepted average error of 0.005 for 4-Generator, 11-Bus system and an average error of 0.010 for 11-Generator, 55-Bus system.
5. Conclusion

The ANN methodology is applied to study the voltage stability problem. First suitable ANN structures are selected and trained by using the results that were obtained by the energy function technique. Then, these trained neural networks are extensively tested under various loading conditions for determination of the voltage stability margin for the two power systems under consideration. The ANN gives identical results with those obtained using the energy function technique. The results has demonstrated that the proposed ANN-based approach is promising for predicting voltage collapse in power systems. The extension of the results of this work is to address the effect of large network structural changes and load pattern changes on voltage stability margins.

6. References


