POWER SYSTEM DYNAMIC SECURITY ASSESSMENT – CLASSICAL TO MODERN APPROACH

A.H.M.A.Rahim
S.K.Chakravarthy
Department of Electrical Engineering
K.F. University of Petroleum and Minerals
Dhahran.

Abstract

Dynamic security analysis is performed to ensure that a power system will survive any recognized contingency and will transfer to a new but acceptable steady-state condition. This article deals with one of the very important dynamic security indices – the critical clearing time. Some of the popular methods of calculating the critical clearing time (CCT) have been reviewed. A more recent method of determining CCT through artificial neural networks (ANN) has been presented. ANN approach of determining CCT is based on classical pattern recognition method. The CCT of a test power system has been estimated through two artificial neural networks – the back-propagation algorithm and the radial-basis function network. The neural networks were trained for a large number of simulated data obtained from numerical integration of the system dynamical equations. The trained networks were then tested with randomly selected data. It was observed that the radial-basis function network was more suited in terms of speed of computation and accuracy of prediction.

1. Introduction

An important feature of a reliable power system is that it should supply power to the customers without causing disruption of service under all conditions. If an emergency condition like a severe disturbance or fault appears on the system, it should be removed quickly enough so that the system stability under the transient condition is not affected. The maximum duration the fault can sustain without rendering the post fault system unstable is termed as the critical clearing time (CCT). The CCT is a complex function of the pre-fault and post fault system conditions, fault type, fault location, etc. and its determination is of paramount importance to power system planners. A variety of approaches for assessing this transient stability index such as, numerical integration, the second method of Lyapunov, probabilistic methods, pattern recognition, expert systems, artificial neural networks, etc. have been proposed in the literature [1-4].

The simplest way of determining the CCT is from the famous equal area criterion. However, this method is applicable only for a single machine infinite bus model or a general two-machine system. Fig.1 shows the power angle curve for the pre-fault, post fault and the faulted power angle curves. The critical clearing time t_{cr} corresponds to angle δ_{cr} when area A_1 equals A_2. The most widely used method of determining CCT is the numerical integration technique, where the system dynamics is solved repetitively until the fault duration is obtained which takes the system to the threshold of instability. For accurate results the step size should small, making the process very slow. The idea of the second method of Lyapunov is to replace the post-fault system equations by a stability criterion. The value of suitably designed Lyapunov function V is calculated at the instant of the last switching of the system and is compared to the previously determined critical value V_{cr} . If V is smaller than V_{cr}, post-fault system is stable. Fig. 2 shows the stable and unstable manifolds in the δ - ω phase plane.

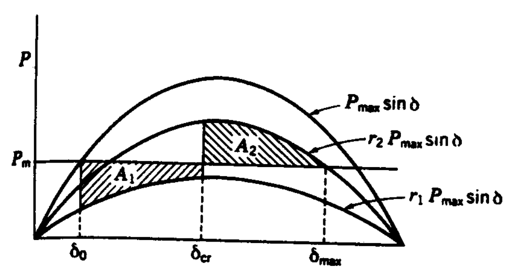

Fig.1 The equal area method.

The probabilistic methods attempt to assess the probability of stability of a system following exposure to a disturbance. The probabilistic nature of the initiating factors of a disturbance is introduced. In some studies, probability functions, called the security function, are compared with a maximum tolerable insecurity or risk level to determine if and when some control action has to be taken. Generally, the determination of CCT through these methods is quite involved. The most familiar view of pattern recognition is based on classification model characterized by three principle elements – feature extraction, classifier synthesis, and classification. In pattern recognition based transient stability studies, efforts have been focused on selection of the initial system description, feature extraction and classifier design.

The expert system approach combines the time domain numerical approach with human expert knowledge coded in a rule based program [4]. The methods used in artificial neural network employ adaptive pattern recognition approach, which trains the neurons to learn from the sets of input-output presented to it [5].

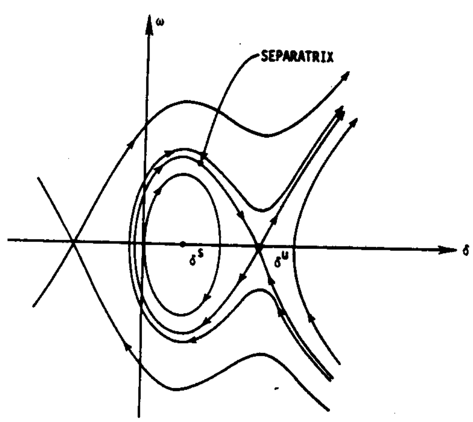

Fig.2 The phase plane trajectory.

In this article, the dynamic security assessment problem of evaluating the CCT has been investigated for a multi-machine power system through back-propagation as well as radial basis function networks. It has been observed that the radial-basis function network is superior in terms of accuracy as well as speed of estimation.

2.The Power System Model

A modern power system comprises of a large number of generators, its transmission network, transformers and loads. For reliable supply of power, the system must be capable of returning to stable operation following a transient disturbance or fault in the system. The transient stability assessment requires the following steps.

1. Evaluation of steady state system operating condition obtained through a load flow study, and
2. Analysis of the transient performance of the faulted as well as post-fault system.

If the disturbance or the fault, which caused the transient, is removed before it reaches the critical clearing time (CCT), the system is stable.

The load flow study involves solution of the nonlinear current, voltage and power relations of the network, while the stability study requires modeling and simulation of the system dynamics. In the dynamic model, a fourth order model represents each synchronous generator. The state variables chosen for each generator are – the direct and quadrature axes transient voltages, the generator angular speed and rotor angle. The major non-linearity appears in the electromechanical swing equation, written as

$$\frac{2H}{\omega_0}\frac{d^2\delta}{dt^2} = P_m - P_e \qquad (1)$$

where, P_m is the input power to the machine, H is the inertia constant, δ is the rotor angle and ω_0 is the base frequency. The electrical power output in terms of direct and quadrature axes voltages and currents, which are nonlinear functions of δ, is written as

$$P_e = V_d I_d + V_q I_q \qquad (2)$$

Each generator is assumed to be equipped with an IEEE Type 1 exciter with two time constants – one in the forward and the other in the feedback loops. Non-linearities in the excitation model are in the saturation and regulator and exciter limits. Combining the dynamics of all the generators in the system, the state equation is expressed as

$$\dot{x} = f[x, y] \qquad (3)$$

Here, y is a vector of non-state variables like the various currents and voltages in the power system. The transient stability program used in this study converts (3) into a set of algebraic equations and solves them simultaneously with the network load flow equation

$$g[x,y]=0 \qquad (4)$$

through a trapezoidal integration procedure. For a certain fault on the system, the procedure is repeated for each integration step, until the post fault system stability is determined.

The four-machine power system given in Fig.3 was selected for this study. Network parameters, machine data, and nominal operating conditions are provided in reference [6]. Faults were simulated on buses 2 and 3 and fault-clearing policy is to restore pre-fault topology. In addition to normal system topology, simulations were made with line 2-5 being removed. Twenty different loading conditions were considered and 80 simulation studies were run.

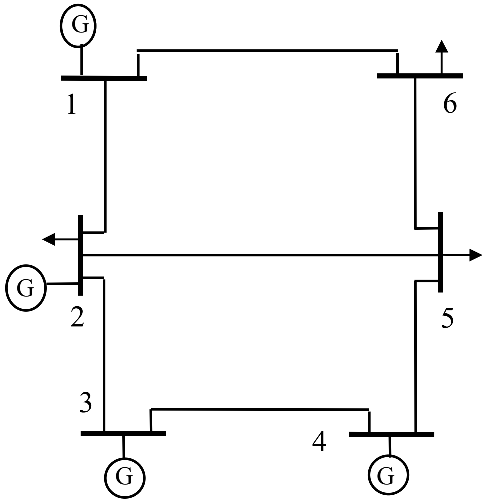

Fig. 3 The power system configuration

3.The Artificial neural Networks

Two artificial neural networks, the back-propagation and the radial-basis function network, were employed to estimate the critical clearing time for a particular fault condition. The theory of artificial neural network is widely available in the literature. It is included here, in brief, to show the computational steps involved.

3.1 The Back-propagation Network

Fig.4 shows the layout of a three-layer perceptron – the input, the hidden and the output layers with activation functions in the hidden and output layers. The number of neurons in these layers is assumed to be p, r and m, respectively. The training starts by arbitrarily assuming weighting function w_{ji} and the signals at the hidden and output layers are computed as[7]

$$v_{jn}(n) = \sum_{i=0}^{p} w_{ji}(n)\, x_i(n) \qquad y_j(n) = \varphi_j(v_j(n)) \tag{5}$$

Here, x_i are the input data and w_{j0} corresponds to the fixed input x_0 = -1 and is the threshold applied to neuron j. φ is a logistic activation function of the sigmoid type. For neuron k at the output layer, the net internal activity level is

$$v_k(n) = \sum_{j=0}^{r} w_{kj}(n)\, y_j(n) \tag{6}$$

The error signal at the output node k , which is the difference between the desired and actual outputs, is expressed as

$$e_k(n) = d_k(n) - \varphi_k(v_k(n)) \tag{7}$$

the activation function φ_k at the output neuron usually is of linear type; d_k is the desired output and y_k is the output of the k-th node.

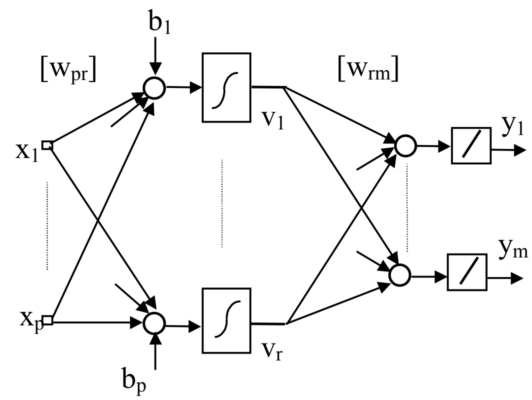

Fig.4 The back-propagation net layout.

In the training process, the network is presented with a pair of patterns – an input pattern and a corresponding desired output pattern. In the back-propagation algorithm, there are two distinct passes of computation. In the forward pass, the outputs are computed on the basis of selected weights and the error is computed. In the backward pass the weights are updated so as to minimize the sum of the squares of errors, given as

$$E_{av} = \frac{1}{2}\sum_{k=1}^{m} e_k^2 \tag{8}$$

The synaptic weights w_{ji} at any layer l is updated through the steepest descent technique. The solution is accelerated through a proper choice of momentum constant α and learning rate parameter η and is finally expressed as

$$w_{ji}(n+1) = w_{ji}(n) + \alpha[w_{ji}(n) - w_{ji}(n-1)] + \eta\,\delta_j(n)\, y_i^{l-1}(n) \tag{9}$$

where,

$$\delta_j(n) = \varphi'(v_j(n)) \sum_k \delta_k^{l+1}(n)\, w_{kj}^{l+1}(n) \tag{10}$$

3.2 The Radial-basis Function Network

A more popular type of neural network, which is finding acceptance with control engineers, employs the radial basis functions (RBF) to train the input-output data [8]. The general structure of the network with a Gaussian distribution function is shown in Fig. 5.

The input output relationship of a general RBF network with p inputs, r-hidden nodes and m outputs is expressed as

$$y_j = \sum_{k=1}^{r} w_{kj} g(\|(x - c_k)\|, \sigma_k) \quad (11)$$

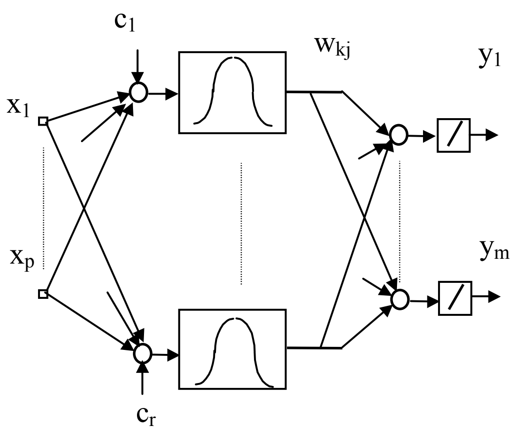

Fig.5 Radial- basis function configuration.

where, w_{kj} are the set of adjustable weights for the k-th node's contribution to the j-th output. c_k and σ_k (k=1,2, …. r) represent the center and width, respectively of the basis or activation function. The basis function is a Gaussian as shown in the figure and is expressed as

$$\exp\left(-\frac{\|x - c_k\|}{\sigma_k^2}\right) \quad (12)$$

Here, the norm implies the sum of the distances of all the components of input x to each center c_k.

In training the RBF network, the centers and the width need adjusting. The linear weights w_{kj} in equation (11) are estimated so as to minimize the sum of the square of the error between the desired output d(k) and the network output y(k), where the error is

$$e(k)=d(k) -y(k), \quad k=1,2, \ldots m \quad (13)$$

An orthogonal least squares procedure proposed by Chen [9] chooses the centers of the radial basis functions as subsets of the weighting matrix from a linear regression model of the error equation. This method has been employed in this study.

4. Results

Each input pattern to the network is composed of 3 input features from each generator in the system. These are:

- The rotor angle of each machine relative to the center of inertia δ_0 at the instant of fault initiation

$$x_i = \delta_i - \delta_0 , \quad i=1,2,\ldots 4 \quad (14)$$

where,

$$\delta_0 = \frac{\sum_{i=1}^{4} H_i \delta_i}{\sum_{i=1}^{4} H_i} \quad (15)$$

- Accelerating power of each generator immediately following the fault

$$x_{i+4} = P_{mi} - P_{ei} , \quad i=1,2,\ldots 4 \quad (16)$$

- Accelerating kinetic energy of each machine given as

$$x_{i+8} = (P_{mi} - P_{ei})/ H_i , \quad i=1,2,\ldots 4 \quad (17)$$

A total of 80 sets of input-output data were prepared. Of these, 60 cases were selected for training the nets and the rest 20 were used to test them. The selection was done randomly, but taking care that the test data belongs to the class of input the nets were trained for.

The effect of the number of neurons in the hidden layer of the back-propagation net was investigated. Training was carried out with a range of neurons from 2 to 40. Over a total of 10,000 presentations the sum-squared-error converged to 6×10^{-2} with 2 neurons, while it reached 10^{-3} with 40 neurons. Large number of neurons though improves the training error, results in data overfit. Training with very small number of neurons, on the other hand, fails to train the nets properly. About 10-12 neurons in the hidden layer gave the overall best training error and also good estimates on the test samples. Figure 6 shows the sum-squared error over 10,0000 epochs with 10 neurons in the hidden layer. The error converged to about 5×10^{-3} in the training process and test data shows a reasonably good fit. Error is relatively higher with the larger values having lower distribution.

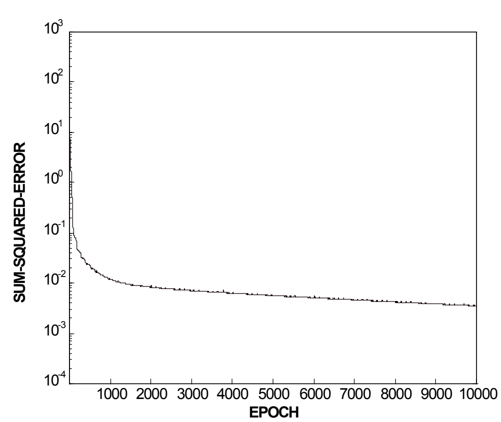

Fig.6 Training error with the back-propagation net .

In contrast with the back propagation algorithm, the radial basis function networks can train the input-output data to any desired accuracy. However, better accuracy requires a large number of neurons in the hidden layer and may result in data overfitting, making the training results useless. The width of the bell shaped basis function has to be pre-specified. For reasonable prediction, the width should not be too wide. Again, it should not be too narrow to avoid overlap of the centers. The width in the range 0.07 - 0.08 was found to provide good training for the system under study. Fig. 7 shows the error variation against the number of presentations. To achieve a convergence to 10^{-4}, the number of neurons needed was 44. To converge to $5x10^{-3}$, as in the case of Fig.6, only 19 neurons were needed. However, the number of neurons should not be a decisive issue because the RBF training is tremendously fast compared to BP. It has been observed that reasonable prediction can be made only if the number of neurons involved in the hidden layer is not too large.

A comparison of the estimated CCT with the two nets is given in Fig. 8. The test samples were selected arbitrarily from amongst the input-output data set. As can be seen, the estimates from the RBF net fits the actual outputs very closely compared with the BP algorithm.

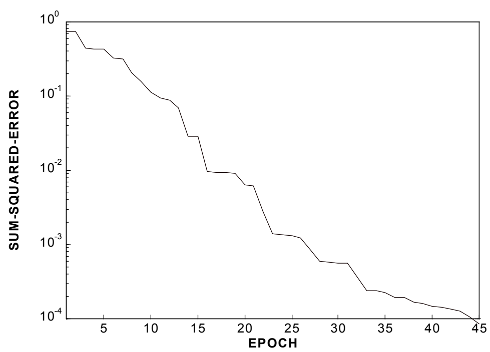

Fig.7 Error convergence with radial basis function networks.

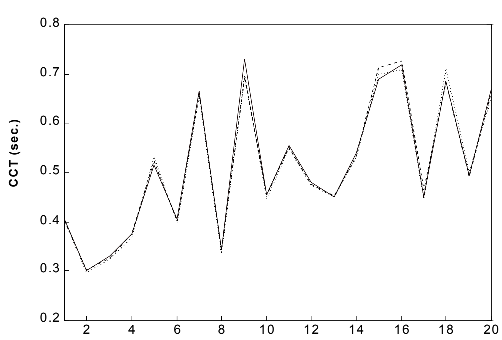

Fig.8 Comparison of critical clearing times, actual —— , ----- by back-propagation, …… by radial- basis function networks.

5. Conclusions

Various methods of determining CCT have been reviewed, and a relatively modern method of estimating CCT through artificial neural networks has been presented. The back-propagation as well as the radial-basis function neural networks were trained to estimate the critical fault clearing times of a multi-machine power system. It was observed that the RBF networks with orthogonal least square technique could be easily trained to estimate the CCT accurately. Once the width of the basis functions in the RBF net is properly adjusted, the training is extremely fast.

6. Acknowledgement

The authors wish to acknowledge the facilities provided by the King Fahd University of Petroleum and Minerals towards this research.

7. References

[1]. M.A.Pai, "Energy Function Analysis for Power System Stability", Kluwer Academic Publishers, Bosto, MA,1989.

[2].P.M.Anderson and A.Bose, "A Probabilistic Approach to Power System Analysis", IEEE Trans. PAS, Vol. 102, no. 2, pp. 2430-2439,1983.

[3]. S. Chang, "Online Transient Stability Evaluation of Interconnected Power Systems Using Pattern Recognition Strategy", IEE Proc. Generation, Transmission and Distribution, Vol. 140, no. 2, pp.115-122, 1993.

[4]. R.D. Christie, *et al*, "CQR: A Hybrid Expert System for Security Assessment", IEEE Trans. on Power Systems, Vol.5, no. 4, pp.1503-1509, 1990.

[5]. D.Sobajic and Y. H. Pao, "Artificial Neural Net Based Dynamic Security Assessment for Electric Power Systems", IEEE Trans. on Power Systems, Vol. 4, no. 4, pp. 220-228, Feb. 1989.

[6]. A.H.El-Abiad and K.Nagappan, "Transient Stability Regions of Multi-machine Power Systems", IEEE Trans. PAS, Vol. 85, pp.169-179, Feb. 1966

[7]. S. Haykin, "Neural Networks", Macmillan, New York, 1994.

[8]. G.Fathala and M. Farsi, "Modeling and Control of Nonlinear System Using Radial Basis Function Neural Network", Proc. 11th Intl. Conf. on Systems Engineering, pp.25-30, Las Vegas, Nevada, July 1996.

[9]. S.Chen, *et al*, "Orthogonal Least Squares Learning Algorithm for Radial Basis Function Networks", IEEE Trans. on Neural Networks, Vol. 2, no. 2, pp. 302-309, March 1991.