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# PARAMETER ESTIMATION OF POWER SYSTEM DYNAMIC EQUIVALENTS USING ANN

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## ABSTRACT

A novel method of estimating the parameters of dynamic equivalent of a power system from the transient features of the local generator is proposed. Transient stability indices like the peak overshoot, decay constant and frequency of oscillations are used as input features to train back-propagation and radial-basis function artificial neural networks. Simulation results indicate that the radial-basis function network can estimate the parameters of the dynamic model with sufficient accuracy.

## INTRODUCTION

Assessment of dynamic performance of a power system is a complex procedure because of the very large number of generating units and their associated control elements in a modern system. Efforts to find a suitable equivalent of the power system which could faithfully approximate its dynamic behavior have been reported since the 70's [Debs 1975;Podmore 1978]. Usually, the system to be equivalenced is replaced by one or more coherent groups of synchronous machines. Dynamic equivalents using frequency response and modal coherency [Van Oirsouw 1990], angular speed deviation based coherency [Pires de Souza 1992], acceleration and velocity based coherency[Hussain and Rau 1992], and energy function and rotor angle based coherency analysis[6Haque and Rahim 1990], etc. have been reported. Identification and estimation procedures to find the parameters of a dynamic equivalent have been reported in the work of [Yu *et al* 1979 ] and [Rahim and Al-Baiyat 1982]. The parameters of the unknown equivalents are computed iteratively based on least square techniques.

Besides the computational requirements of iterative methods, one serious disadvantage of these methods is that the convergence of the solutions is not guaranteed. Neural networks provide an alternative method of estimation of these parameters. However, matching the electromechanical and electrical transient time response with the parameters of the unknown equivalent, as such, will be a formidable task.

In this work, transient stability indices of the study system, like the peak overshoot, decay constant, natural frequency of oscillation, etc are utilized as input features to predict parameters of the equivalent machine. Two artificial neural networks -- the back-propagation (BP) and radial basis function (RBF) were trained. RBF nets were found to be superior to the BP network in this estimation process.

## THE POWER SYSTEM PROBLEM

Modern power networks are highly complicated systems containing a huge number of generators, transmission networks, loads etc. Because of load growth, the system sizes are ever growing. Addition of a new plant requires, in turn, a large number of planning studies. The dynamic study is one of the very complicated analyses requiring solution of hundreds of differential equations. Since in such studies the primary concern is the behavior of the new (local) unit, the analysis would be much simpler if the rest of the network could be replaced by an equivalent. Viewed from the local system, the rest of the grid behaves like a huge load running at synchronous frequency.

The power system model considered is shown in Fig.1. It comprises of a known (local) system connected to a large interconnected network through a transmission system. The external (unknown) system is represented by a synchronous motor whose parameters are unknown. The local system has also its own load lumped at its generator bus.

The local generator (i) is represented dynamically as

$$\dot{x}_i = f_i[x_i, v_o, u_i] \qquad (1)$$

where, $u_i$ is the vector of controls for the local system. The state vector $x_i$ comprises of the generator speed deviation, rotor angle, and internal voltage of the machine and the exciter voltage.

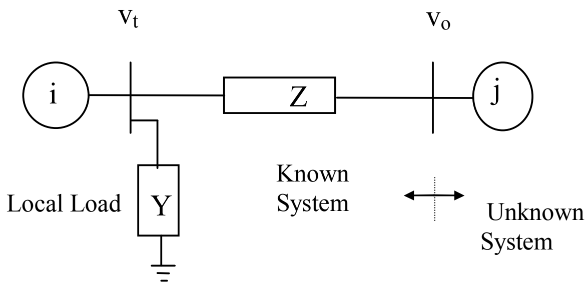


Fig.1. The power system configuration

The unknown equivalent (j) is represented as

$$\dot{x}_j = f_j[x_j, v_t, \alpha] \tag{2}$$

where, α is the vector of parameters through which the unknown system is characterized. These are the inertia constant (M), damping coefficient (D), direct axis synchronous reactance ($x_d$), direct axis transient reactance ($x_d'$) and the open circuit field time constant ($T_{do}'$) of the equivalent motor. The state variables selected are the motor speed deviation, rotor angle position and the internal voltage of the equivalent motor. Expressing $v_t$ and $v_o$ in terms of state variables selected, the composite state model for the system is expressed as follows.

$$\dot{x} = f[x, \alpha, u] \tag{3}$$

Disturbances are simulated on the local system, and the electromechanical and electrical transients are recorded. For a 35% input torque pulse for 0.5 second on the local generator, a sample plot for the rotor speed deviation is given in Fig. 2. Similarly, the terminal voltage variation is also recorded. From the transient records the following data has been collected.

- Peak overshoot, decay coefficient, and natural frequency of oscillations of the electromechanical transients as exhibited by rotor angular frequency deviation.
- The same indices for electrical transients obtained from change in terminal voltage (not shown).
- The steady state power flow between the local and external systems.

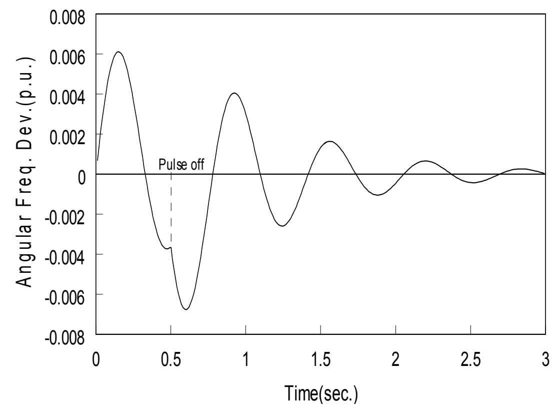


Fig.2. Angular speed deviation of local generator following a 35% input torque pulse for 0.5 sec.

A total of 100 simulation studies were made representing different power system equivalents.

## ARTIFICIAL NEURAL NETWORKS

ANNs have been widely used in power system applications in recent times. The application in dynamic security analysis has largely been devoted to determination of fault clearing strategies [Sobajic and Pao 1989; Moechtar 1996]. The theory is widely available in the literature and is outlined here, in brief, to show the computational steps.

### *The Back-propagation Network*

Fig.2 shows the layout of a back-propagation network with a three layer perceptron – the input, the hidden and the output layers having 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 a weighting function $w_{ji}$, which relates the input and output of hidden neuron j at any iteration n as follows [Haykin 1994].

$$v_{jn}(n) = \sum_{i=0}^{p} w_{ji}(n)\, x_i(n)$$
$$y_j(n) = \varphi_j(v_j(n)) \tag{4}$$

where, $x_i$ are the input data and $w_{jo}$ corresponds to the fixed input $x_o = -1$ 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

$$v_k(n) = \sum_{j=0}^{r} w_{kj}(n)\, y_j(n) \tag{5}$$

The error signal at the output node k is defined as

$$e_k(n) = d_k(n) - \varphi_k(v_k(n)) \quad (6)$$

The activation function $\varphi_k$ 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.

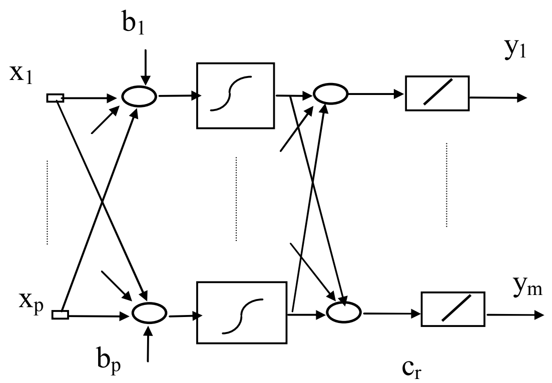


Fig.3 The back-propagation neural net configuration.

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

$$E_{av} = \frac{1}{2}\sum_{k=1}^{m} e_k^2 \quad (7)$$

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

$$\begin{aligned} w_{ji}(n+1) = w_{ji}(n) + \alpha[w_{ji}(n) - w_{ji}(n-1)] \\ + \eta\,\delta_j(n)\, y_i^{l-1}(n) \end{aligned} \quad (8)$$

where,

$$\delta_j(n) = \varphi'(v_j(n))\sum_k \delta_k^{i+1}(n)\, w_{kj}^{l+1}(n) \quad (9)$$

*The Radial-Basis Function Network*

Fig.4 shows the general structure of a neural network that employs the radial basis functions (RBF). The input output relationship of a general RBF network with p inputs, r hidden nodes and m outputs is expressed as,

$$y_j = \sum_{k=1}^{r} w_{kj}\, g(\|(x - c_k)\|, \sigma_k) \quad (10)$$

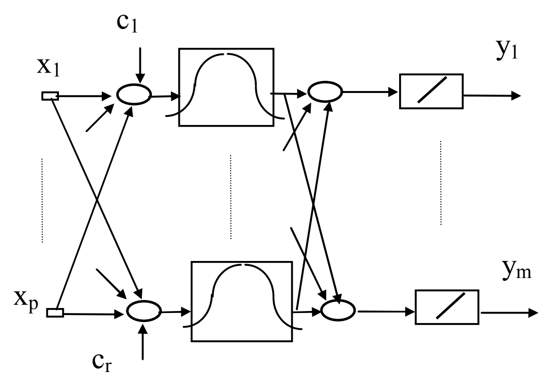


Fig.4 Radial basis function net configuration.

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

$$\exp\left(-\frac{\|x - c_k\|}{\sigma_k^2}\right) \quad (11)$$

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 (10) 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

$$e(k) = d(k) - y(k), \quad k = 1, 2, \ldots m \quad (12)$$

An orthogonal least squares (OLS) procedure proposed by [Chen, *et al* 1991] chooses the centers of the radial basis functions as subsets of the weighting matrix from a linear regression model of the error equation written in matrix form as

$$d = X\,a + e \quad (13)$$

where,d is the vector of desired response, a is the model parameter matrix, X is the regressor and e is the residue.

The OLS method involves the transformation of the regressor vectors X=[$x_1$, $x_2$, …$x_r$] into a corresponding set of orthogonal vectors [$w_1$, $w_2$, ….$w_r$]. Through an orthogonalization procedure it is shown that [11]

$$w_1 = x_1$$
$$\alpha_{ik} = (u_i^T x_k)/(u_i^T u_k) \qquad 1 \le i \le k \tag{14}$$
$$w_k = x_k - \sum_{i=1}^{k-1} \alpha_{ik} x_i$$

where, k=2,3, …. r.

The training vector $w_1$, $w_2$,…. , which include the centers are determined in a well defined manner until the procedure is terminated at the s-th step when

$$1 - \sum_{j=1}^{s} [err]_j < \rho \tag{15}$$

Here, $0<\rho<1$ is a chosen tolerance and the error at the n-th step is computed as

$$\max_n \{((w_k^T d/w_k^T w_k)^2 w_k^T w_k)/ d^T d, \quad k=1,2, \ldots r \tag{16}$$

## RESULTS

The input features that were considered to train the neural nets are the peak-overshoot, decay coefficient, frequency of natural oscillation of the electromechanical and electrical transients obtained from the angular frequency and terminal voltage variation records. It is expected that the effect of parameters M and D of the equivalent external machine will be embedded in the transients in variation of rotor angular frequency. Similarly, $x_d'$ and $T_{do}'$ can be assessed through the transient indices of terminal voltage. The steady state power flow will be affected by the synchronous reactance $x_d$, so this is also included in the input features.

The convergence characteristics of the training error from the back-propagation network are shown in Fig.5. The sum-squared error of equation (7) converged to 0.1 approximately after about 10,00 presentations with 100 neurons in the hidden layer. This is almost the optimum number in terms of error convergence. The trained network was then tested on the 20 randomly selected data samples. The mean error between the actual and network converged values for the 5 outputs calculated through equation (17) is shown in Fig.6.

$$\text{Mean error} = \frac{1}{5}\sqrt{\sum_{k=1}^{5}(e_k^{\ 2})} \tag{17}$$

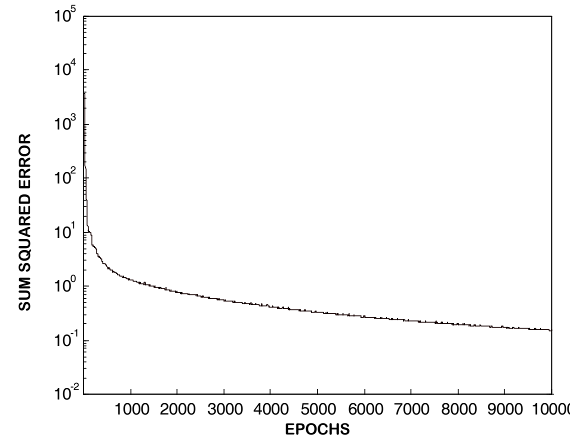


Fig.5 Training error convergence characteristics for the for the back-propagation network.

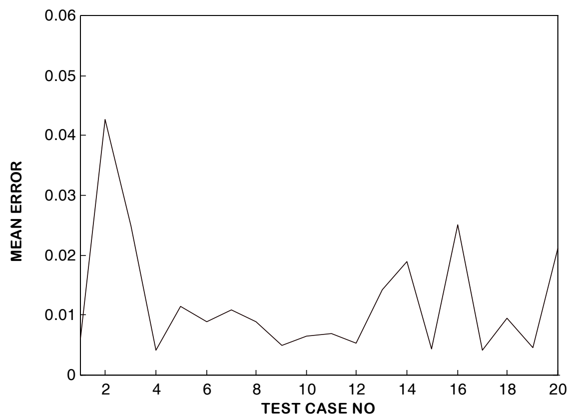


Fig.6 Mean error for the randomly selected test samples.

As can be observed from Fig.6 the maximum error is about 0.04 for sampling #2 which does not appear to be too bad. Since the output contains quantities like inertia constant (range 2-15), transient reactance of the order of 0.1 -0.3, the mean error fails to show the level of convergence of these smaller quantities. Comparison of the actual estimated values from the BP algorithm for the smallest parameter $x_d'$ is shown in Fig. 7.

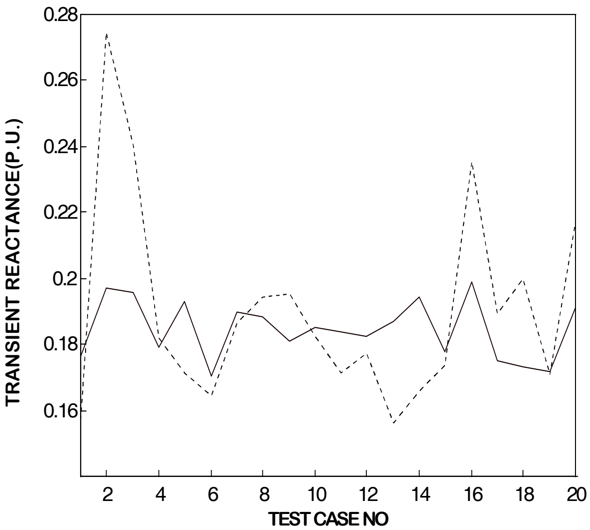


Fig. 7 The comparison of transient reactance $x_d'$. Symbols are as in Fig. 8.

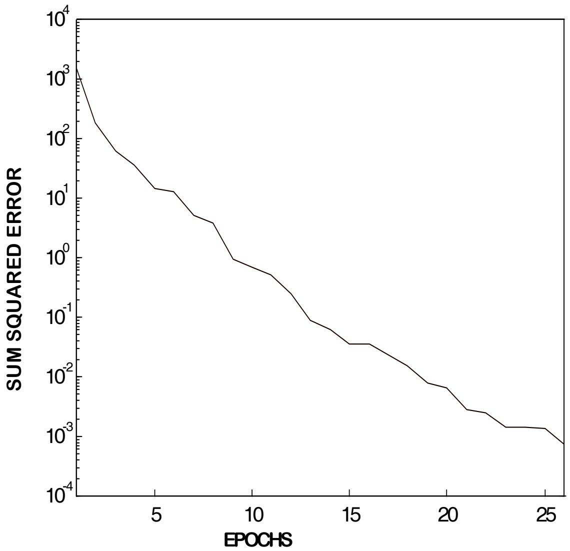


Fig.8.Training error convergence characteristics for RBF network.

Contrary to the BP algorithm, the RBF network can be trained to almost any level of accuracy of convergence. Since higher accuracy involves excessively large number of neurons in the hidden layer, care should be taken that there is no overfitting of data in which case the training becomes useless. Also the width of the basis functions have to be properly selected to get a good match. For an error convergence limit of $10^{-3}$ and the width of the basis function of 0.01, Fig. 8 shows the convergence characteristics of the training error. The mean error for the test samples obtained through the RBF network, as calculated through equation (17), is plotted in Fig. 9.

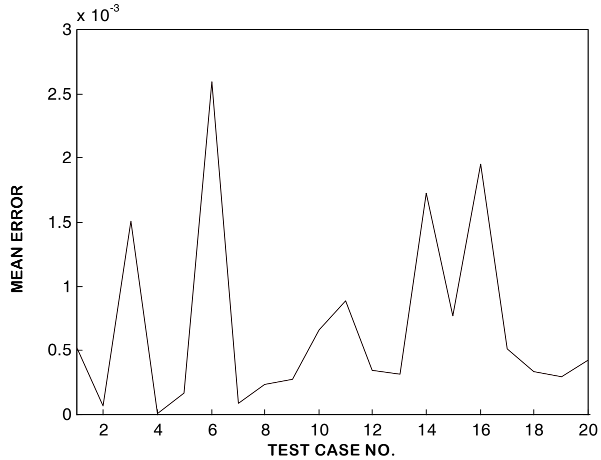


Fig.9 Mean error with the randomly selected test cases with the RBF network.

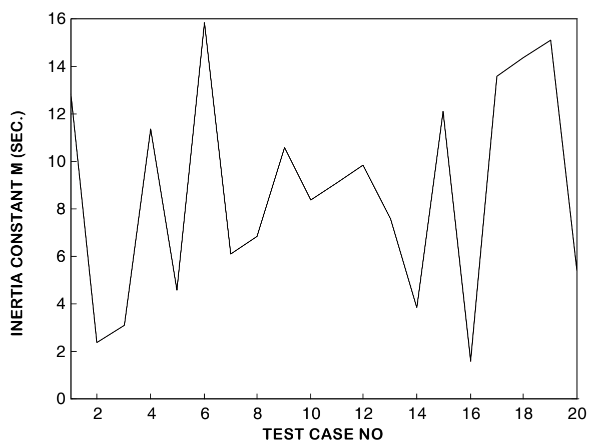


Fig.10 Inertia constant M obtained through the RBF network for various test cases. The actual and estimated values are completely overlapping.

Fig.8 shows that the RBF network needs only 26 neurons in the hidden layer in the training phase. The computation time is of the order of seconds compared to that of hours in the back-propagation network. The mean error for the test samples is of the order of $10^{-3}$, which is virtually negligible. Comparison of the predicted outputs with the actual quantities for the largest variable M (inertia) and the relatively smaller reactance $x_d'$ are plotted in Figs. 10 and 11, rspectively. The difference is so little that they are undistinguishable. The convergence of other parameters $x_d$, D and $T_{do}'$ are equally good.

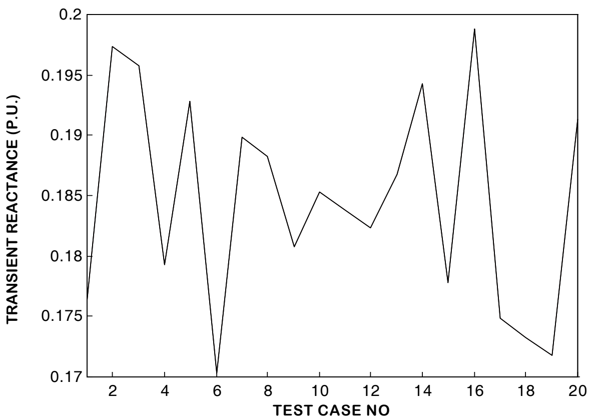


Fig. 11. Transient reactance ($x_d'$) with the RBF network. The actual values and the network predicted values are completely overlapping.

## CONCLUSIONS

A power network has been represented dynamically by a synchronous motor with unknown parameters. Transient stability indices of the study system were selected as input features for training artificial neural networks to predict the unknown parameters of the dynamic equivalent. Back-propagation and radial-basis function networks were trained. It was observed that the RBF network could be trained with extreme precision for the selected input features. Training a network with transient stability indices like peak response, decay constant, etc. to estimate the dynamic equivalence of a power system is a novel idea.

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**REFERENCES**

Chen,S. *et al*, 1991 “Orthogonal Least Squares Learning Algorithm for Radial Basis Function Networks”, *IEEE Trans Neural Networks*, 2, no 2, 302-309.

Debs, A.S. 1975 “Estimation of External Network Equivalents from Internal System Data”, *IEEE Trans. Power Apparatus and Systems* 94, 273-279.

Haque,M.H. and Rahim, A.H.M.A 1990 “Identification of Coherent generators Using Energy Function”, *IEE Proceedings-C*, 137, no. 4, 255-260.

Haykin, S. 1994. *Neural Networks*. Macmillan, New York.

Hussain,M.Y. and Rau,V.G. 1993 “Coherency Identification and Construction of Dynamic Equivalent for Large Power System”, *IEE 2nd Intl. Conf. on Advances in Power System Control, Operation and Management,* Hong Kong, 887-892.

Moechtar,M. 1996 “Combination of Neural Network and Genetic Algorithm Methods for Assessing the Transient Stability of Power Systems”, *Ph. D. Dissertation,* University of Southern California.

Pires de Souza, E.J.S. 1992 “ An Efficient Methodology for Coherency Based Dynamic Equivalents”, *IEE Proceedings – C,*139, no. 5, 371-382.

Podmore, R. 1978 “Identification of Coherent generators for Dynamic Equivalents”, *IEEE Trans. Power Apparatus and Systems* 97, 1344-1354.

Rahim, A.H.M.A and Al-Baiyat, I.A. 1982 “A Weighted Least Squares Method for Determination of Power System Equivalents”, *Electric Power Systems Research,* 5, 207-218.

Sobajic,D. and Pao,Y.H. 1989 “Artificial Neural Network Based Dynamic Security Assessment of Electric Power Systems”, *IEEE Trans. Power Systems*, 4, no 4, 220-228.

Van Oirsouw, P.M. 1990 “ Dynamic Equivalents Using Modal Coherency and Frequency Response”, *IEEE Trans Power Systems*, Vol. 5, no. 1, 289-295.

Yu, Y., El-Sharkawi, M.A. and Yvong, M.A. 1979 “Estimation of Unknown Large power System Dynamics”, *IEEE Trans Power Apparatus and Systems* 98, pp. 279-289.