Radial Basis Function Network Based Power System Stabilizers for Multimachine Power Systems

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Abstract - A Radial Basis Function Network (RBFN) based Power System Stabilizer (PSS) is presented in this paper to improve the dynamic stability of multimachine power systems. The proposed RBFN is trained over a wide range of operating conditions in order to re-tune the parameters of the PSS in real-time. Time domain simulations of a multimachine power system with different operating conditions subject to a three phase fault are studied and investigated. The performance of the proposed RBFN PSS is compared to that of conventional power system stabilizer (CPSS). The results show the good damping characteristics of the proposed RBFN PSS over a wide range of operating conditions.

1. Introduction

In the past two decades, the utilization of supplementary excitation control signals for improving the dynamic stability of power systems has received much attention [1-5]. Nowadays, the conventional power system stabilizer (CPSS) is widely used by power system utilities [3]. The gain settings of these stabilizers are determined based on the linearized model of the power system around a nominal operating point to provide optimal performance at this point. However, CPSS performance is degraded whenever the operating point changes from one to another because of fixed parameters of the stabilizer.

Alternative controllers using adaptive control algorithms have been proposed to overcome such problems [4-5]. However, most of the adaptive controllers are designed based on the parameter identification of the system model in real-time which is a time consuming task.

Recently, it has been shown that artificial neural networks (ANNs) with one hidden layer can uniformly approximate any continuous function to any chosen degree of accuracy [6]. ANNs trained with backpropagation algorithm have been applied to various power system problems [7-10]. However, there are several problems associated with these networks such as getting stuck in local minima and slow convergence rate.

It has recently been acknowledged that approximation accuracy properties of RBFN are advantageous as compared to the other ANN models [11]. The "linear in parameters" property of the radial basis functions guarantees the convergence of the parameters to the global minimum. Moreover, the local tunability of the radial basis functions makes only a part of the nodes to be affected by any given input [11], and only a portion of the model parameters may need to be adjusted, thus reducing the training time and computational overhead.

In power systems, RBFN has been successfully applied to modeling and control of synchronous machines [12-13]. However, applications of RBFN to more complex problems have not yet been exploited.

In this paper, a radial basis function network based power system stabilizer (RBFN PSS) for a multimachine power system is proposed. An RBFN is employed to estimate the stabilizer parameters based on real-time measurements of the loading conditions. In order to investigate the performance of the proposed RBFN PSS, time domain simulations of a multimachine power system under several loading conditions and major disturbances are examined. Simulation results show the superiority of the proposed RBFN PSS to the CPSS and its capability to enhance system damping over a wide range of operating conditions.

2. Radial basis function network

2.1. RBFN structure

Like most feedforward networks, RBFNs have three layers, namely, an input layer, a hidden layer, and an output layer. The nodes within each layer are fully

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connected to the previous layer nodes. A schematic diagram of an RBFN with n inputs and m outputs is given in Fig. 1. The input variables are each assigned to a node in the input layer and pass directly to the hidden layer without weights. The hidden layer nodes are the RBF units. Each node in this layer contains a parameter vector called a center. The node calculates the euclidean distance between the center and the network input vector, and passes the result through a nonlinear function, $\Phi(.)$. The output layer is a set of linear combiners. The overall input-output response of the RBFN is a mapping $f: R^n \rightarrow R^m$, that is,

$$y_i = w_{0i} + \sum_{j=1}^{n_h} w_{ji}\Phi\left(\|x - c_j\|, \beta_j\right) \qquad (1)$$

where c_j and β_j are the center and the width of the jth RBF unit respectively. In (1), y_i is the ith output, $\mathbf{x}=[x_1 \ldots x_n]^T$ is the input vector, n_h is the number of RBF units, and w's are the connection weights. In this study, $\Phi(.)$ is chosen to be gaussian activation function, that is,

$$\Phi(z,\beta) = \exp(-z^2/\beta^2) \qquad (2)$$

2.2. Learning algorithm

The centers, the widths, and the connection weights represent the network parameters that have to be determined by the learning algorithm. These parameters are determined in three steps. First, the centers are determined using k-means clustering algorithm by prespecifying the number of clusters, n_h,[14]. Secondly, the width parameter of the ith hidden unit, β_i, is chosen to be the root mean square distance between c_i and a number of the nearest neighboring unit centers, n_n, as

$$\beta_i = \left[\frac{1}{n_n}\sum_{j=1}^{n_n}\left(\|c_i - c_j\|\right)^2\right]^{1/2} \qquad (3)$$

Finally, the weights between the hidden units and the output units are determined by rearranging (1) as

$$y_i = \sum_{j=1}^{n_h+1} w_{ji}\Phi_j \qquad (4)$$

where Φ_j is the output generated by the jth hidden node. In (4), the $(n_h+1)^{st}$ hidden node produces a constant unity output which allows for implementation of bias on the output layer. In matrix form, (4) can be rewritten as

$$AW=D \qquad (5)$$

The matrix A is an $n_p \times (n_h+1)$ matrix which stores the results of the n_h hidden nodes for each of the training patterns presented to the network in addition to the constant value node. Here n_p is the number of the training patterns. The matrix W is an $(n_h+1) \times m$ matrix. The matrix D is an $n_p \times m$ matrix which represents the desired outputs. Using orthogonal triangularization technique [15], (5) can be solved for W.

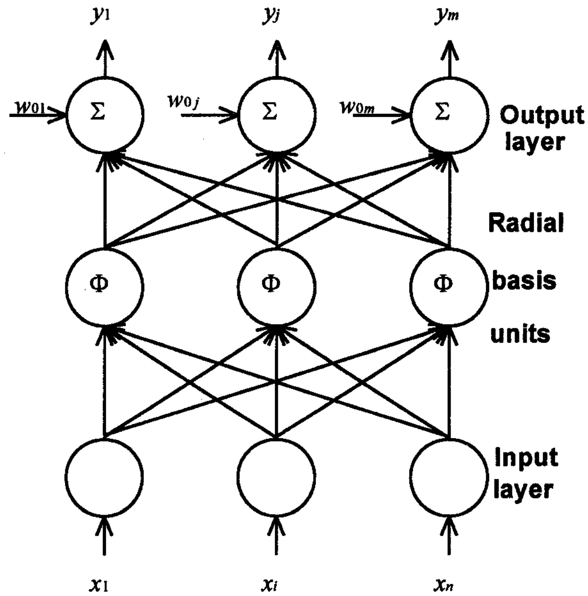

Fig. 1. Schematic diagram of RBFN.

3. Problem formulation

Consider a multimachine power system whose stability is to be enhanced by installing PSSs. The commonly used lead-lag PSS is chosen in this study. The ith local stabilizer can be described as

$$U_i = \frac{sT_w}{1+sT_w}\frac{K_{ci}(1+sT_{1i})}{1+sT_2}\Delta\omega_i \qquad (6)$$

where U_i and $\Delta\omega_i$ are the stabilizer input and output signals respectively. The time constants T_w and T_2 are usually prespecified [2]. The other parameters K_{ci} and T_{1i} are determined by linearizing the nonlinear model of the system around a nominal operating point to provide optimal performance at this point. Having been determined, these parameters remain fixed. Generally, the power systems are highly nonlinear and the operating conditions can vary over a wide range. Consequently, these fixed-gain PSSs no longer ensure the optimal performance. Thus the gain settings of these controllers must be re-tuned on-line to provide good damping characteristics over a wide range of operating conditions. In the proposed approach, the trained RBFN will re-tune the stabilizer parameters based on real-time measurements of loading conditions. The RBFN PSS control scheme is shown in Fig. 2.

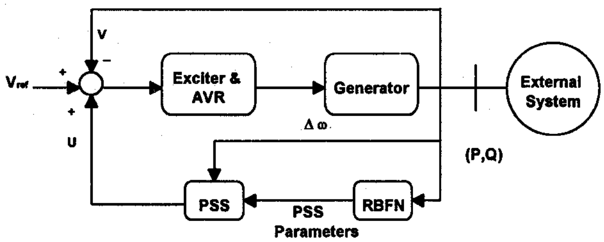

Fig. 2. The proposed RBFN PSS control scheme

4. Training of RBFN based PSS

The purpose of the training in this paper is to make the proposed RBFN able to re-tune the values of K_{ci} and T_{1i} parameters based on real-time measurements of the *i*th machine loading conditions. To generate the training patterns, the load admittances have been randomly varied in the range of 0.5 to 2.0 of their nominal values. With each variation, the load flow solution of the system is obtained and the CPSS is designed by linearizing the system model around the current operating point. Therefore, each training pattern consists of the real power P_i and the reactive power Q_i to represent the network inputs and the values of K_{ci} and T_{1i} to represent the desired outputs.

In order to evaluate the performance of the trained network, we define an average percentage error (APE) as

$$APE = \frac{\sum_{i=1}^{np} |d(i) - y(i)|}{\sum_{i=1}^{np} |d(i)|} * 100 \qquad (7)$$

where n_p is the number of training patterns and $d(i)$ and $y(i)$ are the *i*th desired and actual outputs respectively.

5. Results and simulations

5.1. Test system and optimum PSS locations

To evaluate the effectiveness of the proposed RBFN based PSS, the nine-bus three-machine power system shown in Fig. 3 was considered. Each machine has been represented by a fourth order two-axis nonlinear model. Details of the system data are given in [1]. Without PSSs, the system response curves due to a 6-cycle three phase fault at bus 7 are shown in Fig. 4. It is observed from Fig. 4 that the system damping is poor and the system is highly oscillatory. Therefore, it is necessary to install stabilizers in order to have good dynamic performance. To identify the optimum locations of PSSs, sensitivity of PSS effect (SPE) method [16] was used. The results indicate that the generators G2 and G3 are the optimum locations for installing PSSs to damp out the electromechanical modes of oscillations. Therefore, the generators G2 and G3 are equipped with two of the proposed RBFN based PSS. The performance of the proposed stabilizers was compared to that of CPSSs installed on G2 and G3 with the transfer function [1]

$$G(s) = \frac{10s}{1+10s}\frac{(1+0.568s)^2}{(1+0.0227s)^2} \qquad (8)$$

5.2. Network training

Two RBFNs are proposed to re-tune the stabilizers installed on G2 and G3. Each RBFN was trained using a set of 500 input-output patterns. The number of RBF units n_h and the number of the nearest neighboring centers n_n are chosen by trial and error to get the minimum APE. The trained networks were tested by another set of 500 input-output patterns that have not been presented before to the networks. The errors APE and the structure of the networks are given in Table 1.

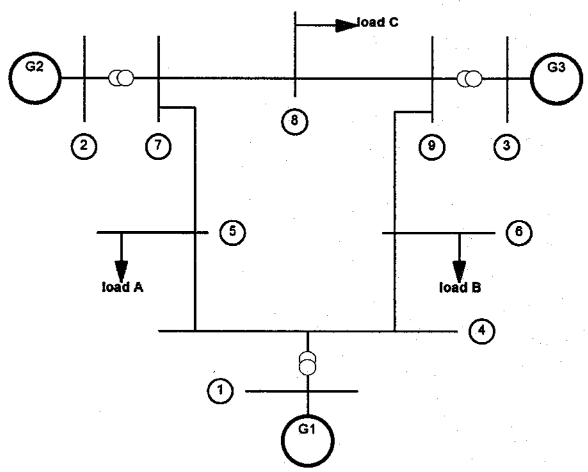

Fig. 3. Three-machine nine-bus power system.

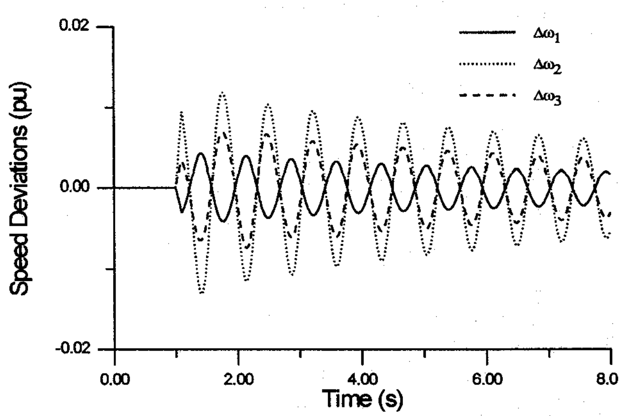

Fig. 4: Response to a three phase fault without PSSs.

Table 1: APE and RBFN structures

PSS Location	APE		RBFN Structure	
	K_c	T_1	n_h	n_n
G2	0.020	0.026	25	6
G3	0.031	0.028	25	6

Table 2: Loading conditions

Loading Condition		G1	G2	G3
Nominal	P (pu)	0.713	1.630	0.852
	Q (pu)	0.275	0.068	-0.108
Heavy	P (pu)	2.207	1.920	1.280
	Q (pu)	1.092	0.565	0.360
Light	P (pu)	0.362	0.800	0.450
	Q (pu)	0.166	-0.107	-0.203

Table 3: Load admittances

Load	Nominal	Heavy	Light
A	1.261-j0.504	2.314-j0.925	0.640-j0.542
B	0.878-j0.293	2.032-j0.677	0.431-j0.335
C	0.969-j0.339	1.584-j0.634	0.472-j0.236

5.3. Numerical results

To demonstrate the capability of the proposed RBFN based PSS to enhance system damping over a wide range of operating conditions, three different loading conditions were considered as given in Table. 2. Load admittances in each case are given in Table 3. With each loading condition, a three phase fault disturbance at bus 7 was applied. The fault duration was 6 cycles. The simulation results are shown as follows.

5.3.1. Nominal loading condition: The dynamic response of the system is shown in Fig. 4. It is obvious that with the proposed RBFN PSSs, the system returns to its previous operating point faster than the CPSSs. This is very helpful in the improvement of the disturbance tolerance ability of the system.

5.3.2. Heavy loading condition: With heavy loading conditions, the simulation results are shown in Fig. 5. The results show the superiority of the proposed RBFN PSSs to the CPSSs. It can be concluded that the proposed RBFN PSS provides very good damping over a wide range of operating conditions.

5.3.3. Light loading condition: The simulation results are shown in Fig. 6. It can be seen that the proposed RBFN PSSs produce much better results and the oscillations are damped out much quicker as compared to CPSSs.

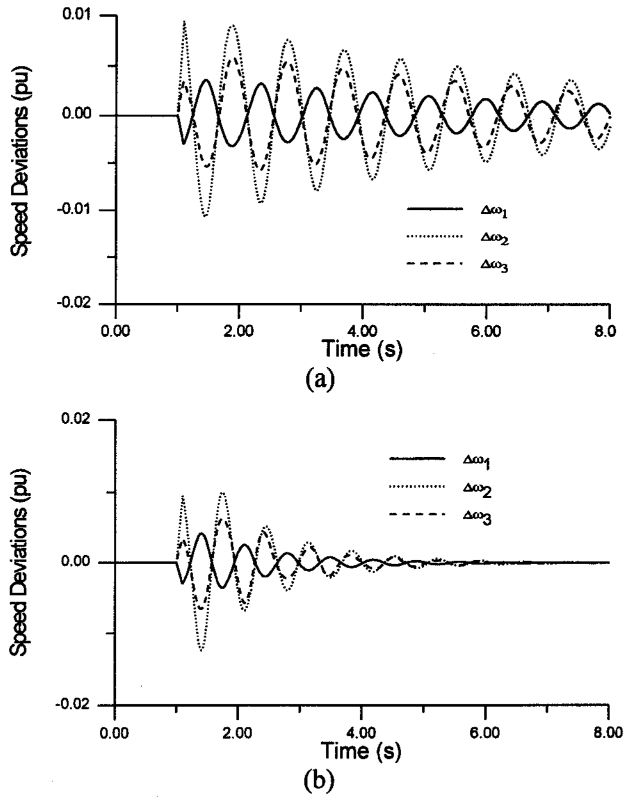

Fig. 5: Response with nominal loading condition.
(a) CPSS (b)Proposed RBFN PSS

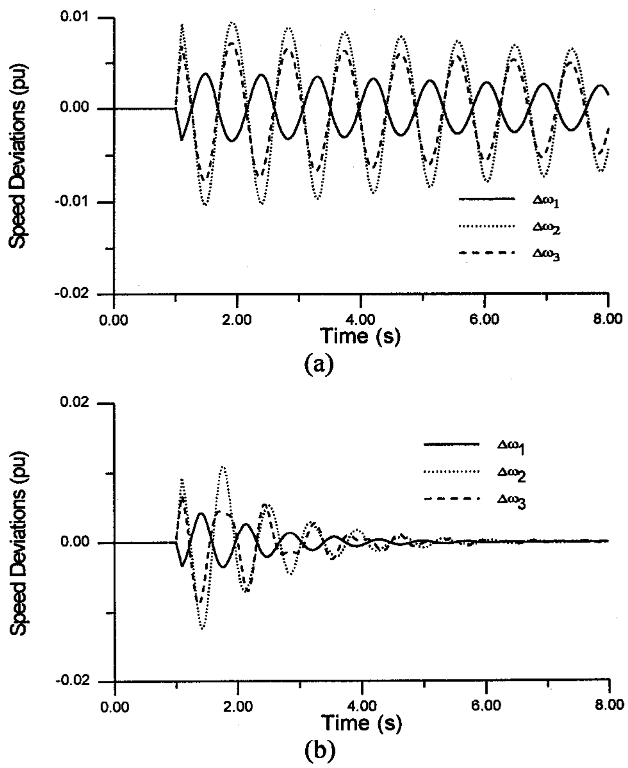

Fig. 6. Response with heavy loading condition
(a) CPSS (b)Proposed RBFN PSS

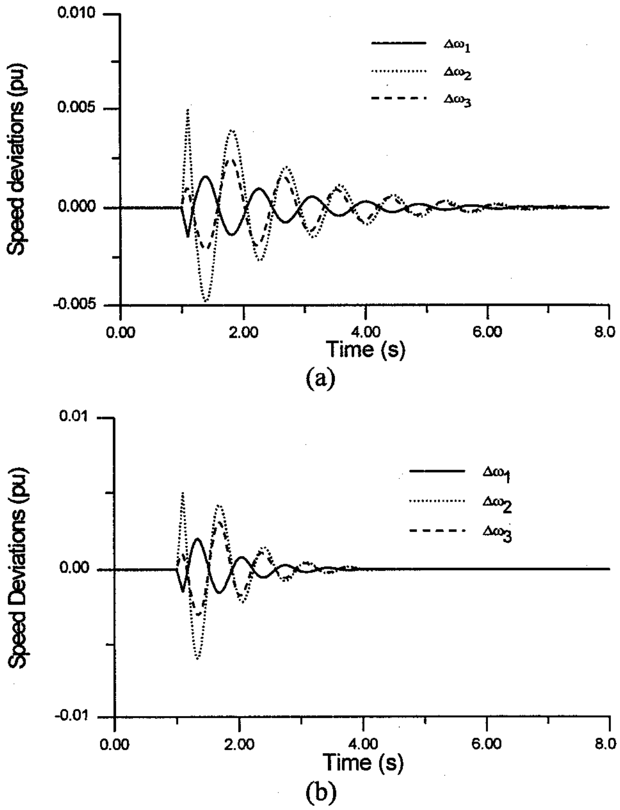

Fig. 7. Response with light loading condition
(a) CPSS (b)Proposed RBFN PSS

6. Conclusions

In this study, a radial basis function network trained by *k*-means algorithm was employed to adapt the PSS parameters to improve power system dynamic stability. The proposed RBFN PSS was trained based on real-time measurements of the real powers and reactive powers. The training has been carried out over a wide range of operating conditions. The effect of major disturbances such as three phase fault on the proposed RBFN PSS performance has been studied. Simulation results show that the proposed RBFN PSS can provide good damping characteristics over a wide range of loading conditions

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