A HYBRID NEURO-FUZZY POWER SYSTEM STABILIZER FOR MULTIMACHINE POWER SYSTEMS

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Abstract **– A Fuzzy Basis Function Network (FBFN) based Power System Stabilizer (PSS) is presented in this paper to improve power system dynamic stability. The proposed FBFN based PSS provides a natural framework for combining numerical and linguistic information in a uniform fashion. The proposed FBFN is trained over a wide range of operating conditions in order to re-tune the PSS parameters in real-time based on machine loading conditions. The orthogonal least squares (OLS) learning algorithm is developed for designing an adequate and parsimonious FBFN model. Time domain simulations of a single machine infinite bus system and a multimachine power system subject to major disturbances are investigated. The performance of the proposed FBFN PSS is compared with that of conventional (CPSS). The results show the capability of the proposed FBFN PSS to enhance the system damping of local modes of oscillations over a wide range of operating conditions. The decentralized nature of the proposed FBFN PSS makes it easy to install and tune.**

Keywords: power system stabilizer, neural networks, fuzzy logic, fuzzy basis function network.

1. INTRODUCTION

In the past two decades, the utilization of supplementary excitation control signals for improving the dynamic stability of power system has received much attention [1-17]. Nowadays, the conventional lead-lag power system stabilizer (CPSS) is widely used by power system utilities [3]. Other types of PSS such as proportional-integral and proportional-integral-derivative have also been proposed [5-6]. The gain settings of these controllers are determined based on the linearized model of the power system around a nominal operating point to provide optimal performance at this point. Generally, the power systems are highly nonlinear and the operating conditions can vary over a wide range. Thus the gain settings of these controllers must be re-tuned on-line to provide good damping characteristics.

Alternative controllers using adaptive control algorithms have been proposed to overcome such problems [6-8]. However, most adaptive controllers are designed on the basis of parameter identification of the system model in real-time which results in time consuming and computational burden.

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Recently, many intelligent system techniques have been developed and introduced such as neural networks (NN) and fuzzy logic systems (FLS). A neural network that mimics the function of the brain has a large number of massively interconnected processing elements (nodes) that demonstrate the ability to learn and generalize from training examples. Distributed representation and learning capabilities are the major features of NN. On the other hand, FLS base their decisions on inputs in the form of linguistic variables derived from membership functions which are used to determine the fuzzy set to which a crisp value of the input belongs and the degree of membership in that set. The variables are then matched with the preconditions of linguistic IF-THEN rules and the response of each rule is obtained through fuzzy implication. The response of each rule is weighted according to the degree of membership of its inputs. Finally, the centroid of responses is calculated to generate the appropriate output. The salient feature of NN and FLS techniques that distinguish them from the traditional control and adaptive approaches is that they provide a model-free description of the control system.

NN and FLS have been successfully applied to various power system control problems with promising results [9-17]. In [9-12] the NN used are nonlinear in the parameters and the backpropagation training algorithm is used to estimate the network parameters. However, there are several problems associated with these networks such as getting stuck in local minima and slow convergence rate. In addition, the application is limited to a single machine infinite bus system. Generally, using NN alone to design a PSS might be insufficient if the test input used to generate training input/output pairs is not rich enough to excite all modes of the system. On the other hand, fuzzy logic controllers in [13-17] are subjective and somewhat heuristic. In most cases, the determination of fuzzy rules, input and output scaling factors, and the choice of membership functions depend on trial-and-error that makes the design of fuzzy logic controller a time-consuming task.

However, it is important to clarify that the proposed approach brings the learning capabilities of NN to the robustness of FLS in the sense that the fuzzy logic concepts are imbedded in the network structure and operation. It also provides a natural framework for combining both numerical information in the form of input/output pairs and linguistic information in the form of IF-THEN rules in a uniform fashion and overcomes NN and FLS weaknesses.

In this paper, we propose a fuzzy basis function network based power system stabilizer (FBFN PSS) to enhance power system dynamic stability. The FBFN is trained to adapt the parameters of PSS based on real-time measurements of real power (P), reactive power (Q), and terminal voltage (V) which characterize the machine loading conditions. Since FBFN is linear in the parameters, classical Gram-Schmidt orthogonal least squares (OLS) learning algorithm [18] is developed to determine a set of significant fuzzy basis functions and the network parameters. The OLS learning algorithm requires only one pass of the training examples, therefore, it is much faster than backpropagation algorithm [9-12]. Unlike backpropagation algorithm, OLS algorithm is a linear optimization technique, hence, it guarantees the convergence of the network parameters to global minimum. While the most of the learning algorithms require a prespecified network structure, OLS algorithm provides a systematic approach to the selection of FBFN structure in an intelligent way in the sense that adequate and parsimonious structure is self-organized.

The proposed FBFN PSS is applied to a single machine infinite bus system and to a multimachine power system. The main features of this study can be summarized as follows:

a) The proposed FBFN PSS is of a decentralized output feedback form since only local measurements are employed as the inputs to each stabilizer. This makes the proposed FBFN PSS easy to tune.
b) The proposed FBFN PSS can be easily implemented on a microcomputer since, unlike other adaptive techniques, it does not require real-time model identification.
c) The proposed FBFN PSS incorporates the linguistic and numerical information in a uniform fashion and combines the strengths of NN and FLS.
d) The simulation results reveal that the proposed FBFN PSS enhance system stability over a wide range of operating conditions.

2. PROBLEM FORMULATION

Power systems experience low frequency oscillations due to disturbances. The oscillations may sustain and grow to cause system separation if no adequate damping is available. To enhance system damping to these oscillations, the synchronous generator is equipped with a PSS. A widely used conventional PSS (CPSS) is considered in this study. It can be described as [2,19]

$$U = \frac{sT_w}{1+sT_w}\frac{K_c(1+sT_1)}{1+sT_2}\Delta\omega \quad (1)$$

Many researchers to compare the results of their work [11-16] have used the structure of the PSS considered in (1). The PSS parameters are determined by linearizing the system model around a nominal operating point to provide optimal performance at this point. Having been determined, these parameters remain fixed. Generally, power systems are highly nonlinear and the operating conditions can vary over a wide range. Consequently, the operating point will change and these fixed-gain PSSs no longer ensure the optimal performance.

The proposed approach is to use an FBFN to continuously re-tune the PSS parameters based on real-time measurements of loading conditions by training an FBFN over a wide range of operating conditions. When the FBFN has been trained, it will yield the desired PSS parameters for any monitored generator loading condition (P,Q,V) even if this condition has not been seen by the network before. The proposed FBFN PSS control scheme is shown in Fig. 1.

3. FUZZY BASIS FUNCTION NETWORK

Fig. 2 shows an FBFN with four layers. In what follows, we will denote the output of the ith node in the kth layer by O_i^k. The operation of the network with n inputs and m outputs can be described as follows:

Layer 1: For the ith input, every node in this layer computes the degree of membership of the input. Every node j has a function of

$$O_j^1 = \mu_{ij}(x_i)\ , \quad j=1,2,\ldots,M \quad (2)$$

where $\mu_{ij}(x_i)$ is a gaussian membership function associated with the ith input and jth rule. It can be expressed as

$$\mu_{ij}(x_i) = \exp\left(-\frac{1}{2}\left(\frac{x_i - c_{ij}}{\sigma_{ij}}\right)^2\right) \quad (3)$$

where c_{ij} and σ_{ij} are the mean and the variance of the jth function.

Layer 2: Every node in this layer multiplies the incoming signals and sends the product out, i.e.,

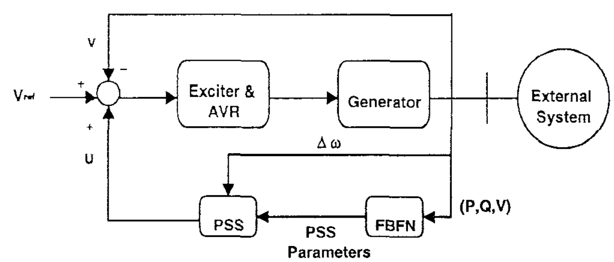


Fig. 1. The proposed FBFN PSS control scheme

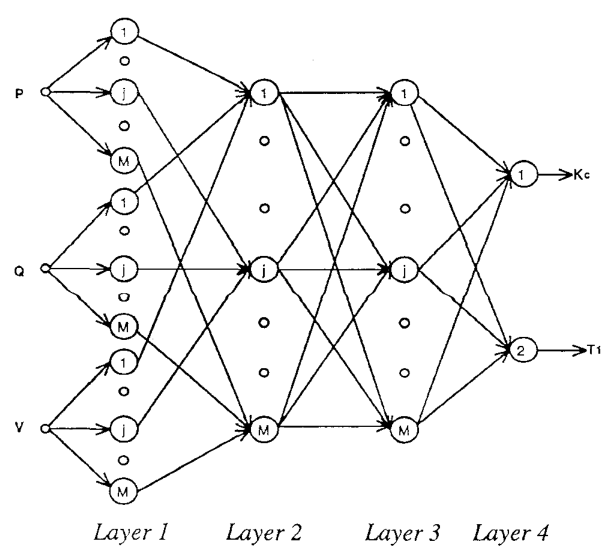


Fig. 2. A schematic diagram of the proposed FBFN

$$O_j^2 = \prod_{i=1}^{n} \mu_{ij}(x_i) \quad ,j=1,2,\ldots,M \tag{4}$$

Basically, each node output represents the firing strength of a fuzzy rule.

Layer 3: Every node in this layer calculates the ratio of the jth rule's firing strength to the sum of all rules' firing strengths, i.e.,

$$O_j^3 = \frac{\prod_{i=1}^{n} \mu_{ij}(x_i)}{\sum_{j=1}^{M} \prod_{i=1}^{n} \mu_{ij}(x_i)} \quad ,j=1,2,\ldots,M \tag{5}$$

In other words, nodes in this layer compute the normalized firing strength of each rule. In fact, the output of each node in this layer represents a fuzzy basis function, $p_j(\boldsymbol{x})$, that is,

$$p_j(\boldsymbol{x}) = O_j^3 \quad ,j=1,2,\ldots,M \tag{6}$$

where $\boldsymbol{x} = [x_1, \ldots, x_n]^T$ is the input vector.

Layer 4: In this layer each node represents an output and linearly combines the fuzzy basis functions as

$$O_k^4 = \sum_{j=1}^{M} p_j(x)\theta_{jk} \quad ,k=1,2,\ldots,m \tag{7}$$

where θ_{jk} is the weight between the jth node in layer 3 and the kth node in layer 4.

4. OLS LEARNING ALGORITHM

The objectives of the training in this paper are to construct an adequate and parsimonious model of the network, to select a set of appropriate means, c_{ij}s, of the membership functions, and to estimate the weights, θ_{jk}s, between layer 3 and layer 4. Although each membership function may have a different variance, σ_{ij}, a same variance is sufficient for universal approximation [20-21]. All the variances in the network can therefore be fixed to a value σ, and this can simplify the training strategy. The training input-output pairs are in the form of $\{\boldsymbol{x}(t),\boldsymbol{d}(t)\}$, $t=1,2,\ldots,N$ where N is the number of training patterns, $\boldsymbol{x}(t)=[x_1(t),\ldots,x_n(t)]^T$ is the input vector, and $\boldsymbol{d}(t)=[d_1(t),\ldots,d_m(t)]^T$ is the desired output vector. Initially, all the training data $\{\boldsymbol{x}(t)\}$ are considered as candidates for centers. Therefore, the initial number of centers M is equal to N. The network output in (7) can be considered as a special case of the linear regression model

$$d_k(t) = \sum_{j=1}^{M} p_j(t)\theta_{jk} + e_k(t) \quad ,k=1,2,\ldots,m \tag{8}$$

where $p_j(t)$ are known as regressors which are fixed functions of the input vector $\boldsymbol{x}(t)$, i.e.,

$$p_j(t) = p_j(\boldsymbol{x}(t)) \tag{9}$$

and $e_k(t)$ are the errors between the kth desired and network outputs which are assumed to be uncorrelated with the regressors. By defining

$$\boldsymbol{d}_i = [d_i(1)\ldots d_i(N)]^T \quad , i=1,2,\ldots,m \tag{10}$$

$$\boldsymbol{e}_i = [e_i(1)\ldots e_i(N)]^T \quad , i=1,2,\ldots,m \tag{11}$$

$$\boldsymbol{p}_j = [p_j(1)\ldots p_j(N)]^T \quad ,j=1,2,\ldots,M \tag{12}$$

then for $t=1,2,\ldots,N$, (8) can be expressed as

$$[\boldsymbol{d}_1 \ldots \boldsymbol{d}_m] = [\boldsymbol{p}_1 \ldots \boldsymbol{p}_M]\begin{bmatrix} \theta_{11} & \cdot & \cdot & \theta_{1m} \\ \cdot & & & \cdot \\ \cdot & & & \cdot \\ \theta_{M1} & \cdot & \cdot & \theta_{Mm} \end{bmatrix} + [\boldsymbol{e}_1 \ldots \boldsymbol{e}_m] \tag{13}$$

or in matrix form

$$D = P\Theta + E \tag{14}$$

The OLS algorithm involves the transformation of the set of $\boldsymbol{p}_j$ into a set of orthogonal basis vectors and uses only the significant ones to form the final FBFN. In general, the number of significant basis vectors in the final network, M_s, is much less than the initial number, M. The regression matrix P can be decomposed into

$$P = WA \tag{15}$$

where A is an $M_s \times M_s$ upper triangular matrix with unity diagonal elements, that is,

$$A = \begin{bmatrix} 1 & a_{12} & \cdot & a_{1M_s} \\ 0 & 1 & \cdot & \cdot \\ \cdot & \cdot & \cdot & a_{M_s-1M_s} \\ 0 & 0 & \cdot & 1 \end{bmatrix} \tag{16}$$

and W is an $M \times M_s$ matrix with orthogonal columns $\boldsymbol{w}_i$ such that

$$W^T W = H \tag{17}$$

where H is a diagonal matrix. Using (15), (14) can be rewritten as

$$D = WG + E \tag{18}$$

The OLS solution for (18) is given by

$$G = H^{-1} W^T D \tag{19}$$

or

$$g_{ij} = \boldsymbol{w}_i^T \boldsymbol{d}_j / (\boldsymbol{w}_i^T \boldsymbol{w}_i) \quad , i=1,2,\ldots,M_s,\ j=1,2,\ldots,m \tag{20}$$

The matrices G and Θ satisfy the triangular system

$$A\Theta = G \tag{21}$$

The classical Gram-Schmidt method can be used to derive (21) and thus to solve for Θ. The criterion for determining the significance of candidates is the contribution of a candidate to the trace of the desired output covariance matrix. Because the error matrix E is orthogonal to W, it can be shown that trace of the covariance of $d(t)$ is

$$trace(D^T D/N) = \sum_{j=1}^{M_s} \left(\sum_{i=1}^{m} g_{ji}^2\right) w_j^T w_j / N + trace(E^T E/N) \tag{22}$$

The error reduction ratio due to $\boldsymbol{w}_k$ can be defined as

$$[err]_k = \left(\sum_{i=1}^{m} g_{ki}^2\right) w_k^T w_k / trace(D^T D) \quad ,k=1,\ldots,M_s \tag{23}$$

A candidate regressor is selected at the kth step if it produces the largest value of $[err]_k$ from among the rest candidates.

The regressor selection procedure can be summarized as follows.

* At the first step, for $i=1,2,...,M$ compute

$$w_1^{(i)}=p_i$$

$$g_{1j}^{(i)}=(w_1^{(i)})^T d_j/((w_1^{(i)})^T w_1^{(i)}) \qquad , j=1,2,...,m$$

$$[err]_1^{(i)}=(\sum_{j=1}^{m} (g_{1j}^{(i)})^2)(w_1^{(i)})^T w_1^{(i)}/trace(D^T D)$$

Find

$$[err]_1^{(i1)}=max\{[err]_1^{(i)},\ i=1,2,...,M\}$$

and select

$$w_1=w_1^{(i1)}=p_{i1}$$

$$g_{1j}=g_{1j}^{(i1)} \qquad , j=1,2,...,m$$

* At the kth step where $k=2,3,...,M_s$, for $i=1,2,...,M$ and $i\neq i_1,...,i\neq i_{k-1}$, compute

$$a_{jk}^{(i)}=w_j^T p_i/(w_j^T w_j) \qquad , j=1,2,...,k-1$$

$$w_k^{(i)}=p_i-\sum_{j=1}^{k-1} a_{jk}^{(i)} w_j$$

$$g_{kj}^{(i)}=(w_k^{(i)})^T d_j/((w_k^{(i)})^T w_k^{(i)}) \qquad , j=1,2,...,m$$

$$[err]_k^{(i)}=(\sum_{j=1}^{m} (g_{kj}^{(i)})^2)(w_k^{(i)})^T w_k^{(i)}/trace(D^T D)$$

Find

$$[err]_k^{(ik)}=max\{[err]_k^{(i)},\ i=1,2,...,M, i\neq i_1,...,i\neq i_{k-1}\}$$

and select

$$w_k=w_k^{(ik)}$$

$$g_{kj}=g_{kj}^{(ik)} \qquad , j=1,2,...,m$$

* The procedure is terminated at M_sth step when

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

where $0<\rho<1$ is a chosen tolerance. This gives a subset model containing M_s significant regressors.

It is worth noting that Fig. 2 shows the initial network structure where the number of fuzzy rules, M, is equal to the number of training patterns, N, whereas the final structure is much simpler since $M_s << M$.

5. EXAMPLE 1: SINGLE MACHINE SYSTEM

In this study, a single machine infinite bus system is considered. The system model and parameters are given in the Appendix.

5.1 Network Training

The inputs to the FBFN are the real power (P), the reactive power (Q), and the terminal voltage (V) while the outputs are the desired PSS parameters, K_c and T_1. A set of 500 training patterns was presented to the network. The training patterns were uniformly distributed to cover all the input space in order to get better performance, that is, P ranging from 0.1 pu to 1.5 pu, power factor ranging from 0.9 leading to 0.8 lagging, and V ranging from 0.95 up to 1.05 pu. At each operating condition specified by P, Q, and V, the CPSS parameters, K_c and T_1, are tuned to yield the best performance at this operating point by prespecifying the damping coefficient [2]. Out of the training patterns presented to the network, a set of 41 patterns was selected by the OLS algorithm to represent the significant fuzzy basis functions, i.e., $M_s = 41$.

5.2 Simulation Results

A number of studies have been performed with the proposed FBFN PSS. For the sake of comparison, a CPSS is designed first to yield the best performance at the operating condition of P=1.0 pu with a power factor of 0.85 lagging. In order to mimic the operation of the real power system, the CPSS parameters are optimized at a nominal operating point and kept constant for all the simulation studies [11-16].

a) Operating Condition I: A 0.4 pu step in mechanical torque disturbance was applied while the generator is operating lightly at P=1.0 pu with power factor of 0.85 lagging. Results of the study are shown in Fig. 3. It is obvious that, the system with the proposed FBFN PSS returns to its previous operating point much faster. This is very helpful in the improvement of the disturbance tolerance ability of the system. In addition, the damping torque coefficient increases from 14.972 pu with CPSS to 19.233 pu with the proposed FBFN PSS while the synchronizing torque coefficient slightly changes from 0.6929 pu with CPSS to 0.6921 pu with the proposed FBFN PSS.

b) Operating Condition II: With the generator operating at a heavy loading condition specified by a power of 1.3 pu and a power factor of 0.85 lagging, a three phase fault was applied at the infinite bus for 0.05s. The simulation results are shown in Fig. 4. It is seen that the proposed FBFN PSS provides better damping characteristics than CPSS. It is worth mentioning that the proposed FBFN PSS increases the critical fault duration from 56.3 ms with CPSS to 63.2 ms.

c) Operating Condition III: It is also very important to test the PSS under the leading power factor operating condition. A 0.1 pu step increase in mechanical torque was applied at t=1.0 s while the generator is operating at a power of 0.7 pu with 0.9 power factor leading. The simulation results are shown in Fig. 5. It is clear that the system response with CPSS is highly oscillatory and eventually becomes unstable while the performance of the proposed FBFN PSS is much better and the oscillations are damped out.

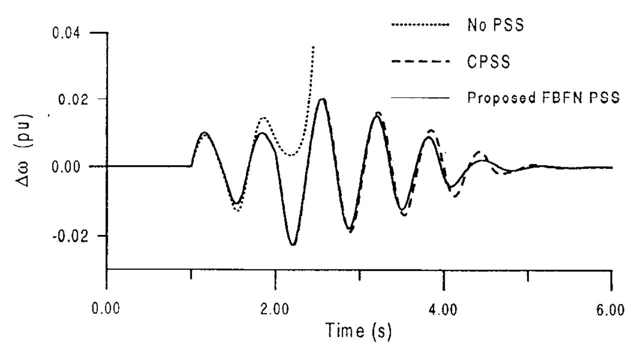


Fig. 3: Response to 0.4 pu step in torque for condition I

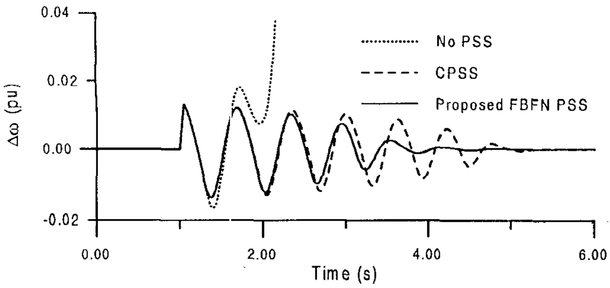


Fig. 4: Response to three phase fault for condition II

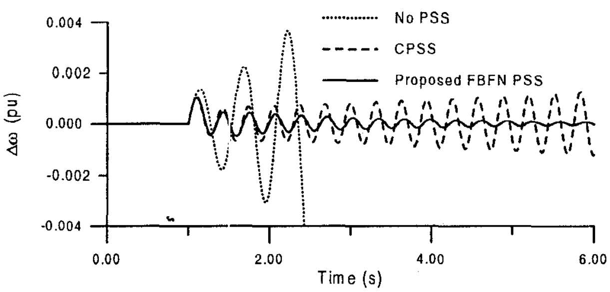


Fig. 5: Response to 0.1 pu step in torque for condition III

6. EXAMPLE 2: MULTIMACHINE SYSTEM

6.1 Test System and Optimum PSS Locations

To evaluate the effectiveness of the proposed FBFN PSS to improve the stability of multimachine power systems, the nine-bus three-machine power system shown in Fig. 6 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. 7. It is observed from Fig. 7 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, the participation factor method [22] and the sensitivity of PSS effect (SPE) method [23] were used. The results of both methods indicate that the generators G2 and G3 are the optimum locations for installing PSSs to damp out the local modes of oscillations. Therefore, the generators G2 and G3 are equipped with two of the proposed FBFN PSS. The performance of proposed stabilizers was compared to that of CPSSs installed on G2 and G3 with the transfer function [1,6,13]

$$G(s) = \frac{10s}{1+10s}\frac{(1+0.568s)^2}{(1+0.0227s)^2} \tag{24}$$

6.2 Network Training

Two FBFNs are proposed to re-tune the stabilizers installed on G2 and G3. Each FBFN was trained using a set of 500 input-output patterns. 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 [2]. Therefore, each training pattern consists of P_i, Q_i, and V_i to represent the network inputs and the values of K_{ci} and T_{1i} to represent the desired outputs. The subscript i denotes to the ith machine. It is worth noting that the inputs and the outputs of the proposed FBFN PSS are local parameters which facilitate its tuning and installation. At the end of the training, the number of the significant fuzzy basis functions selected for G2 and G3 are 33 and 20 respectively.

6.3 Simulation Results

To demonstrate the capability of the proposed FBFN PSS to enhance system damping over a wide range of operating conditions, three different loading conditions were considered as given in Table 1. The load admittances in each case are given in Table 2. With each loading condition, a three phase fault disturbance at bus 7 at the end of line 5-7 was applied. The fault duration was 6 cycles. The simulation results are shown as follows.

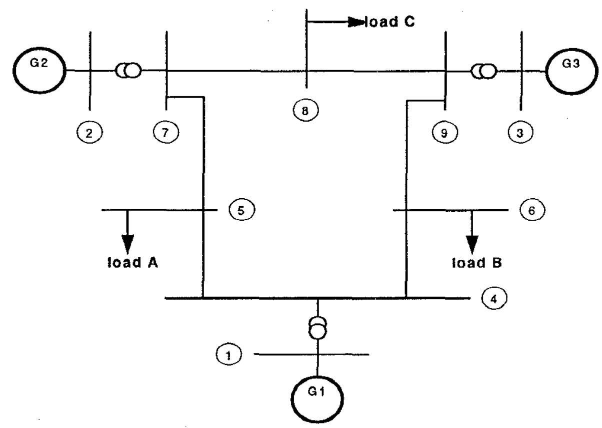


Fig. 6: Nine-bus three-machine power system

Table 1: Operating conditions in pu [1]

Loading Condition	G1 P	G1 Q	G2 P	G2 Q	G3 P	G3 Q
Nominal	0.71	0.28	1.63	0.07	0.85	-0.11
Heavy	2.21	1.09	1.92	0.57	1.28	0.36
Light	0.36	0.17	0.80	-0.11	0.45	-0.20

Table 2: Load admittances in pu

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

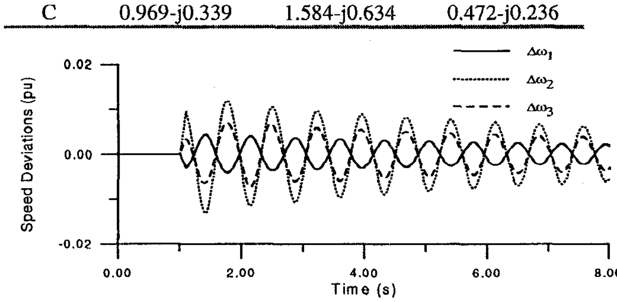


Fig. 7: Response of the system without PSSs

a) Nominal loading condition: The dynamic response of the system is shown in Fig. 8. It is obvious that with the proposed FBFN PSSs, the system returns to its previous operating point faster than the CPSSs. The stabilizing signals are shown in Fig. 9. It is worth pointing out that the proposed FBFN PSSs provide more efficient stabilizing signals compared to those of CPSS.

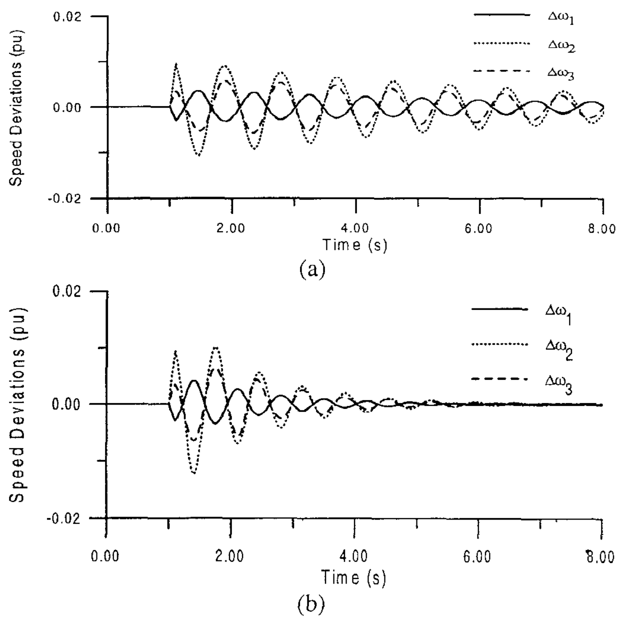


Fig. 8: Response to three phase fault with nominal loading condition a) with CPSS b) with FBFN PSS

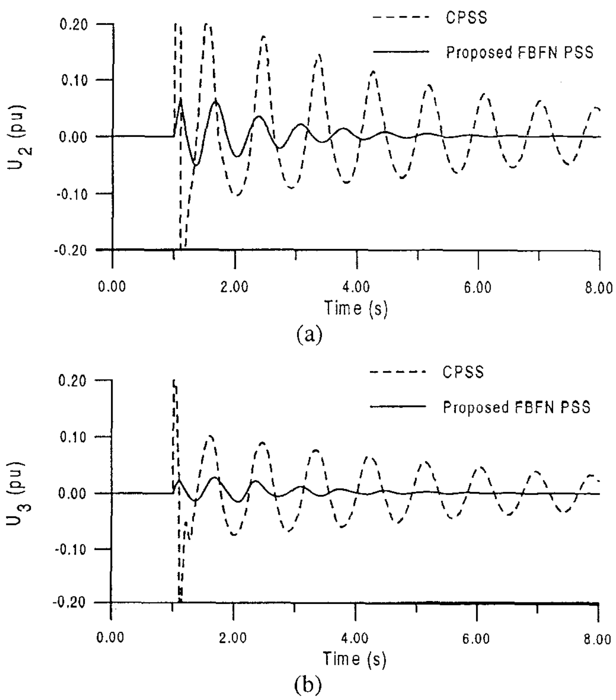


Fig. 9: Response of PSSs installed with nominal loading condition a) PSS on G2 b) PSS on G3

In addition, a more severe case is investigated to show the superiority of the proposed FBFN PSS to CPSS, namely, the fault is cleared by tripping the faulty line. The simulation results are shown in Fig. 10. It is quiet clear that while the system response with CPSSs is unstable, The proposed FBFN PSSs are still able to stabilize the system.

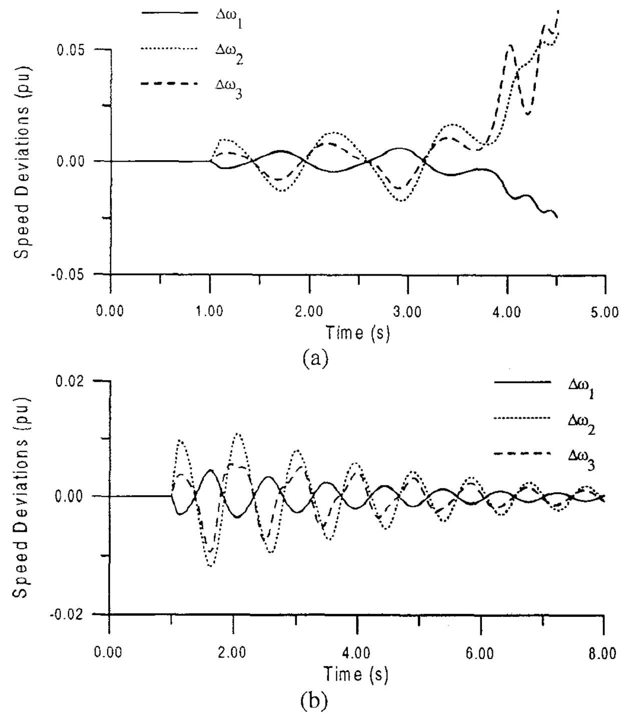


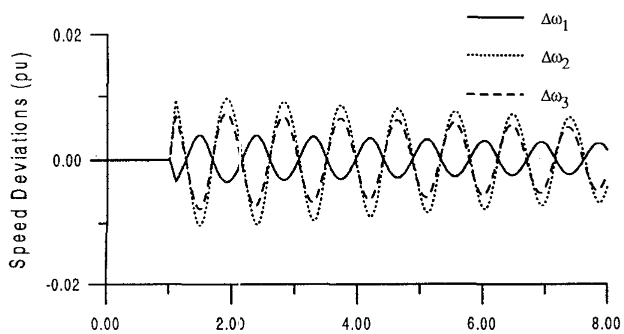
Fig. 10: Response to three phase fault with nominal loading condition and tripping the line 5-7
a) with CPSS b) with FBFN PSS

b) Heavy loading condition: The simulation results are shown in Fig. 11. The results here show the superiority of the proposed FBFN PSSs to the CPSSs. It can be concluded that the proposed FBFN PSS provides very good damping over a wide range of operating conditions.

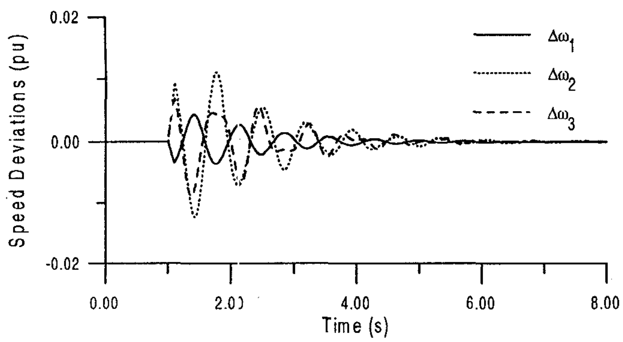
c) Light loading condition: The simulation results are shown in Fig. 12. It can be seen that the proposed FBFN PSSs produce much better results and the oscillations are damped out much quicker as compared to CPSSs.

7. CONCLUSIONS

In this study, an FBFN trained by OLS learning algorithm was employed to adapt the PSS parameters. The proposed FBFN PSS was trained based on real-time measurements of the generator loading conditions. The training has been carried out over a wide range of operating conditions using OLS learning algorithm. The effect of major disturbances has been studied. The most important advantage of the FBFN is that it provides a natural framework to combine both numerical information in the form of input-output pairs and linguistic information in the form of fuzzy IF-THEN rules in a uniform fashion. The simulation results of a single machine infinite bus system and a multimachine power system show that the system performance was greatly improved by combining fuzzy rules and input-output pairs. The effects of the proposed FBFN PSS on torque coefficients and critical clearing time were also demonstrated. On the other hand, the proposed FBFN PSS can be easily implemented. In addition, the decentralized nature of the proposed FBFN PSS makes it easy to install and tune.

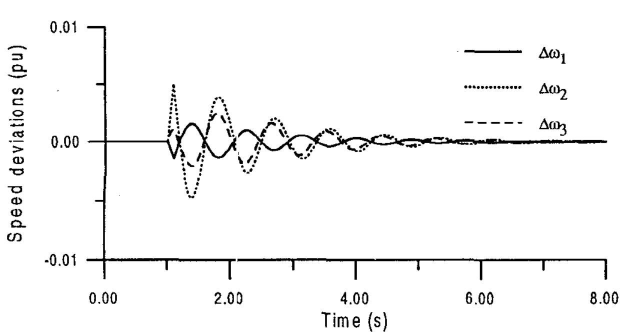


(a)

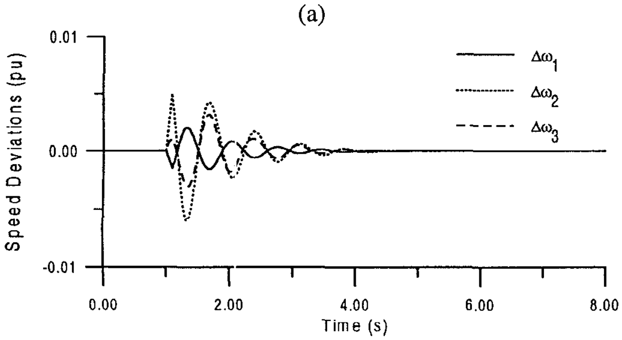


(b)

Fig. 11: Response to three phase fault with heavy loading condition a) with CPSS b) with FBFN PSS



(a)



(b)

Fig. 12: Response to three phase fault with light loading condition a) with CPSS b) with FBFN PSS

8. ACKNOWLEDGMENT

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10. APPENDIX

System Model

$$\delta = \omega_b(\omega - 1) \quad \text{(A.1)}$$

$$\omega = (T_m - T_e - D(\omega - 1)) / M \quad \text{(A.2)}$$

$$E_q' = (E_{fd} - (x_d - x_d')i_d - E_q') / T_{do}' \quad \text{(A.3)}$$

$$E_{fd} = (K_a(V_{ref} - V + U_c) - E_{fd}) / T_a \quad \text{(A.4)}$$

$$V_d = V_b \sin\delta + R_e i_d - X_e i_q \quad \text{(A.5)}$$

$$V_q = V_b \cos\delta + R_e i_q + X_e i_d \quad \text{(A.6)}$$

$$V = (V_d^2 + V_q^2)^{1/2} \quad \text{(A.7)}$$

$$T_e = E_q' i_q - (x_d' - x_q) i_d i_q \quad \text{(A.8)}$$

Parameters

M=4.74s, w_b=377rad/s, x_d=1.7, x_q=1.64, x_d'=0.245, R_e=0.02, X_e=0.4, D=0.0, T_{do}'=5.9, T_a=0.05, K_a=400, T_w=5.0, T_2=0.1

$-7.3pu \le E_{fd} \le 7.3pu$, $-0.12pu \le U_c \le 0.12pu$

All resistances and reactances are in per-unit and time constants are in seconds.

11. NOMENCLATURE

δ	torque angle
ω	speed and speed deviation respectively
M	inertia constant
ω_b	synchronous speed
E_q'	internal voltage behind x_d'
E_{fd}	equivalent excitation voltage
D	damping coefficient
i_d, i_q	currents in d and q axis circuits respectively
V, V_{ref}	terminal and reference voltages respectively
V_b	infinite bus voltage
R_e, X_e	line resistance and reactance respectively
x_d, x_q	synchronous reactances in d and q axes
x_d'	d-axis transient reactance
T_{do}'	time constant of excitation circuit
T_m, T_e	mechanical and electric torques respectively
K_a, T_a	regulator gain and time constant respectively
U	PSS control signal
K_c	CPSS gain
T_1, T_2	CPSS time constants
T_w	washout time constant

BIOGRAPHY

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