A Fuzzy Basis Function Network for Generator Excitation Control

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Abstract

A Fuzzy Basis Function Network (FBFN) based Power System Stabilizer (PSS) is presented in this paper. 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 generator loading conditions. The orthogonal least squares (OLS) learning algorithm is developed for designing an adequate and parsimonious FBFN model. Time domain simulations of a synchronous machine equipped with the proposed stabilizer subject to major disturbances are investigated. The performance of the proposed FBFN based PSS is compared with that of a conventional power system stabilizer (CPSS). The results show the robustness of the proposed FBFN PSS and its ability to enhance system damping over a wide range of operating conditions and system parameter variations.

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 [1-8]. Nowadays, the conventional power system stabilizer (CPSS) is widely used by power system utilities [3]. Other types of PSS such as proportional-integral (PI PSS) and proportional-integral-derivative (PID PSS) have also been proposed [4-5]. 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 as a result of load changes, line switchings, and unpredictable major disturbances such as three phase faults. 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.

Alternative controllers using adaptive control algorithms have been proposed to overcome such problems [5-6]. 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.

Recently, many intelligent system techniques have been developed and introduced such as neural networks [7] and fuzzy logic systems [8]. Unlike the most conventional methods, an explicit mathematical model of the system dynamics is not required to design a controller using neural networks and/or fuzzy logic systems. The recent direction is to integrate neural networks and fuzzy logic systems in order to combine their different strengths and overcome each other's weaknesses.

In this paper, we propose a fuzzy basis function network based power system stabilizer (FBFN PSS) to enhance power system dynamic stability. An FBFN which brings the learning capabilities of neural networks to fuzzy logic systems is trained to adapt the parameters of PSS based on real-time measurements of the machine loading conditions.

2. Problem Formulation

To enhance system damping, the generator is equipped with a PSS. A widely used CPSS is considered in this study. It can be described as [2]

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

The time constants T_w and T_2 are always given while K_c and T_1 remain to be determined. These parameters are

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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, power systems are highly nonlinear and the operating conditions can vary over a wide range. Consequently, the operating point will change and the fixed-gain PSS no longer ensure the optimal performance.

The proposed FBFN will re-tune the PSS parameters based on real-time measurements of loading conditions by training a FBFN over a wide range of operating points. The FBFN PSS control scheme is shown in Fig. 2. The system model and parameters are given in the Appendix.

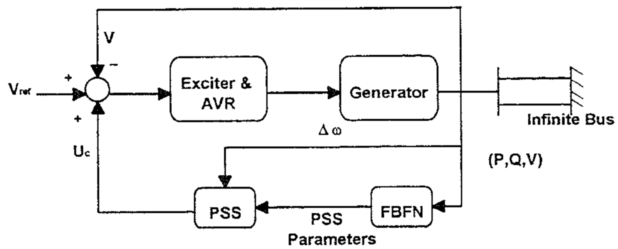

Figure 1. FBFN PSS control scheme

3. Fuzzy Basis Function Network

Like the feedforward networks, FBFN has four layers as shown in Fig. 2. 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. In the following we will denote the output of the ith node in the kth layer by O_i^k. The proposed network structure 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

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

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

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

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.,

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

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, $p_j(x)$, that is,

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

where $x=[x_1,\ldots,x_n]^T$ 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.

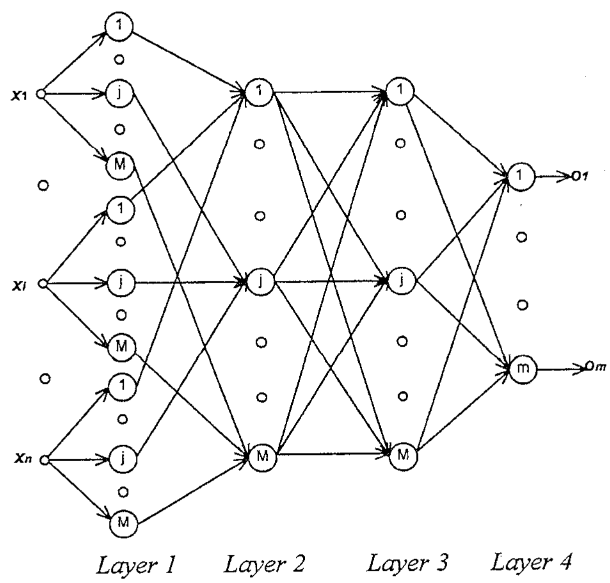

Figure 2. A schematic diagram of the proposed FBFN

4. OLS Learning Algorithm

The OLS algorithm is a linear optimization technique, therefore, it guarantees the convergence of the network parameters to global minima. 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 of adequate and parsimonious structure is self-organized. The objectives of the training in this paper are to select a set of appropriate means of the membership functions and to estimate the network weights. Although each membership function may have a different variance, a common variance is sufficient for universal approximation [9-10]. All the variances in the network can therefore be fixed to a value σ to simplify the training strategy. The training input-output pairs are in the form of $\{x(t), d(t)\}$, $t=1,2,...,N$ where N in the number of training patterns, $x(t)=[x_1(t),...,x_n(t)]^T$ is the input vector, and $d(t)=[d_1(t),...,d_m(t)]^T$ is the desired output vector. Initially, all the training data 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 $x(t)$, i. e.,

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

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

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

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

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

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

$$[d_1\ldots d_m]=[p_1\ldots p_M]\begin{bmatrix}\theta_{11} & . & . & \theta_{1m}\\ . & & & .\\ . & & & .\\ \theta_{M1} & . & . & \theta_{Mm}\end{bmatrix}+[e_1\ldots e_m] \tag{13}$$

or in matrix form

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

The OLS algorithm involves the transformation of the set of 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,

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

and W is an $M\times M_s$ matrix with orthogonal columns w_i such that

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

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

$$G=H^{1}W^TD \tag{19}$$

or

$$g_{ij}=w_i^Td_j/(w_i^Tw_i) \quad , i=1,2,\ldots,M_s, \quad j=1,2,\ldots m \tag{20}$$

The matrices G and Θ satisfy the triangular system

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

The classical Gram-Schmidt method [11] can be used to derive (21) and thus to solve for Θ.

5. The Proposed FBFN Based PSS

The OLS learning algorithm is used to train the proposed FBFN so that the trained FBFN will be able to re-tune the conventional PSS parameters based on real-time measurements of loading conditions. 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_l. Generally, the input-output training patterns must cover most of the working range in order to get better performance, that is, P ranging from 0.5 pu to 1.5 pu, Q ranging from 0.0 pu to 0.5 pu, and V ranging from 0.95 pu to 1.05 pu.

In this study, we introduce two types of the proposed FBFN PSS as follows.

5.1. FBFN PSS type 1

In this type, an FBFN was trained based on input-output pairs only. A set of 500 training patterns was presented to the network. The training patterns were uniformly distributed to cover all the input space. Out of these patterns 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. FBFN PSS type 2

This type is proposed to demonstrate that the proposed linguistic rules are very important and may contain information which is not contained in the input-output pairs. This type is a hybrid stabilizer that combines an FBFN and a traditional fuzzy logic controller. First, an FBFN was trained using a set of only 50 training patterns and a maximum of 20 significant fuzzy basis functions. Secondly, a traditional fuzzy logic controller was designed based on only proposed nine rules that relate the input fuzzy variables P and Q with the output fuzzy variables K_c and T_l. Each of these variables is interpreted into three linguistic fuzzy subsets. These subsets are High (H), Medium (M), and Low (L). Each subset is associated with a gaussian membership function in the form of (3). The means and variances of these functions are given in Table 1. The input and output gains are used to properly scale the fuzzy. Their values are also given in Table 1.

The proposed fuzzy control rules can be stated as follows:

R_1: **IF** P is H and Q is H **THEN** K_c is M and T_l is M
R_2: **IF** P is H and Q is M **THEN** K_c is L and T_l is H
R_3: **IF** P is H and Q is L **THEN** K_c is L and T_l is H
R_4: **IF** P is M and Q is H **THEN** K_c is H and T_l is L
R_5: **IF** P is M and Q is M **THEN** K_c is M and T_l is M
R_6: **IF** P is M and Q is L **THEN** K_c is L and T_l is H
R_7: **IF** P is L and Q is H **THEN** K_c is H and T_l is L
R_8: **IF** P is L and Q is M **THEN** K_c is H and T_l is L
R_9: **IF** P is L and Q is L **THEN** K_c is M and T_l is M

It is worth pointing out that these rules are determined by studying the performance of CPSSs. The membership function parameters and input and output gains are chosen by trial-and-error approach.

The output of this type is the average of the network and the fuzzy logic controller outputs.

Table 1. Membership function parameters

		P	Q	K_c	T_l
Mean	H	0.65	0.40	0.75	0.40
	M	0.50	0.25	0.50	0.30
	L	0.35	0.10	0.25	0.20
Variance		0.25	0.25	.4	0.2
Gain		0.5	1.0	0.083	1.0

6. Studies and Simulations

In order to investigate the performance of the proposed FBFN PSS, a number of studies has been performed and the results of time domain simulations of the two proposed types are compared with that of the CPSS [2]. All time simulations are carried out using the nonlinear model of the system.

6.1. Fault test

To verify the behavior of the proposed FBFN PSS under transient conditions, a three phase fault was applied at the generator terminals for 0.11s while the generator is operating at P=1.0 pu with 0.85 power factor lagging and terminal voltage of 1.0 pu. Results of the study are shown in Fig. 3. It is obvious that for both types of the proposed FBFN PSS, the system returns to its previous operating point faster than the conventional controller.

6.2. Input torque change test

With the same operating conditions in subsection 6.1, the input mechanical torque was increased by 50% from t=1.0s to t=4.0s. The simulation results of this case are shown in Fig. 4. The results here demonstrate the superiority of the proposed FBFN PSS to the CPSS, that is, only both types of the proposed FBFN PSS return to the previous operating point.

6.3 Leading power factor operation test

With the leading power factor, the stability margin is reduced and it becomes very important to test the PSS under this difficult situation. A 0.1 pu step in mechanical torque was applied at t=1.0 s while the generator was 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 performance of the proposed FBFN PSS is much better than that of the CPSS and the oscillations are damped out much quicker.

6.4 Parameter variation test

To verify the robustness of the proposed FBFN PSS, the system inertia has been reduced in steps until instability has been reached. In each step, a 50% pulse in the input torque has been applied from t=1.0s to t=2.0s with the same operating conditions in subsection 6.1. The results are shown in Figs. 6 and 7. It was found that the system inertia can be reduced up to 30% for FBFN PSS type 1 and 35% for type 2. It is worth mentioning that increasing the system inertia increases the system damping. The simulation results verify the robustness of the proposed FBFN PSS and its ability to work over a wide range of operating conditions and system parameter variations.

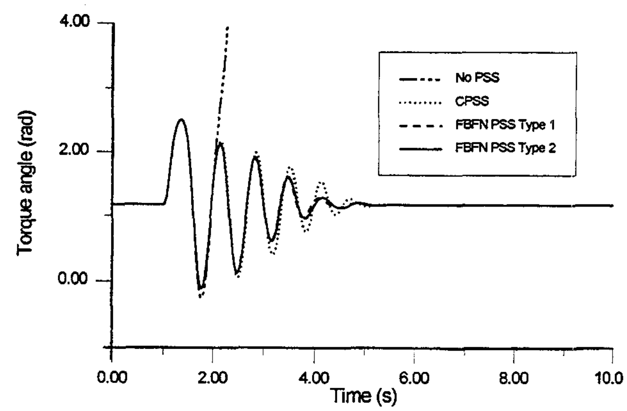

Figure 3. Response to the three phase fault test

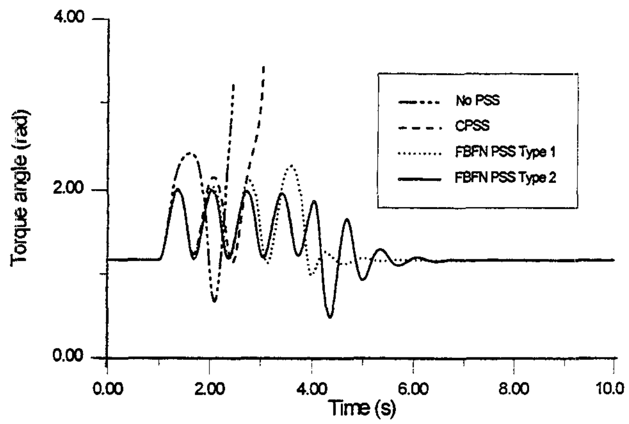

Figure 4. Response to the input torque change test

Some comments on these simulation studies are now in order:

a) The proposed FBFN based PSS in type 1 has good performance under major disturbances and robust for system parameter changes; this suggests that given a sufficient number of input-output pairs, the OLS learning algorithm can determine a successful FBFN based PSS.
b) Type 2 of the proposed FBFN based PSS showed better results than type 1. This demonstrate that the control performance was greatly improved by incorporating the linguistic fuzzy rules into the controller. Moreover this type is more robust than type 1.

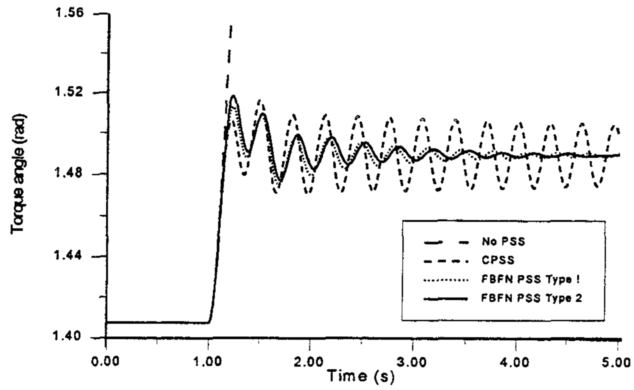

Figure 5. Response to the leading power factor operation test

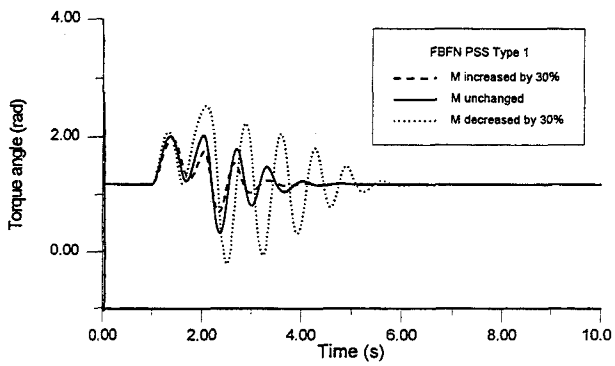

Figure 6. Type 1 response to parameter variation test

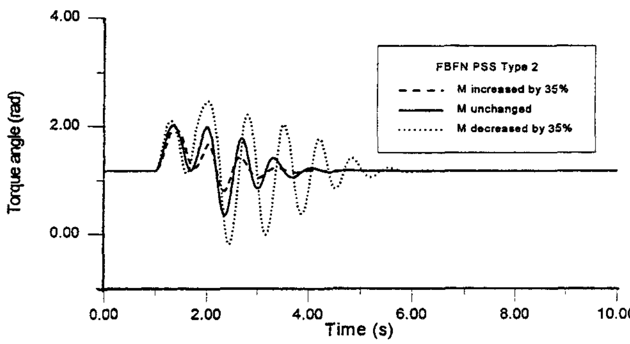

Figure 7. Type 2 response to parameter variation test

7. Conclusions

In this study, a fuzzy basis function network trained by OLS learning algorithm was employed to adapt the PSS parameters to improve power system dynamic stability. 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. Simulation results show the robustness of the proposed FBFN PSS and its ability to provide good damping characteristics during transient conditions. The most important advantage of the proposed FBFN based PSS 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.

8. Acknowledgment

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10. Appendix

<u>*System Model and parameters:*</u>

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

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

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

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

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

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

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

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

M=4.74 s, ω_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, -7.3 pu $\le E_{fd} \le$ 7.3 pu, -0.12 pu $\le U_c \le$ 0.12 pu.

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

11. Nomenclature

ρ	first derivative d/dt
δ	torque angle
ω, $\Delta\omega$	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	stator 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_c	PSS control signal
K_c	conventional controller gain
T_1, T_2	conventional controller time constants
T_w	washout time constant