

NEURO-FUZZY BASED POWER SYSTEM STABILIZERS FOR DAMPING OSCILLATIONS IN MULTI-MACHINE POWER SYSTEMS

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Abstract: A very important matter of discussion in power system operation is the oscillation damping problem. Power System Stabilizers (PSSs) are used to generate supplementary control signals for the excitation system in order to damp the low frequency power system oscillations. To overcome the drawbacks of conventional PSS (CPSS), numerous techniques have been proposed in the literature. This article describes the design procedure for a fuzzy logic based PSS (FLPSS) and a self-learning adaptive network based fuzzy inference system (ANFIS) type PSS (ANFPSS) which provides supplementary signals thus extending the power stability limits. Speed deviation of a synchronous machine and its derivative are chosen as the input signals to the fuzzy logic controller. The proposed technique has the features of a simple structure, adaptivity and fast response and is evaluated on a multi-machine power system under different operating conditions to demonstrate its effectiveness and robustness. The effect of detuning of one of the generator parameters on the dynamic performance of the system is also analyzed.

Key words: ANFPSS, CPSS, FLPSS, multi-machine power system, power system oscillations, PSS.

1. Introduction

Power systems are usually large non-linear systems, which are often subjected to low frequency electromechanical oscillations. Power System Stabilizers (PSSs) are often used as an effective and economic means for damping the generators' electromechanical oscillations [1] and enhance the overall stability of power systems. Power system stabilizers have been applied for several decades in utilities and they can extend power transfer stability limits by adding modulation signal through excitation control system. They provide good damping; thereby contribute in stability enhancement of the power systems.

Designing PSS is an important issue from the view point of power system stability. Conventional PSS (referred to as CPSS) controllers use transfer functions designed for linear models representing the generators at a certain operating point [2, 3]. However, as they work around a particular operating point of the system for which these transfer functions are obtained, they are not able to provide satisfactory results over wider ranges of operating conditions. In other words,

according to the fact that the gains of the mentioned controller are determined only for a particular operating condition, they may not yet be valid for a wider range around or for other new conditions [4].

This problem is overcome by using Fuzzy logic based technique for designing of PSSs. Fuzzy logic systems allow us to design a controller using linguistic rules without knowing the exact mathematical model of the plant [5, 6]. The application of Fuzzy logic based PSSs (FLPSSs) has been motivated because of some reasons such as improved robustness over that obtained using conventional linear control algorithm, simplified control design for difficult-to-be modeled systems and simplified implementation [4, 7]. Fuzzy logic controllers (FLCs) are very useful in the case a good mathematical model for the plant is not available, however, experienced human operators are available for providing qualitative rules to control the system. In some papers to improve the performance of FLPSS, a hybrid FLPSS has been presented. In [8, 9], a FLC is used with two CPSS controllers, also Hybrid PSSs using fuzzy logic and neural networks have been reported..

However, there is no systematic procedure for designing FLCs. The most common approach is to define Membership Functions (MFs) and IF-THEN rules subjectively by studying an operating system or an existing controller. So, an adaptive network based approach has been presented in [10] to choose the parameters of fuzzy system using a training process. In this technique, an adaptive network is used to find the best parameter of fuzzy system.

In this paper, an adaptive neuro fuzzy inference system based PSS (ANFPSS) is developed, which uses the speed of a synchronous machine and its derivative as the inputs. The ANFPSS uses a first-order Sugeno-type fuzzy logic controller whose membership functions and consequences are tuned by backpropagation algorithm alone, or in combination with a least squares type of method.. Fuzzy rules and MFs of the controller can be tuned automatically by learning algorithm.

The proposed technique is illustrated on a 3-machine, 9-bus power system. MATLAB/SIMULINK and fuzzy logic toolbox have been used for system

simulation. The results demonstrate that the proposed self-learning ANFPSS provides a very good damping performance over a wide range of operating conditions and improves the stability margin of the system as well.

This paper is organized as follows. The single line diagram of a 3-machine 9-bus power system model is given in Section 2. The Conventional Power System Stabilizer is discussed in Section 3. FLPSS and ANFPSS controllers are described in Section 4. Simulation results and discussions are illustrated in Section 5. Some conclusions are given in Section 6.

2. Power System Model

The single line diagram of a 3-machine 9-bus power system model shown in Fig.1, is used for the analysis and study of the inter-area oscillation control problem [1]. In Fig.1, the bus 1, to which the generator G1 is connected, is considered as reference bus. The base MVA is 100 and the system frequency is 50 Hz. This system exhibits inter-area mode of electromechanical oscillations whose frequency varies from 0.35 to 0.75 Hz depending on the operating conditions. Two sets of conventional PSS controllers are used; one for the generator G2 and another one for the generator G3. The system data are given in Appendix.

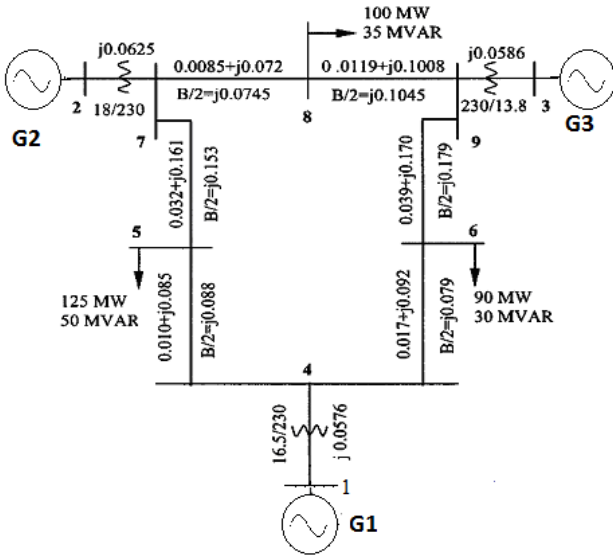


Fig.1 Single line diagram of a 3-machine 9-bus power system; All impedances are in per unit on 100 MVA base

3. Conventional Power System Stabilizer

The PSS is used to provide damping to electromechanical oscillations. The PSS counters the oscillations by forcing the change in excitation level appropriately. Without PSS, the reduced damping in power system is due to phase lags resulted by the field time constants and the phase lags in the normal voltage regulation loop. The PSS uses phase compensation by adjusting the timing of correction signal opposing the

rotor oscillations. A PSS can therefore increase the generator's damping coefficient. The conventional PSS (CPSS) shown in Fig.2 has three components; the phase compensation block, the signal washout block and gain block. The phase compensation block provides the appropriate phase lead characteristics to compensate for the phase lag between exciter input and generator electrical torque. The signal washout block serves as high pass filter, with time constant T_w high enough to allow signals associated with oscillations in ω to pass unchanged. The stabilizer gain K_{stab} determines the amount of damping introduced by PSS. For the conventional PSS, the following transfer functions are considered:

$$\Delta v_2 = \frac{pT_w}{(1+pT_w)} (K_{stab})(\Delta\omega) \quad (1)$$

$$\Delta v_s = \frac{1+pT_1}{(1+pT_2)} (\Delta v_2) \quad (2)$$

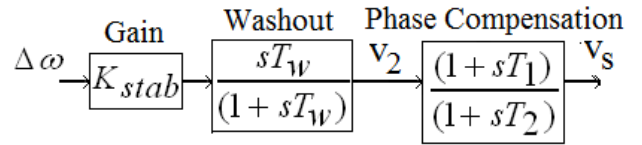


Fig.2 Conventional lead-lag PSS

4. Fuzzy Logic based Power System Stabilizer

The initial step in designing the Fuzzy logic based power system stabilizer (FLPSS) is the determination of the state variables which represent the performance of the system. The input signals to the FLPSS are to be chosen from these variables. The input values are normalized and converted into fuzzy variables. Rules are executed to produce a consequent fuzzy region for each variable. The expected value for each variable is found by defuzzifying the fuzzy regions. The speed deviation ($\Delta\omega$) of the synchronous machine and its

derivative ($\dot{\Delta\omega}$) are chosen as inputs to the fuzzy logic controller and the output is the stabilizing signal U_{PSS} .

The proposed controller uses seven linguistic variables such as: Positive Big (PB), Positive Medium (PM), Positive Small (PS), Zero (ZE), Negative Small (NS), Negative Medium (NM) and Negative Big (NB). The membership functions are chosen to be Gaussian as shown in Fig.3. The defuzzification of the variables into crisp outputs is tested by using the centroid method.

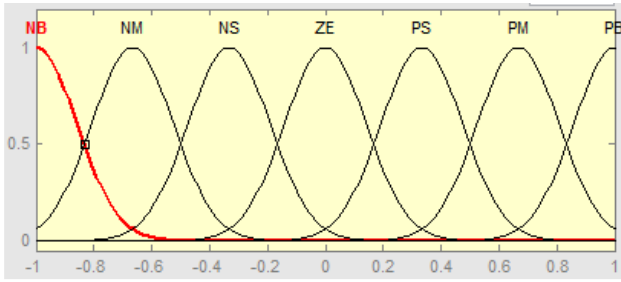


Fig.3 Gaussian membership functions

4.1 Training the PSS Controller

Physical domains can be calculated from the generated data for simulation by the conventional PSS controllers attached initially at both generators G2 and G3. For the rule-base, the relationship between the fuzzy controller inputs and its output can be extracted from the following algorithm:

1. Simulate the conventional PSS controller.

2. Save each sample value of $(\Delta\omega, \Delta\dot{\omega}, \text{ and } U_{PSS})$.

3. At each sample time t :

$\Delta\omega$ belongs to the class with maximum membership among (NB,NM,NS,ZE,PS,PM,PB), so at sample time t , $\Delta\omega$ is ω_1 .

$\Delta\dot{\omega}$ belongs to the class with maximum membership among (NB,NM,NS,ZE,PS,PM,PB),

so at sample time t , $\Delta\dot{\omega}$ is $d\omega_1$.

This will form the contents of the rule-antecedent (If-part of a rule).

U_{PSS} belongs to the class with maximum membership among (NB,NM,NS,ZE,PS,PM,PB),

so at sample time t , U_{PSS} is u_1

This will form the contents of the rule-consequent (then-part of the rule).

Thus the total rule can be formed as:

“If $\Delta\omega$ is ω_1 and $\Delta\dot{\omega}$ is $d\omega_1$, then U_{PSS} is u_1 ”.

After generating the rules, the tuning procedures are carried out manually by observation of the control surface relating to the controller. A sample of these rules is shown in Table 1.

Table 1 Rules extracted from the conventional PSS controller

Speed Dev.	Acceleration						
	NB	NM	NS	ZE	PS	PM	PB
NB	NB	NB	NB	NB	NM	NS	ZE
NM	NB	NB	NM	NM	NS	ZE	PS
NS	NB	NM	NS	NS	ZE	PS	PM
ZE	NM	NM	NS	ZE	ZE	PM	PM
PS	NM	NS	ZE	ZE	PS	PM	PB
PM	NS	ZE	PS	PM	PM	PM	PB
PB	ZE	ZE	PM	PS	PB	PB	PB

4.2 ANFIS Controller for PSS

The proposed ANFIS controller also uses seven linguistic variables such as: Positive Big (PB), Positive Medium (PM), Positive Small (PS), Zero (ZE), Negative Small (NS), Negative Medium (NM) and Negative Big (NB). The membership functions are chosen to be Gaussian as shown in Fig.3. The defuzzification of the variables into crisp outputs is tested by using the weighted average method.

In MATLAB, the ANFIS editor graphics user interface is available in Fuzzy Logic Toolbox [11]. Using a given input/output data set, the toolbox constructs a fuzzy inference system (FIS) whose membership function parameters are adjusted using either a backpropagation algorithm alone, or in combination with a least squares type of method. This allows the fuzzy systems to learn from the data they are modeling. For the backpropagation-based neuro-fuzzy approach, it includes the Sugeno's model with the following format:

If the speed deviation error is $\Delta\omega$ and the acceleration is $\Delta\dot{\omega}$, then

$$U_{PSS} = p_i \Delta\omega + q_j \Delta\dot{\omega} + r_i \quad (3)$$

where, $i = \{1, n\}$ refers to the rule numbers,

$j = \{1, n\}$ refers to the Speed deviation error terms in the fuzzy set,

n, m refers to the number of terms generated,

$k = \{1, m\}$ refers to the acceleration terms in the fuzzy set, $\{p_i, q_j, r_i\}$ are the i^{th} consequent (PSS output) parameters.

The input signals to the ANFIS controller for the

PSS are $\Delta\omega$ and $\Delta\dot{\omega}$. In the ANFIS editor, the fuzzy inference can be generated using two partitioning methods; grid partitioning and subtractive clustering. Here, grid partitioning method is used. For grid partitioning, it uses the Fuzzy C-means (FCM) clustering data clustering technique. FCM is a data clustering algorithm in which each data point belongs to a cluster with a degree specified by a membership grade.

After generating the fuzzy inference, the generated information describing the model's structure and parameters of both the input and output variables are used in the ANFIS training phase. This information will be fine-tuned by applying the hybrid learning or the backpropagation schemes. The generated model is of a first-order Sugeno's form and the generated rules are in the form described by equation.(3). After this stage, the membership functions will be adjusted to optimize the controller action as shown in Fig.4. The scheme of proposed ANFIS based PSS (ANFPSS) is shown in Fig.5.

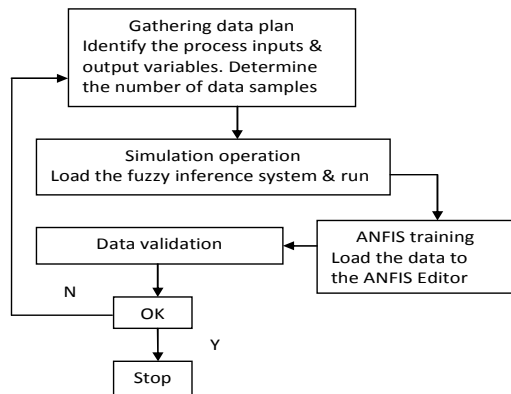


Fig.4 ANFIS design procedure for PSS

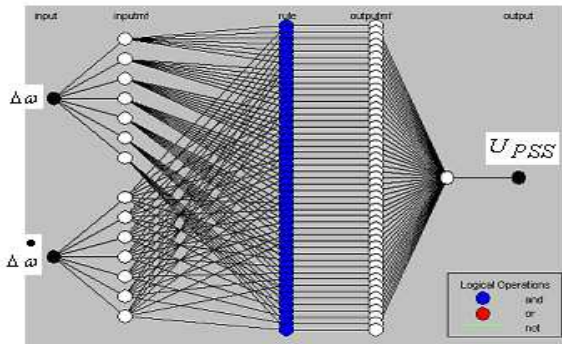


Fig.5 Proposed ANFPSS structure for multi-machine power system

5. Simulation Results and Discussion

In order to test the robustness of the proposed ANFIS based PSS (ANFPSS) controllers to improve the stability of multi-machine power systems, the 3-machine 9-bus power system model shown in Fig.1 is considered. Each machine can be represented by a fourth order two-axis nonlinear model. The simulation block diagram for low frequency oscillation studies using PSS controllers in the system under consideration is shown in Fig.6. Details of the system data [12, 13] are given in Appendix. To evaluate the performance of the proposed ANFPSS scheme, the system response is compared with the cases: (i). with no PSS controllers, (ii). with conventional PSS (CPSS) controllers. The comparison is carried out under different kinds of operating points ((i). Total Real power of load $P=0.7$ p.u, Total Reactive power of load $Q=0.8$ p.u, Terminal voltage $V_t=1.05$ p.u and (ii). Total Real power of load $P=0.5$ p.u, Total Reactive power of load $Q=0.6$ p.u, Terminal voltage $V_t=1.05$ p.u) and power disturbances. The power disturbance is applied in the form of a step signal as shown in Fig.6. Without PSS, the system response curves due to a power disturbance of 0.006 p.u and disturbance clearing time of 50 seconds are

shown in Figs.7 - 14. From these Figures, it is observed 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. The generators G2 (Area 1) and G3 (Area 2) are equipped with two of the proposed ANFPSS controllers.

5.1 Case 1: $P = 0.7$ p.u, $Q = 0.8$ p.u, $V_t = 1.05$ p.u

A step power disturbance of 0.006 p.u was applied and it was cleared in 50 seconds. From the Figs.7 - 10, it can be seen that CPSS provides better damping of the speed deviation and power angle oscillations than when there is no CPSS in the system, however ANFPSS provides the best damping of oscillations in the form of reduced amplitude and settling times.

5.2 Case 2: $P = 0.5$ p.u, $Q = 0.6$ p.u, $V_t = 1.05$ p.u

A step power disturbance of 0.006 p.u was applied and it was cleared in 50 seconds. From the Figs.11 - 14, it can be seen that CPSS provides better damping of the speed deviation and power angle oscillations than when there is no CPSS in the system, however ANFPSS provides the best damping. The ANFPSS scheme shows improved damping performance even though the operating point is different. The adaptive fuzzy PSS controller is able to track the system operating conditions, and thus, as seen from the results shown in Figs.7 - 14, it is able to adjust and provide a uniformly good performance over a wide range of operating conditions and disturbances. For Case 1 and Case 2 considered above, the per unit inertia constant (M) of generator G2 is taken as 12.8 and that of generator G3 is taken as 6.02.

The control surface for the proposed ANFPSS scheme is shown in Fig.15. There is a small flat region in the origin to guarantee equilibrium. The small flat region in the origin is followed by sharp slopes in all direction to reflect non-linearity and to provide a quick response from the controller to even small deviations in the speed or acceleration of the rotor.

5.3 Effects of Detuning of one of the Generator Parameters

In order to analyze the effect of detuning of one of the generator parameters on dynamic performance of the system, the per unit inertia constant (M) of generator G2 is taken as 7.0 and that of generator G3 is taken as 4.02. The Case 1 operating point shown in section 5.1 is considered for the analysis and the corresponding graphs are shown in Figs.16 – 19. From the Figures, it is clear that due to the reduction of inertia constants of G2 and G3, the amplitude and settling times of oscillations are slightly increased for Area 1, whereas changes in amplitude of oscillations and settling times are very less for Area 2 as compared to Area 1.

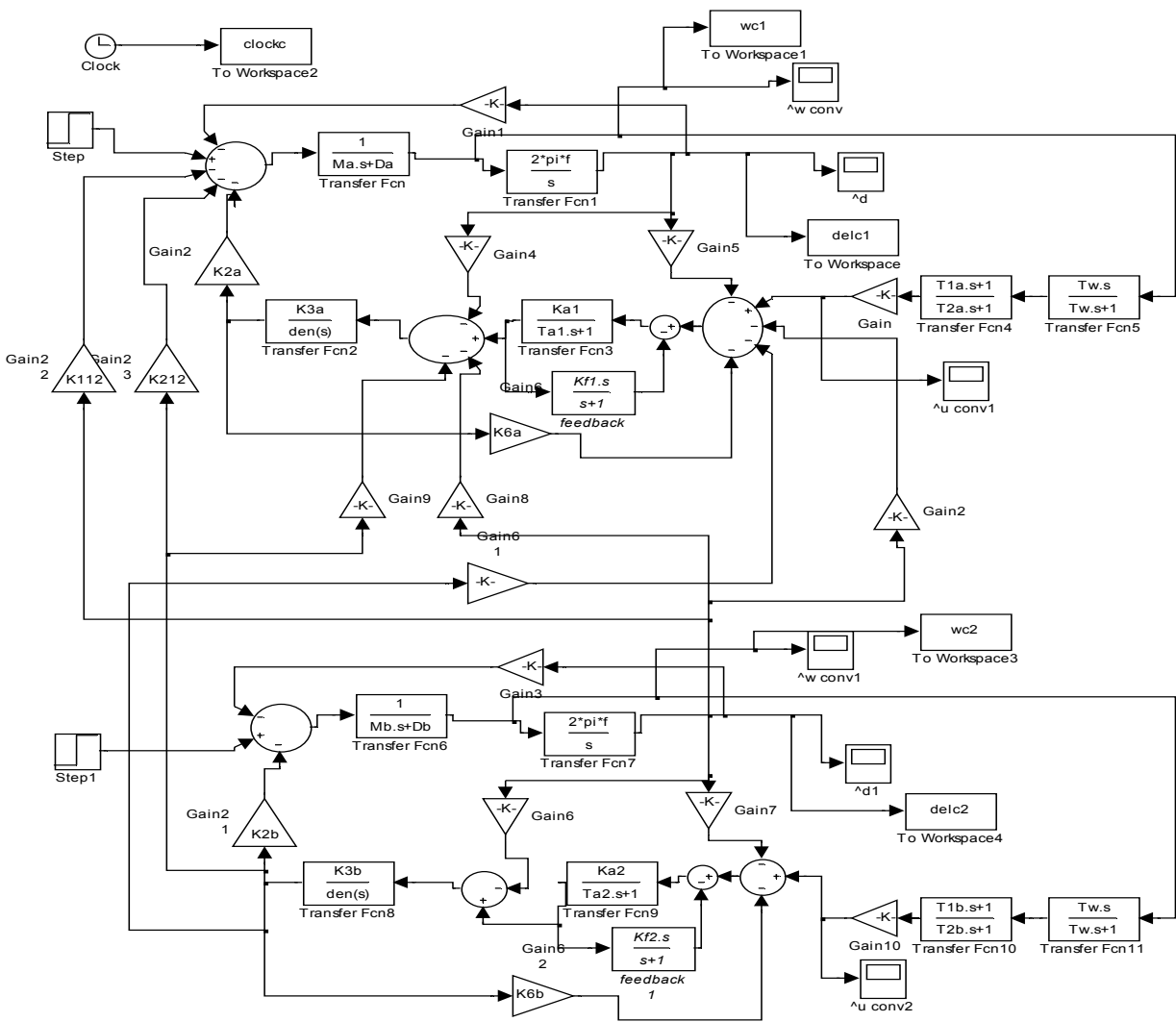


Fig.6 Simulation block diagram for low frequency oscillation studies using PSS controllers

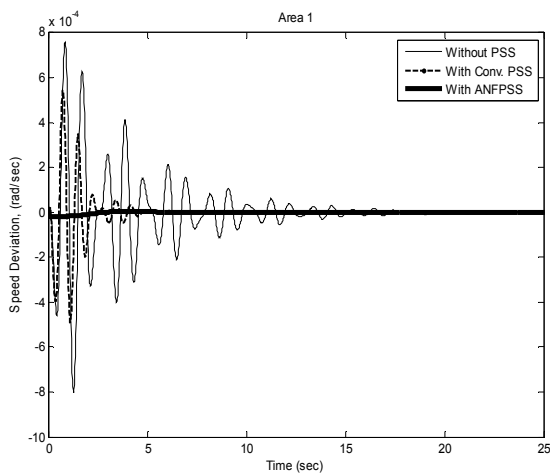


Fig.7 Dynamic response for Speed deviation for Power disturbance of 0.006 p.u with ANFPSS for Area 1 (P = 0.7 p.u, Q = 0.8 p.u)

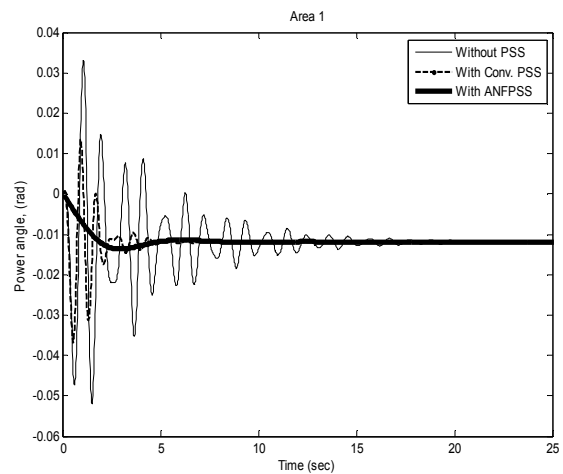


Fig.8 Dynamic response for Power angle for Power disturbance of 0.006 p.u with ANFPSS for Area 1 (P = 0.7 p.u, Q = 0.8 p.u)

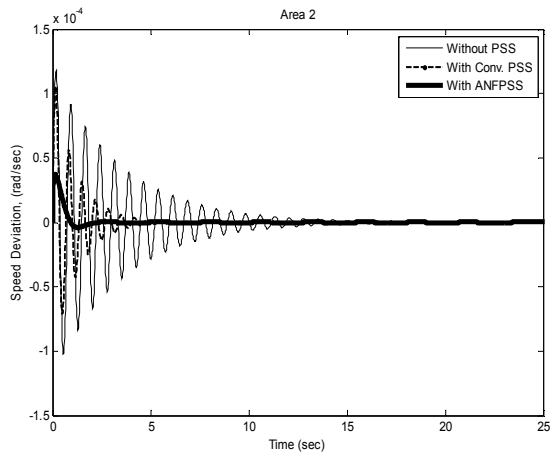


Fig.9 Dynamic response for Speed deviation for Power disturbance of 0.006 p.u. with ANFPSS for Area 2 ($P = 0.7$ p.u, $Q = 0.8$ p.u)

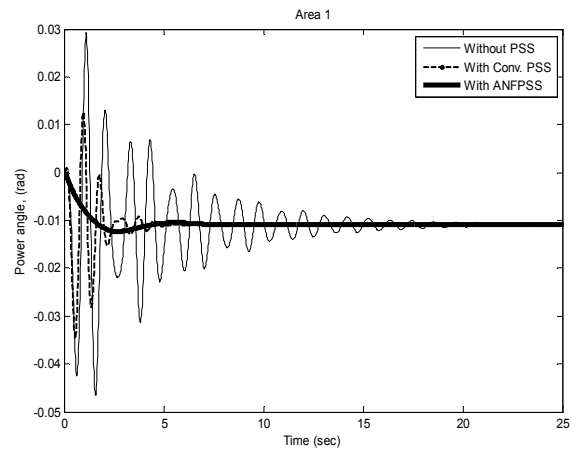


Fig.12 Dynamic response for Power angle for Power disturbance of 0.006 p.u. with ANFPSS for Area 1 ($P = 0.5$ p.u, $Q = 0.6$ p.u)

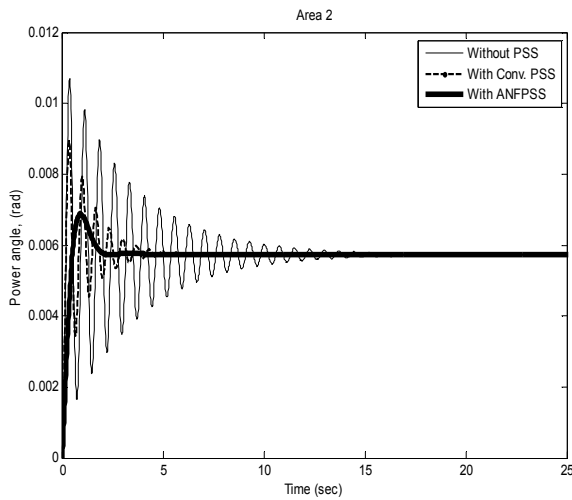


Fig.10 Dynamic response for Power angle for Power disturbance of 0.006 p.u. with ANFPSS for Area 2 ($P = 0.7$ p.u, $Q = 0.8$ p.u)

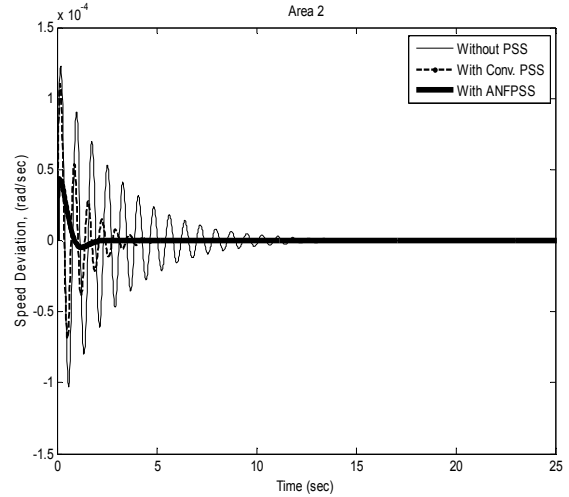


Fig.13 Dynamic response for Speed deviation for Power disturbance of 0.006 p.u. with ANFPSS for Area 2 ($P = 0.5$ p.u, $Q = 0.6$ p.u)

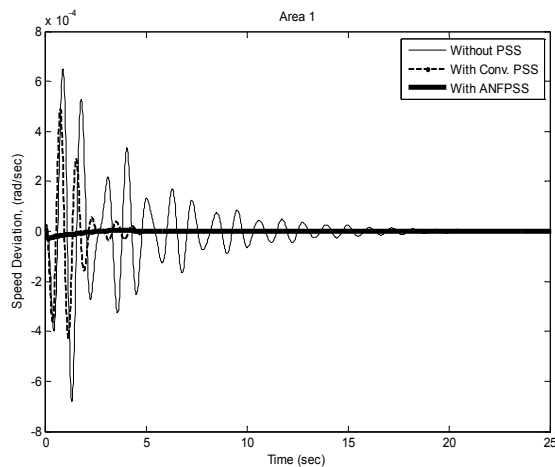


Fig.11 Dynamic response for Speed deviation for Power disturbance of 0.006 p.u. with ANFPSS for Area 1 ($P = 0.5$ p.u, $Q = 0.6$ p.u)

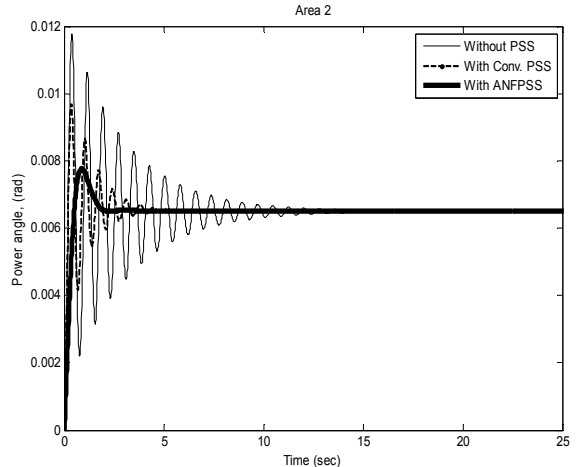


Fig.14 Dynamic response for Power angle for Power disturbance of 0.006 p.u. with ANFPSS for Area 2 ($P = 0.5$ p.u, $Q = 0.6$ p.u)

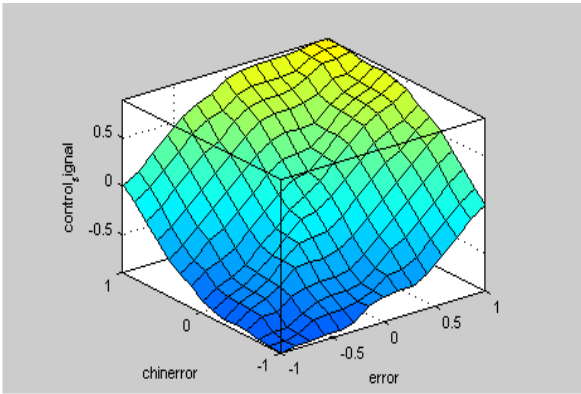


Fig.15 Surface plot of proposed ANFPSS scheme

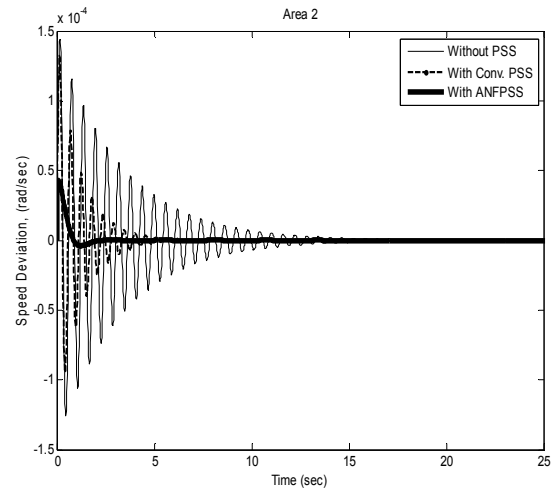


Fig.18 Effect of change in inertia constant of generators on Speed deviation for Area 2

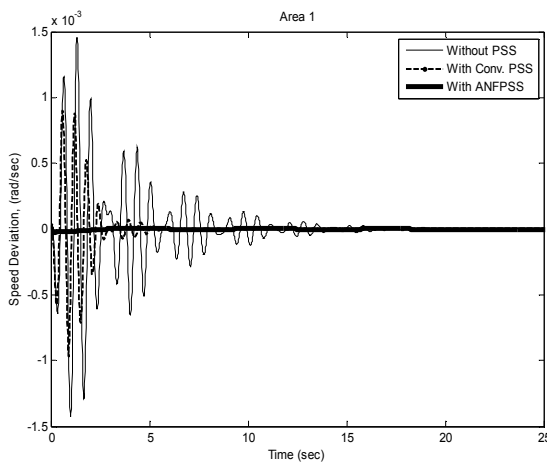


Fig.16 Effect of change in inertia constant of generators on Speed deviation for Area 1

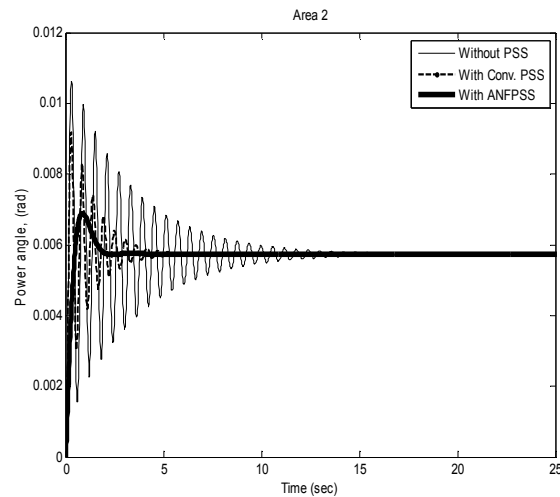


Fig.19 Effect of change in inertia constant of generators on Power angle for Area 2

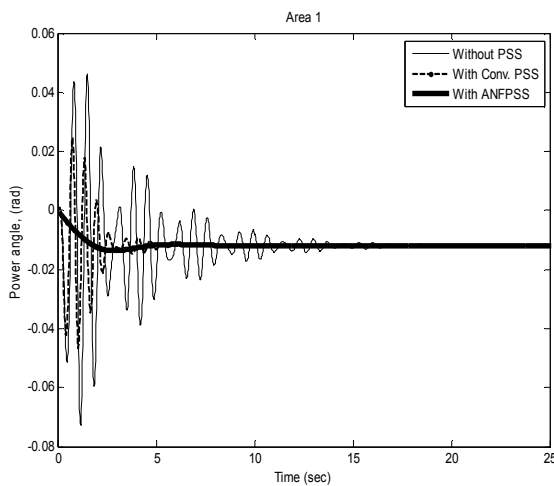


Fig.17 Effect of change in inertia constant of generators on Power angle for Area 1

6. Conclusion

An ANFIS based power system stabilizer is presented in this paper in order to overcome the drawbacks of conventional power system stabilizers. The proposed method is evaluated on a multi-machine power system to demonstrate its effectiveness and robustness. Simulation studies described in this paper demonstrate that the adaptive neuro-fuzzy based PSS can provide very good damping performance over a wide range of operating conditions. Such a nonlinear adaptive PSS control scheme will yield better and fast damping under small and large disturbances even with changes in system operating conditions. Better and fast damping means that generators can operate more close to their maximum generation capacity. The effect of detuning of one of the generator parameters on damping performance of the system has also been analyzed. The proposed technique has the features of simple structure, adaptivity and fast response and easy to be realized in power systems.

Appendix

(1). Reduced Y Matrix :

$$\begin{bmatrix} 0.846 - j2.988 & 0.287 + j1.513 & 0.210 + j1.226 \\ 0.287 + j1.513 & 0.420 - j2.724 & 0.213 + j1.088 \\ 0.210 + j1.226 & 0.213 + j1.088 & 0.277 - j2.368 \end{bmatrix}$$

(2). Generators data :

Data	G2	G3
Rated MVA	192	128
kV	18	13.80
H (s)	6.4	3.01
D	0.0	0.0
T_{do}	6	5.89
T_{qo}	0.535	0.6
x_d	0.8958	1.3125
x'_d	0.1198	0.1813
x_q	0.8645	1.2578
x'_q	0.1969	0.25

(3). Transmission line data:

Bus No.	Impedance	
	R	X
1 - 4	0	0.1184
2 - 7	0	0.1823
3 - 9	0	0.2399
4 - 5	0.0100	0.0850
4 - 6	0.0170	0.0920
5 - 7	0.0320	0.1610
6 - 9	0.0390	0.1700
7 - 8	0.0085	0.0720
8 - 9	0.0119	0.1008

(4). Shunt admittances data:

Bus No.	Admittance	
	G	B
4 - 0	0	0.1670
5 - 0	1.2610	-0.2634
6 - 0	0.8777	-0.0346
7 - 0	0	0.2275
8 - 0	0.9690	-0.1601
9 - 0	0	0.2835

(5). Generator exciter details:

For G2 & G3: $K_a = 400$, $T_a = 0.05$ sec.

(6). PSS data :

$K_{stab} = 400$, $T_w = 3$ sec., $T_1 = 0.1537$ sec., $T_2 = 0.1$ sec.

Note : All impedance and admittance values are in per unit (pu) on a 100 MVA base. All time constants are in seconds.

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