The Journal of CPRI,
Vol. 6, No. 1, March 2010 pp. 5–14

Power System Stabilization by a Coordinated Application of Power System Stabilizers using Hierarchical Neuro-Fuzzy Logic

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Power system stabilizers (PSS) 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. Based on the analysis of existing techniques, this paper presents the stabilization of multi-machine power system based on coordinated Adaptive Hierarchical Neuro-Fuzzy network based power system stabilizer (AHNFPSS) design. The proposed system consists of a Hierarchical neuro fuzzy controller, which is used to generate a supplementary control signal to the excitation system. The proposed method has the features of a simple structure, adaptivity and fast response. The proposed controller is evaluated on a multi-machine power system under different operating conditions and disturbances to demonstrate its effectiveness and robustness. Eigenvalue analysis shows that the undamped modes are sensitive to excitation control while speed governors have little influence on damping.

Keywords: *Hierarchical Neuro-Fuzzy Networks, Power System Stabilizer (PSS), Dynamic Stability*

1. INTRODUCTION

Power system stabilizers are used to generate supplementary control signals for the excitation system in order to damp the low frequency inter-area and intra-area oscillations [1]. A conventional power system stabilizer is widely used in existing power systems and has made a contribution in enhancing power system dynamic stability. The parameters of CPSS are determined based on a linearized model of the power system around a nominal operating point where they can provide good performance. Since power systems are highly nonlinear systems, with configurations and parameters that change with time, the CPSS design based on the linearized model of the power system cannot guarantee its performance in a practical operating environment.

To improve the performance of CPSS's, numerous techniques have been proposed for their design, such as using intelligent optimization methods (simulated annealing, genetic algorithm, tabu search) [2]-[4], fuzzy-neural networks [5]-[6] and many other nonlinear control techniques. The intelligent optimization algorithms are used to determine the optimal parameters for CPSS by optimizing an eigenvalue based cost function in an offline mode. Since the method is based on a linearized model and the parameters are not updated online, they lack satisfactory performance during practical operation. The rule-based fuzzy logic control methods are well known for the difficulty in obtaining and adjusting the parameters of the rules especially online. Recent research indicates that more emphasis has been placed on the combined usage of fuzzy systems and other

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technologies such as neural networks to add adaptability to the design [7, 13, 14]. Currently, most of the nonlinear control based methods use simplified models to decrease complexity of the algorithms. Considering the complexity of practical power systems, more realistic model with less computation time is required for effective robust control over a wide range of operating conditions.

As power systems are nonlinear, and prone to variations in its operating states over a wide range, the conventional PSS cannot provide optimal performance as the operating point changes. The fusion of ideas from fuzzy control and neural networks had acknowledged a significant role in improving controller performances. Fuzzy logic has proven effective for complex, nonlinear and imprecisely defined systems. The common bottleneck in fuzzy logic is the derivation of fuzzy rules and the parameter tuning for the controller. The neural networks have powerful learning abilities, optimization abilities and adaptation. There are many research works focusing on partitioning of the input space, to determine the fuzzy rules and parameters evolved in the fuzzy rules for a single fuzzy system [27], [28]. As it is well known, the curse-of-dimensionality is an unsolved problem in the fields of fuzzy and/or neurofuzzy systems [30]. The fuzzy logic and neural networks can be integrated to form a connectionist Adaptive Hierarchical network based Fuzzy logic controller. Some of the problems mentioned above are partially solved by several researchers working in the hierarchical fuzzy systems domain [16]–[24], [26], [32], and [33]. Torra [15] has summarized the related recent researches. As a way to overcome the curse-of-dimensionality, it was suggested by Brown et al. [24] to arrange several low-dimensional rule base in a hierarchical structure, i.e., a tree, causing the number of possible rules to grow in a linear way according to the number of inputs. A method was proposed to determine automatically the fuzzy rules in a hierarchical fuzzy model [29]. Rainer [22] described a new algorithm which derives the rules for hierarchical fuzzy associative memories that were structured as a binary tree. Wang and Wei [18], [19], [25] proposed specific hierarchical fuzzy systems and its universal approximation property were proved. The approximation capabilities of hierarchical fuzzy systems were further analyzed by Zeng and Keane [31]. The proposed Adaptive Hierarchical Neuro-Fuzzy based PSS (AHNFPSS) is designed for a multimachine machine power system network.

The excitation voltage deviation of AVR, generator speed deviation and its derivative are taken as inputs to the controller. This paper also presents the results of a stability investigation of a power system by coordinated power system stabilizers (PSS). The effects of the existing controllers on system stability are studied. If no PSS's are present, the damping of various swing modes in the system will be very poor and low frequency oscillations present.

The power system model is described in 2.0. The design of the coordinated adaptive Hierarchical neuro-fuzzy network controller is described in 3.0. The implementation process and simulation studies are described in 4.0.

2.0 POWER SYSTEM MODELING

For any electric power system dynamic study, a proper mathematical model must be chosen. There are only a limited number of system components important to the dynamic study: the synchronous generator, the governor and the excitation system.

2.1 Synchronous Generator

The three armature phase windings on the stator of the synchronous machine are replaced by two equivalent armature windings, a d-winding on the d-axis and a q-winding on the q-axis by Park's transformation. The models mainly differ in the number of windings considered along d and q-axis. The third order model [8] represented by the following equations is used for the representation of synchronous generator.

$$\dot{\omega}=1/M(T_m-T_e-T_d) \tag{1}$$

$$\dot{\delta}=\omega_b(\omega-1) \tag{2}$$

$$\dot{e}_q'=\frac{1}{T_{do}'}\left[E_{fd}-e_q'-(x_d-x_d')\,i_d\right] \tag{3}$$

and the auxiliary equations are

$$T_e\cong P_e\cong\frac{e_q'V_t}{x_d}\sin\delta+\frac{V_t^2(x_d'-x_q)\sin 2\delta}{2x_d'\,x_q} \tag{4}$$

$$e_q'=V_t+jx_d'i_d+jx_q*ji_q \tag{5}$$

2.2 Modeling of Excitation System

The excitation system is considered to be of continuously acting IEEE Type-1 excitation system [8]. The CPSS consists of two phase-lead compensation blocks, a signal washout block, and again block. The input signal is the rotor speed deviation $\Delta\omega$. The block diagram of the CPSS is shown in Fig.1

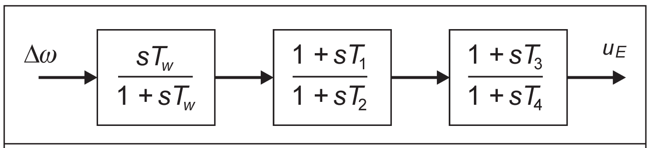


FIG. 1 BLOCK DIAGRAM OF CPSS

3.0 ADAPTIVE HIERARCHICAL NEURO-FUZZY PSS

The Adaptive Hierarchical Network Based Fuzzy Logic PSS is designed with three inputs, excitation voltage deviation of AVRΔE_{fd}, the generator speed deviation $\Delta\omega$ and its derivative $\Delta\dot{\omega}$, and one control output (u_E). The training data is viewed to be very complex hence seven linguistic variables for each input variable were used to get the desired performance. The linguistic variables are specified by Gaussian membership functions and as a result 49+49 rules are devised. The rule-base contains the fuzzy IF-THEN rules of sugeno's first order type [9] in which the output of each rule is a linear combination of input variables plus a constant term. The final output is the weighted average of each rule's output. The universe of discourse for the input-output variables is normalized and the gain parameters chosen based on input-output space are

ΔE_{fd}gain=1.0, $\Delta\omega$gain=1.0, $\Delta\dot{\omega}$ gain=0.08, u_E gain=0.1.

The architecture of the AHNFPSS sensing ΔE_{fd}, $\Delta\omega$ and $\Delta\dot{\omega}$ is shown in Fig. 2A where node functions in each layer are as described below.

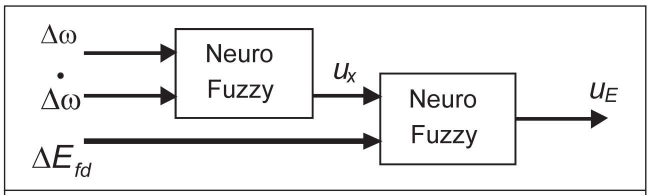


FIG. 2A ARCHITECTURE OF AHNFPSS

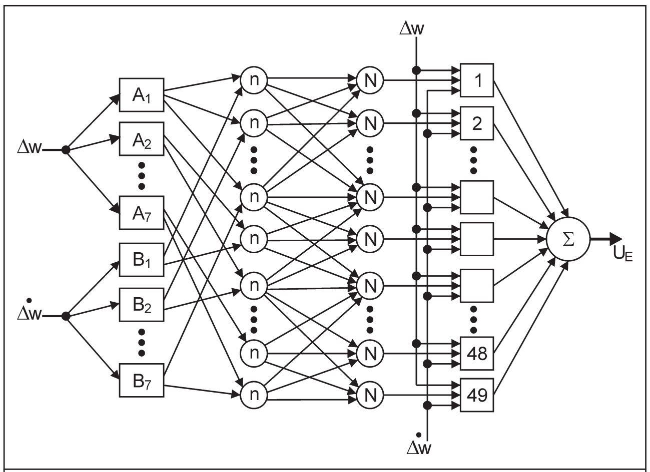


FIG. 2B ONE TREE STRUCTURE OF AHNFPSS

3.1 Layer 1

Each node in this layer is an adaptive node performing Gaussian membership function.

$$O_{1,i}=\mu_{A,i}(x_i)=\exp\left[\frac{(x_i-c_{ij})^2}{\sigma_j^2}\right]$$

where i=1, 2, 3, j=1, 2...7

x_i, is the input to this layer ($\Delta\omega,\Delta\dot{\omega},\Delta E_{fd}$) and c_{ij}, is the center of the membership function.

3.2 Layer 2

Every node in this layer represents the firing strength of the rule.

$$O_{2,i} = w_i = \min(\mu_{Ai}(\Delta\omega), \mu_{Bi}(\Delta\dot{\omega}))$$

$$O_{2,j} = w_j = \min(\mu_{Aj}(\Delta E_{FD}), \mu_{Bj}(u_x)) \qquad i,j=1\ldots7.$$

Eventually the nodes of this layer perform fuzzy AND operation.

3.3 Layer 3

The nodes of this layer calculate the normalized firing strength of each rule.

$$O_{3,i} = \overline{w_i} = \frac{w_i}{\Sigma w_i} \quad O_{3,j} = \overline{w_j} = \frac{w_j}{\Sigma w_j} \qquad i,j=1\ldots49.$$

w_i , w_j – firing strength of a rule.

3.4 Layer 4

The nodes in this layer output the weighted consequent part of the rule table.

$$O_{4,i} = \overline{w_i} f_i = \overline{w_i}(p_i \Delta\omega + q_i \Delta\dot{\omega} + r_i)$$

$$O_{4,j} = \overline{w_j} f_j = \overline{w_j}(p_j u_x + q_j \Delta E_{fd} + r_j) \qquad i,j=1,\ldots49$$

where $\{p_i, q_i, r_i\}$ is the parameter set of this node.

3.5 Layer 5

The single node in this layer computes the overall output as the summation of all the incoming signals.

$$O_{5,i} = \sum \overline{w_i} f_i, \;\; O_{5,j} = \sum \overline{w_j} f_j \qquad i,j=1\ldots49.$$

where $O_{5,i}$, $O_{5,j}$ denote the output of the node in layer 5.

The learning algorithm for the connectionist network structure consists of two separate stages of a learning strategy, which combines unsupervised learning and supervised gradient-descent learning procedure. In phase one a self-organized learning scheme is used to locate initial membership functions and to find the presence of fuzzy logic rules. In phase two a supervised learning scheme is used to optimally adjust the parameters of membership functions for desired output. The back-propagation algorithm is used for the supervised learning. To initiate the learning scheme, training data and the desired or guessed coarse of fuzzy partition (i.e., the size of the term set of each input/output linguistic variable) must be provided from the outside world [9].

The AHNFPSS training is done assuming that there is no expert available and the initial values of the membership functions parameters are equally distributed along the universe of discourse and all consequent parts of the rule table set to zero. The AHNFPSS starts from zero output and during training it gradually learns the rules and functions as close to the desired controller. Thus during training the network structure update membership functions and rule base parameters according to the gradient descent update procedure.

The AHNFPSS was trained by data created from power system stabilizers designed for various operating conditions in which the generator output ranging from 0.2 to 1.0 *p.u* and power factor ranging from 0.85 lead to 0.4 lag. The wide spectrum of possible disturbances used for the training are: reference voltage and infinite bus voltage disturbances in the range of -0.05 *p.u* to 0.05 *p.u*, torque variations from -0.15 *p.u* to 0.15 *p.u*, three phase fault transients, transmission line with different line reactance disturbances, different machine inertia disturbances and one transmission line outage. A total of 4512 input-output data pairs are created for the training of AHNFPSS.

4.0 SIMULATION STUDIES

The performance of the designed AHNFPSS was investigated on a power system model of the three machine nine bus system [10] with third generator considered as the infinite bus. A single-machine part of the schematic diagram of the multi-machine system used for simulation studies is shown in Fig. 3. The Simulink and Fuzzy Logic toolbox of MATLAB [11, 12] are used for modeling the power system and designing the AHNFPSS respectively. A number of studies have been performed to investigate the effect of PSS designed by the Adaptive Network Based Fuzzy Logic control approach. The control output for both the AHNFPSS and CPSS was limited to 0.1 p.u.

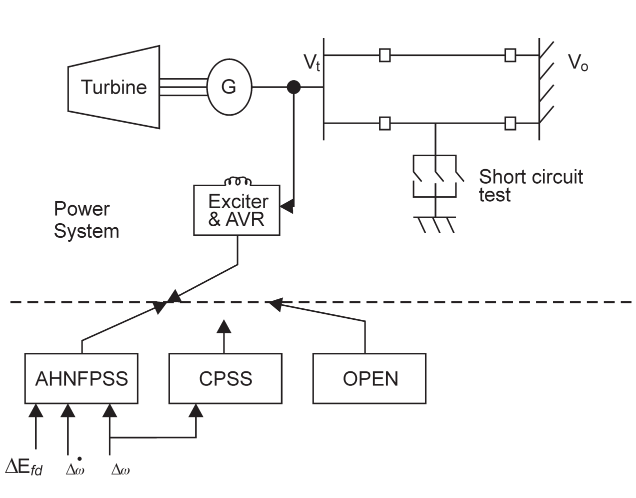


FIG. 3 SYSTEM MODEL FOR SIMULATION STUDIES

4.1 Dynamic Stability Studies

Load test: With the generator operating at an active power of 0.4 p.u and a reactive power of 0.8 p.u lag, a 0.01 p.u step increase in input torque reference was applied in all the machines. The disturbance is large enough to cause the system to operate in the nonlinear region. System response without PSS and with the CPSS and AHNFPSS under these conditions was shown in Fig. 4. The system without stabilizer is highly oscillatory. Although the CPSS is effective in damping the oscillations, the AHNFPSS settles the oscillations smoothly and quickly.

Light load test: With the generator working under a light load condition, 0.2 p.u active power and reactive power of 0.8 p.u lag, a 0.02 p.u step decrease to torque was applied. The

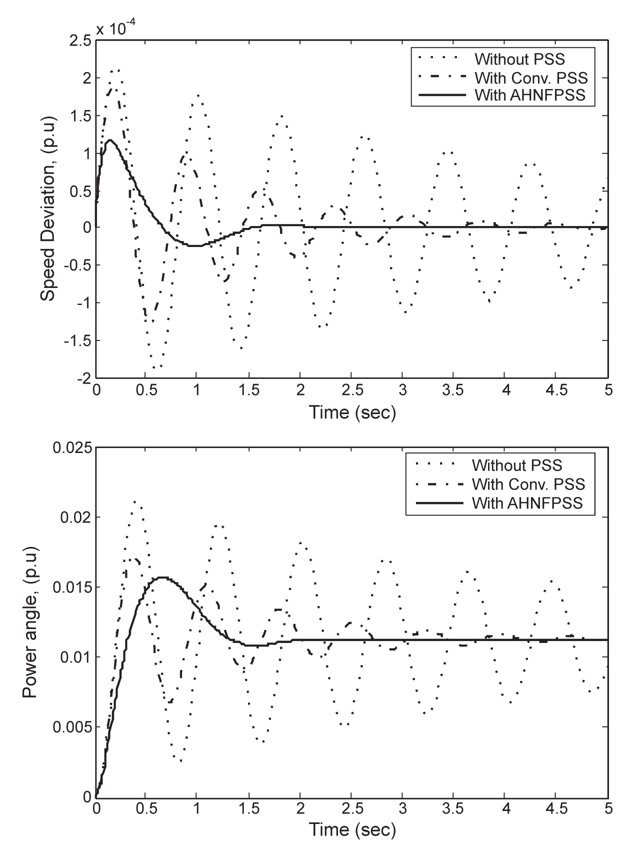


FIG. 4 SIMULATION RESULTS FOR LOAD TEST AT AN ACTIVE POWER OF 0.4 P.U AND REACTIVE POWER 0.8 P.U A 0.01 P.U STEP INCREASE IN INPUT TORQUE IN GENERATOR 1

disturbance is large enough to cause the system to operate in the non-linear region. System performance under such non-linear condition is shown in Fig. 5. It can be seen that the AHNFPSS damps out the oscillations very efficiently.

Leading pf Load test: When the generator is operating at a leading power factor, the situation is much more difficult because the stability margin is reduced. However, in order to absorb the capacitive charging current in a high voltage power system, it may become necessary to operate the generator at a leading power factor. It is therefore desirable that the controller be able to guarantee stable operation of the generator under leading power factor condition.

With the generator operating at an active power of 0.5 p.u and reactive power 0.9 lead, a 0.01 p.u step decrease in torque was applied.

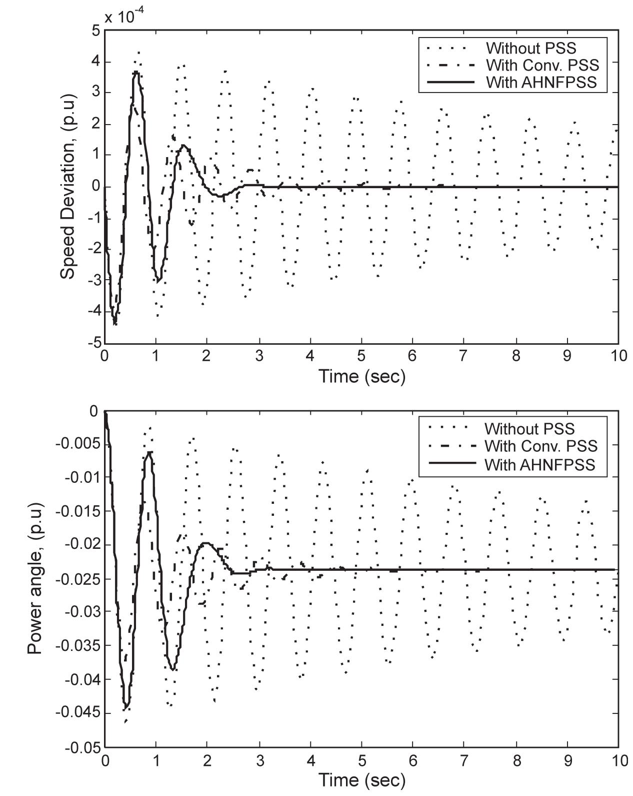


FIG. 5 SIMULATION RESULTS FOR LIGHT LOAD TEST AT AN ACTIVE POWER OF 0.2 P.U AND REACTIVE POWER 0.8 P.U A 0.02 P.U STEP DECREASE IN INPUT TORQUE IN GENERATOR 2

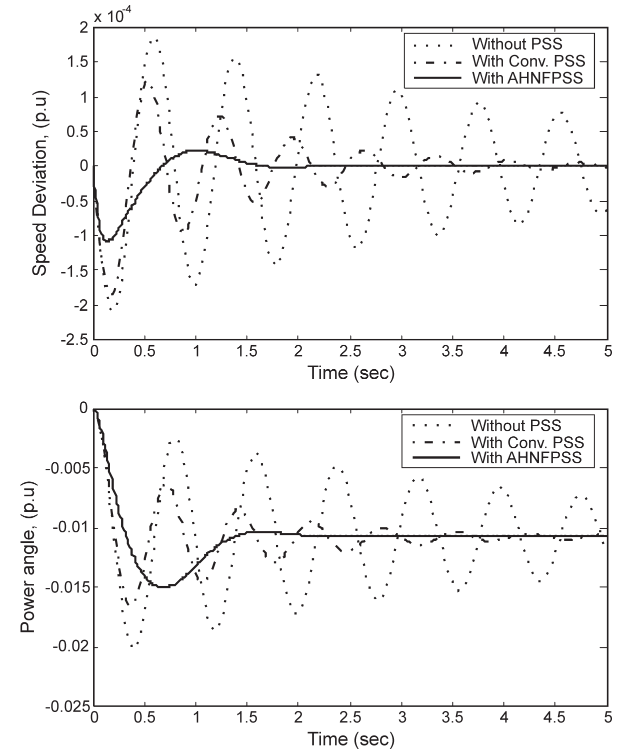


FIG. 6 SIMULATION RESULTS FOR LEADING POWER FACTOR LOAD TEST AT AN ACTIVE POWER OF 0.5 P.U AND REACTIVE POWER 0.9 P.U A 0.01 P.U STEP DECREASE IN INPUT TORQUE IN GENERATOR 1

The results given in Fig. 6 show that the oscillation of the system is damped out rapidly by the AHNFPSS.

4.2 Transient Stability Studies

The behaviour of the AHNFPSS under transient conditions was verified by applying a three phase fault. At an operating condition of active power 0.6 p.u and reactive power 0.8 lag condition a three phase to ground short circuit is applied at the middle of one transmission line, cleared 100ms later by the disconnection of the faulted. The response is shown in Fig. 7. Results show that AHNFPSS help the system to reach the new operating point and damp out the oscillations very quickly.

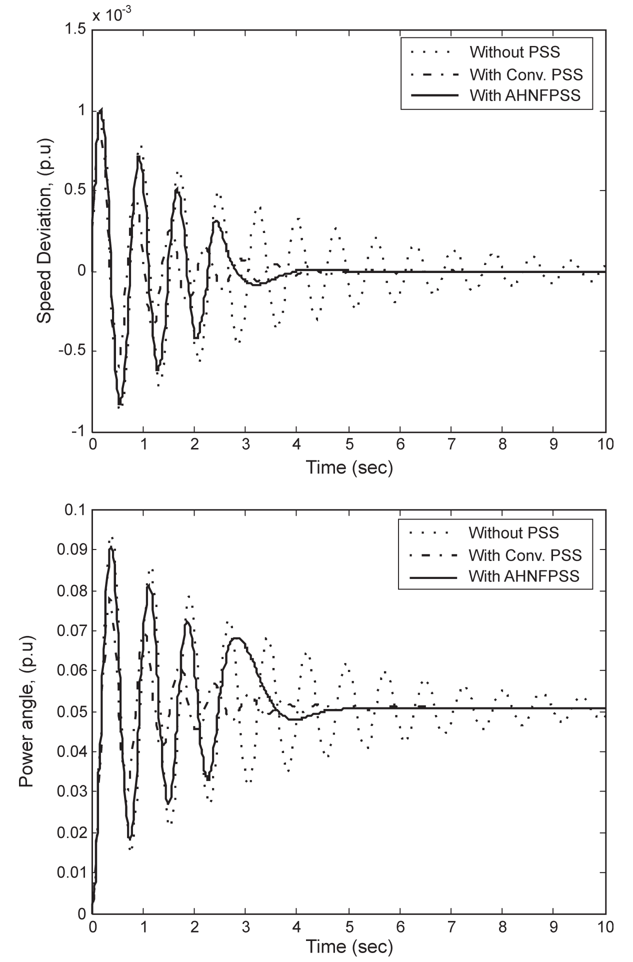


FIG. 7 SIMULATION RESULTS FOR TRANSIENT STABILITY THREE PHASE FAULT TEST AT AN ACTIVE POWER OF 0.6 P.U AND REACTIVE POWER 0.8 P.U AND FAULT CLEARED AFTER 100MSEC IN GENERATOR 2

4.3 Different Oscillation Mode Test

In this test different machine inertia and transmission line impedance were used to introduce different oscillation modes. Tests were conducted for machine inertia, H, changing from 6.4 s to 10.0 s, while the machine was operating at 0.95 pu power and 0.95 reactive power lag. A disturbance of 0.01 pu increase in mechanical input torque was applied to the generator 1. The oscillation frequency of the system varies with different machine inertias. System response with CPSS and AHNFPSS is shown in Fig. 8.

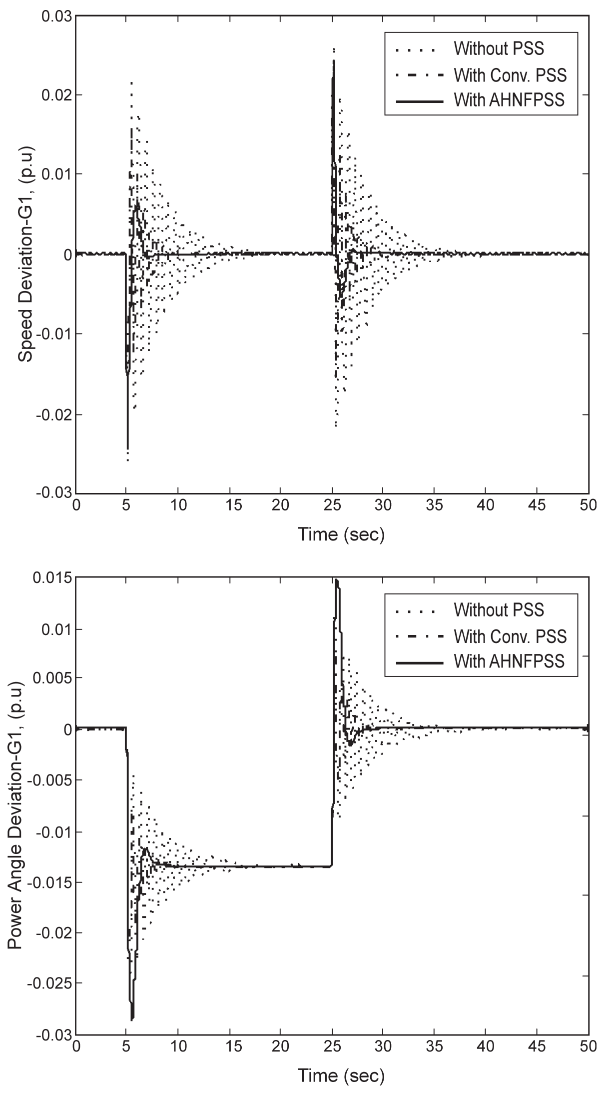


FIG. 8. SIMULATION RESULTS FOR DIFFERENT MACHINE INERTIA TEST IN WHICH H CHANGING FROM 6.4S TO 10S AT 25 S IN GENERATOR 1 WITH AN ACTIVE POWER OF 0.95.U AND REACTIVE POWER 0.95 P.U LAG.

The extent of the coupling of the generator with the infinite bus can be simulated with the change of transmission line impedance. The likelihood of instability of the exciter mode emerges if the transmission line has greater impedance. The transmission line impedance was changed from 0.361 pu to 0.5 pu to simulate tightly and loosely coupled systems. The response of the system with both CPSS and AHNFPSS is shown in Fig. 9. It can be seen from Figs. 4-9 that the AHNFPSS offers a very robust performance.

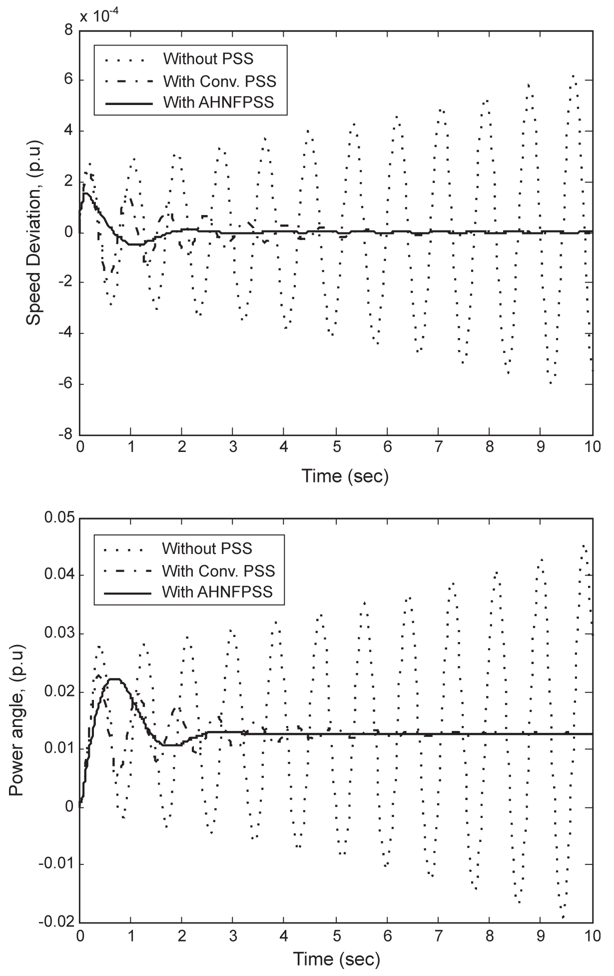


FIG. 9 SIMULATION RESULTS FOR DIFFERENT TRANSMISSION LINE REACTANCE TEST AT AN ACTIVE POWER OF 0.9 P.U AND REACTIVE POWER 0.95 P.U A 0.012 P.U STEP INCREASE IN INPUT TORQUE REFERENCE IN GENERATOR 2.

4.4 Eigenvalue Analysis

The effectiveness and robustness of the proposed AHNFPSS over a wide range of loading conditions are considered. Table 1 shows the eigenvalues, frequencies of swing modes of the participating generators. The third order model is considered and the mechanical and electrical modes are considered for stability analysis. Accordingly $\Delta\omega$, $\Delta\delta$, Δe_q', ΔE_{FD} are taken as state variables for uncontrolled system and eigen analysis was done. In the analysis the $\Delta\omega$, $\Delta\delta$ are taken for mechanical mode analysis and Δe_q, ΔE_{FD} are taken for electrical mode analysis. So totally four eigen values are considered in uncontrolled mode. In PSS controlled system, in addition to the above system states, two state variables are considered the output from the wash out circuit of the PSS block and the compensator block. So totally six state variables are considered and as such eigen analysis was done.

TABLE 1

STABILITY ANALYSIS

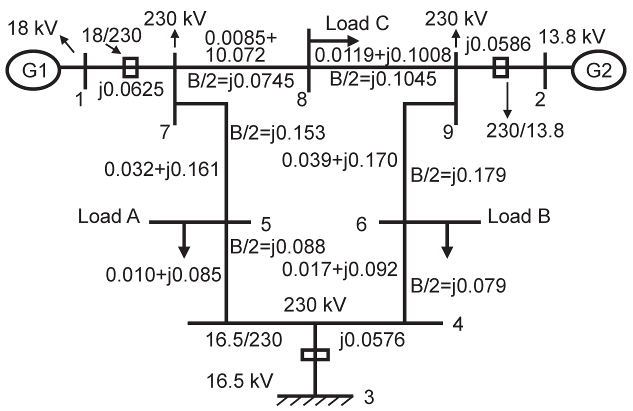
System	Generator 1	Generator 2
Eigen values without PSS	-0.019649 + 5.5135i -0.019649 -5.5135i -10.187 + 30.384i -10.187 - 30.384i	-0.055556 + 7.4902i -0.055556 - 7.4902i -10.189 + 29.132i -10.189 - 29.132i
Eigen values with CPSS	-5.2714 +14.254i -5.2714 -14.254i -1.2476 +10.147i -1.2476 - 10.147i -0.1215 -8.164	-7.0511 + 28.824i -7.0511 - 28.824i -1.1572 + 10.229i -1.1572 - 10.229i -0.1316 -7.521
Eigen values with AHNFPSS	-7.9744 + 30.044i -7.9744 - 30.044i -1.6696 + 5.027i -1.6696 - 5.027i -0.34535 -11.114	-7.0511 + 28.824i -7.0511- 28.824i -2.2753 + 6.7059i -2.2753 - 6.7059i -0.34106 -11.828

5.0 CONCLUSION

To overcome the drawbacks of conventional power system stabilizers, an adaptive coordinated Hierarchical neuro-fuzzy network control based power system stabilizer design is presented in this paper. The proposed method is evaluated on a 9-bus three machine power system. The design of the proposed controller is based on only the speed deviation of the generator. Therefore, the computations involved in the network design are minimal. This is desirable for practical hardware implementation on the power station platforms. Simulation results for different kinds of disturbances and operating conditions demonstrate the effectiveness and robustness of the controller. Such a nonlinear adaptive PSS 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 thus ensuring that generators remain stable under several faults such as three phase short circuits.

APPENDIX I

STUDY SYSTEM



APPENDIX II

LIST OF SYMBOLS

δ	:	Rotor angle
ω	:	Rotor angular velocity
E_{fd}	:	Exciter output voltage
M	:	Inertia constant
T_m	:	Mechanical torque
T_e	:	Electrical torque
T_d	:	Damping torque
Tdo'	:	d-axis open circuit time constant
x_d'	:	d-axis transient reactance
x_d	:	d-axis component of synchronous reactance
x_q	:	q-axis component of synchronous reactance
id,iq	:	d and q axis currents
Vt	:	Generator terminal voltage

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