Indian J.Sci.Res. 4(2) : 15-22, 2013 ISSN : 0976-2876 (Print)
ISSN : 2250-0138 (Online)

A NOVEL PSS CONTROLLER BASED ON ARTIFICIAL NEURAL NETWORK FOR DAMPING POWER SYSTEM OSCILLATIONS

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ABSTRACT

Power system stabilizers (PSS) have been extensively used in large power systems for enhancing stability of the system. For this purpose there are verities of methods for determining of the controller coefficients of the system stabilizers. This paper presents a novel approach for designing a self-tuning power system stabilizer (PSS) controller based on artificial neural network (ANN). The nodes in the input layer of the ANN receive generator real power output, generator reactive power output, and generator terminal voltage. While the nodes in the output layer provide the optimum PSS parameters, e.g. stabilizing gain, time constants. Moreover Effects of changing generator real power on the parameters of the power system stabilizer is studied. Finally, in order to show effectiveness of proposed methodology some simulation results on a power system in different operational points are provided and compared with conventional PSS controller.

KEYWORDS : Power System Stabilizers, Artificial Neural Network, Generator

Electro mechanical oscillations have been observed in many power systems worldwide (Hsu et al.,1987, Rogers, 2000). The oscillations may be local to a single generator or generator plant (local oscillations), or they may involve a number of generators widely separated geographically (inter-area oscillations). Local oscillations often occur when a fast exciter is used on the generator, and to stabilize these oscillations, power system stabilizers (PSS) were developed.

Power system stabilizers (PSS) have been extensively used in large power systems for enhancing stability of the system. The conventional fixed structure PSS, designed using a linear model obtained by linearizing nonlinear model around a nominal operating point provides optimum performance for the nominal operating condition and system parameters. However, the performance becomes suboptimal following deviations in system parameters and loading condition from their nominal values.

In recent years, self-tuning PSSs, variable structure PSSs, fuzzy logic PSSs and artificial neural network (ANN) based PSSs (Klein et al., 1991) and (Mithulananthan and Srivastava, 1998) have been proposed to provide optimum damping to the system oscillations over a wide range of system parameters and loading conditions. Two reasons are put forward for using ANN First, since an ANN is based on parallel processing, it can provide extremely fast processing facility. The second reason for the high level of interest is the ability of ANN to realize complicated nonlinear mapping from the input space to the output space. The ANN based PSS proposed in the literature may be classified into the following two categories.

1. At the first category of the ANN based PSS, the ANN is used for real-time tuning of the parameters of the conventional PSS (e.g. proportional and integral gain settings of the PSS (Kundur; 1994)). The input vector to the ANN represents the current operating condition, while the output vector comprises the optimum parameters of the conventional PSS. The ANN-tuned PSS can be regarded as a kind of selftuning PSSs. The main advantage of ANN tuned PSS over self-tuning PSSs is that the ANN-tuned PSS does not require system identification, while the conventional self-tuning PSS does.

2. In the second category of the ANN based PSS; the ANN is designed to emulate the function of the PSS and directly computes the optimum stabilizing signal (Abed and Varaiya, 1984) and (Caviars and Hranilovic, 1994).

The literature survey shows that in most of the past research work pertaining to ANN based PSS, the numbers of neurons in the hidden layer have been chosen arbitrarily. The main thrust of the research work presented in this paper is to address to some of the important issues pertaining to the design and performance evaluation of ANN based PSS, e.g. selection of elements of input vector of the training patterns, number of training patterns, selection of number of neurons in the hidden layer, and performance of the system with ST-

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ANNPSS under wide variations in loading. The main objectives of the research work presented in this article are:

1. To present a systematic approach for designing a multilayer feed forward artificial neural network based self-tuning PSS (ST-ANNPSS).

2. To suggest an approach for selecting the number of neurons in the hidden layer.

3. To study the dynamic performance of the system with ST-ANNPSS and hence to compare with that of conventional PSS.

4. To investigate the effect of variation of loading condition on dynamic performance of the system with ST-ANNPSS.

The System Modeling

The A single machine-infinite bus (SMIB) system is considered for the present investigations. A machine connected to a large system through a transmission line may be reduced to a SMIB system, by using Thevenin's equivalent of the transmission network external to the machine. Because of the relative size of the system to which the machine is supplying power, the dynamics associated with machine will cause virtually no change in the voltage and frequency of the Thevenin's voltage EB (infinite bus voltage). The Thevenin equivalent impedance shall henceforth be referred to as equivalent impedance (i.e.Re+jXe). The nominal parameters and the nominal operating condition of the system are given in the Appendix.

Conventional PSS comprising cascade connected lead networks with generator angular speed deviation ($\Delta\omega$).

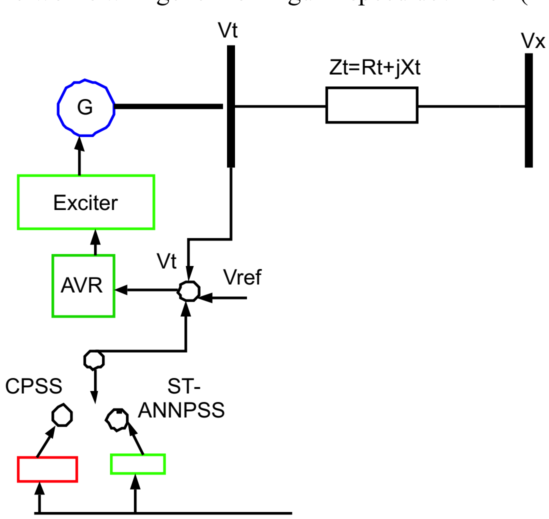

Figure1: A single machine-infinite bus (SMIB) system

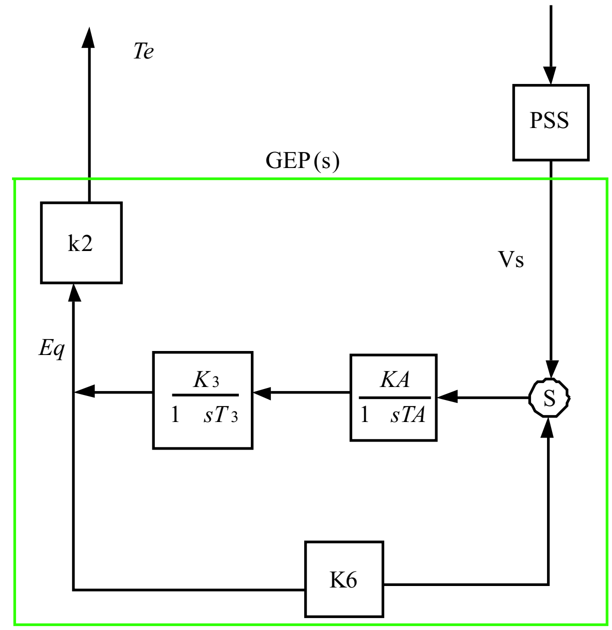

Figure 2: Transfer function block diagram of the system

As input signal has been considered. Figure, 1 shows a single machine-infinite bus (SMIB) system.

The Power System Stabilizer and the Design Considerations

Figure, 2 represents a transfer function block diagram of the system, through which an electrical torque is produced in response to speed deviation signal ($\Delta\omega$), whereas GEP(s) is a transfer function of the system whose output is electrical torque and input is stabilizing signal.

In order to increase damping of the rotor oscillations, a PSS utilizing shaft speed deviation as input signal must compensate for the phase-lag of GEP(s) to produce a component of the torque in phase with speed deviation (Lautenberg et al., 1997). The transfer function of a PSS is represented as

$$(1) \quad \frac{Vs(s)}{\Delta\omega(s)} = K_{STAB}\left[\frac{(sT_w)}{(1+sT_w)}\right]\left[\frac{(1+sT_1)(1+sT_3)}{(1+sT_2)(1+sT_4)}\right]FILT(s)$$

Where K_{STAB} is stabilizer gain, FILT(s) is combined transfer function of torsional filter and input signal transducer, Tw is washout time constant and T_1, T_2, T_3, T_4, are time constants of the lead lag networks. An optimum stabilizer is obtained by a suitable selection of time constants Tw, T_1, T_2, T_3, T_4, and stabilizer gain K_{STAB}. Two identical lead-lag networks can be chosen for a conventional PSS (i.e. $T_1 = T_2$and $T_3 = T_4$). This choice reduces the number of parameters to be optimized. The filter is used for attenuating the stabilizer gains at turbine-generator shaft torsional frequencies and may be neglected while designing PSS. The design considerations and the procedure for selecting the PSS parameters are as follows.

Phase Lead Compensation

To damp rotor oscillations, the PSS must produce a component of electrical torque in phase with the rotor speed deviation. This requires phase-lead circuits to compensate the phase-lag between exciter input (i.e. PSS output) and the resulting electrical torque. The phase characteristic of the system (i.e. GEP(s)) depends on the system parameters and the operating condition. The required phase-lead for a given operating condition and system parameters can be achieved by selecting the appropriate value of time constants T_1-T_4.

Stabilizing Signal Washout

The signal washout is a high-pass filter that prevents steady changes in the speed from modifying the field voltage. The value of the washout time constant Tw should be high enough to allow signals associated with oscillations in rotor speed to pass unchanged. From the viewpoint of the washout function, the value of Tw is not critical and may be in the range of 1-20 s. For local mode oscillations in the range of 0.8-2.0 Hz, a washout time constant of about 1.5 s is satisfactory. From the viewpoint of low-frequency inter-area oscillations, a washout time constant of 10 s or higher is desirable.

Stabilizer Gain

Ideally, the stabilizer gain should be set at a value corresponding to optimum damping. However, this is often limited by other considerations. It is set to a value, which results in satisfactory damping of the critical modes without compromising the stability of the other modes, and which does not cause excessive amplification of stabilizer input signal noise.

Case Study

Figure, 3 depicts the schematic diagram of a synchronous generator with ST-ANNPSS. The ANN is used for tuning the parameters of the PSS in real-time. For a SMIB system, the generator terminal complex power (P +jQ) generator terminal voltage (Vt) equivalent reactance Xe and infinite bus voltage EB are related as

$$E_B = V_t + jXe\left(\frac{P - jQ}{V_t *}\right) \quad (2)$$

Let us consider EB as a reference p hasor, and Vt =Vtd+jVtq From Eq. (2), we get

$$E_B = Vtd - \frac{Xe(P\sqrt{V_t^2 - V_{td}^2} - QV_{td})}{V_t^2} \quad (3)$$

$$E_B = \sqrt{V_t^2 - V_{td}^2} + \frac{Xe(PV_{td}\sqrt{V_t^2 - V_{td}^2}Q)}{V_t^2} \quad (4)$$

The Eqs. (3) and (4) are independent equations in terms of E_B, Vt, P, Q, Vtd and Xe, Assuming $E_B=1_{pu}$. we are left with five variables and two equations. If three of these five variables are assumed then other two can be determined. Thus, the operating condition is characterized by three variables out of the five. Since P, Q and Vt are measurable at the terminals of the generator, these are chosen as the coordinates of the input space. Thus the nodes in the input layer of ANN receive generator real power output (P), generator reactive power output (Q), and generator terminal voltage (Vt). In the present investigations, two identical

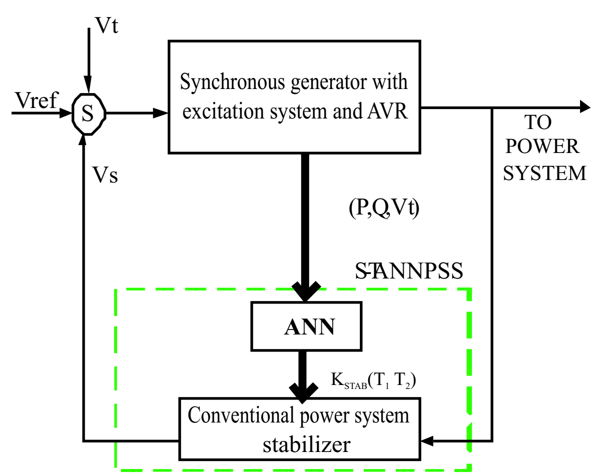

Figure 3 : The Schematic Diagram of A Synchronous Generator With ST-ANNPSS

lead-lag networks are chosen for the conventional PSS (i.e. $T_1 = T_2$ and $T_3 = T_4$), hence the parameters of the PSS to be tuned in real-time are K_{STAB}, T_1, T_2. Thus the nodes in the output layer provide the desired PSS parameters K_{STAB}, T_1 and T_2.

Optimization of parameters of PSS

The phase compensation technique (Hsu and Chen; 1991) is used for optimizing PSS parameters. It comprises the following steps.

1. Computation of the time constants of the lead networks: The phase angle of the transfer function GEP(s) is computed for s=jnω .This phase angle is denoted as γ.

The time constants of the lead networks are computed so as to compensate the phase angle of the system. Hence T_1 and T_2 are computed as follows.

$$T_1 = aT_2 \quad a = (1+\sin\gamma/2)(1-\sin\gamma/2) \tag{5}$$

$$T_2 \quad \frac{1}{(\ _n\sqrt{a})}$$

2. Computation of stabilizer gain for the desired damping ratio ξ. For the electro mechanical mode the stabilizer gain (kSTAB) is computed using the following equation.

$$K_{STAB} = \frac{2\zeta\omega_n M}{K_2 \left|G_C(j\omega_n)\right| \left|GEP(j\omega_n)\right|}$$

Where ω*n* natural frequency of oscillation of the mechanical loop = $\sqrt{(K_1\omega_0/M)}$, G_C(S)= transfer function of the phase compensator 2 and is desired damping ratio (=0.5 is assumed in the research work presented here).

Generation of training patterns

The training set should be so generated that it covers the complete domain of operation (Zhang et al., 1993). For generating training patterns; P, Vt and Q are assumed to vary over the typical ranges given as: P: 0.5-1.0 p.u.; Vt: 0.9- 1.1 p.u.; Xe: 0-0.5 p.u.

A set of 500 operating points is generated, randomly. It is important to highlight that P, Q and Vt are chosen as the elements of input vector since these can be measured easily. For each of the 500 training points, the optimum parameters of the PSS (K^*_{STAB}, T_1^* and T_2^*) are computed using phase compensation technique. The output vector of the training patterns, thus, becomes K^*_{STAB}, T_1^* and T_2^*.

Selection of Number of Neurons in the Hidden Layer

The architecture of the feed forward ANN comprises an input layer, one or more hidden layers and an output layer (Zhang et at., 1995). For the present investigations, the elements of input vector are P, Q and Vt and that of the output vector are K^*_{STAB}, T_1^* and T^{2*} hence three neurons are needed in each of the input and the output layers. One hidden layer is chosen to start with.

The ANN is trained presenting the training patterns using Trainlm function of Neural Network Toolbox of the Matlab software in order to arrive at an optimum number of neurons in the hidden layer. The investigations clearly show that for the present study, a set of 400 training patterns is adequate for training the ANN and hence, 400 training patterns are used for further studies. Figure, 4 shows the general topology of neural network model (Guan et al.; 1996).

Table 1, shows the optimum PSS parameters

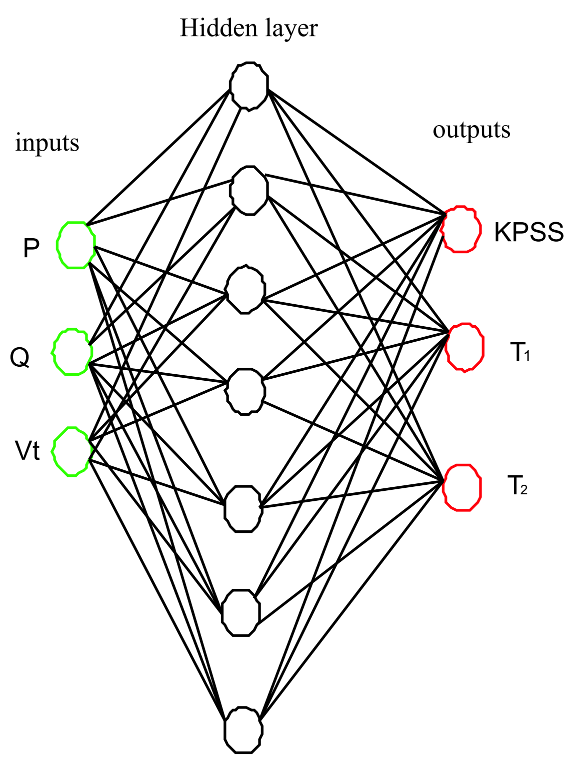

Figure 4 : Designed neural network architecture

Table 1 : PSS Parameters Computed Using Trained ANN and Corresponding Off-Line Computed Optimum Values for 10 Test Operating Conditions

Input				On - Line computing (ANN - PSS)			Off- line computing (CPSS)	
P	Q	V	K_{PSS}	T_1	T_2	K_{PSS}	T_1	T_2
0.730	0.070	0.940	20.52	0.325	0.056	21.09	0.314	0.056
0.970	0.270	0.990	22.37	0.323	0.055	22.01	0.304	0.054
0.760	0.190	0.950	19.95	0.323	0 .056	21.44	0.323	0.056
0.990	0.230	0.930	19.23	0.324	0.056	19.14	0.328	0.057
0.850	0.150	0.960	21.07	0.317	0.056	21.46	0.308	0.055
0.870	0.070	0.910	18.67	0.326	0.057	19.48	0.317	0.058
0.600	0.220	1.060	27.20	0.303	0.055	26.79	0.305	0.056
0.860	0.280	0.980	22.08	0.314	0.055	22.02	0.317	0.054
0.900	0.280	1.020	23.63	0.308	0.055	23.61	0.053	0.053
0.9 00	0.190	0.900	18.33	0.328	0.057	18.51	0.341	0.058

(K^*_{STAB}, $T_1^*$and T_2^*) computed using trained ANN with seven neurons in the hidden layer. It is clearly seen that the PSS parameters computed using ANN match very closely with the corresponding off-line computed optimum values.

Studies were also carried out, by adding second hidden layer, and the investigations revealed that there is no merit in adding second layer. Hence, ANN with seven neurons in the hidden layer is chosen for further studies.

Dynamic Simulation of the System with ST-ANNPSS

The dynamic performance of the system with ST-ANNPSS is now evaluated over a wide variation in loading condition. Following three typical loading conditions

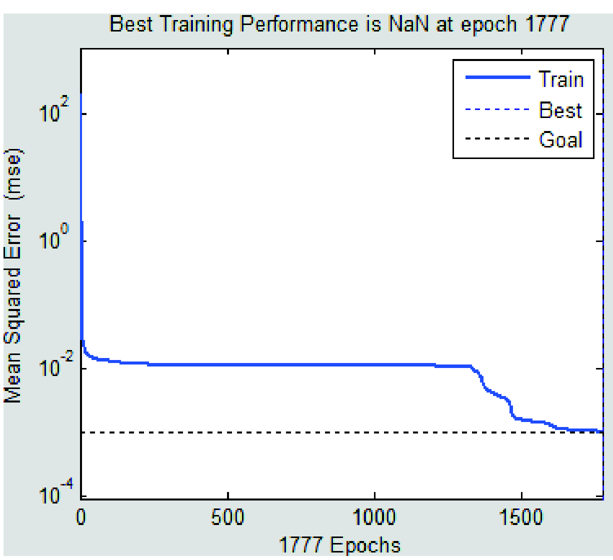

Figure 5 : Error graph of neural network model

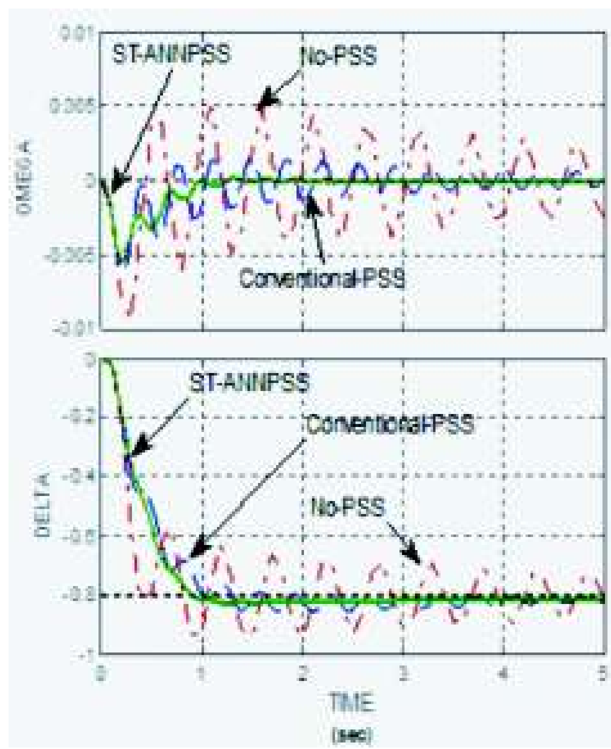

Figure 6 : Dynamic responses for ω, δ in the first operating point

spread over the entire domain of operation for which the ANN was trained, are chosen for assessing the robustness of the ST-ANNPSS

P=0.6 p.u, Q=0.2 p.u, Vt=1 p.u

P=0.8 p.u, Q=0.32 p.u, Vt=1 p.u

P=0.1 p.u, Q=0.5 p.u, Vt=1.1 p.u

It may be noted that the equivalent reactance, Xe= 0.4 p.u. is considered for all the above operating conditions.

Figure 5 shows Error graph of neural network model. Predefined error was determined 0.0001 that neural network model reached to this error after 1777 epochs. The simulation results of this part are shown in fig 6, 7 and 8. AS it seen, the ST-ANNPSS response has less settling time and

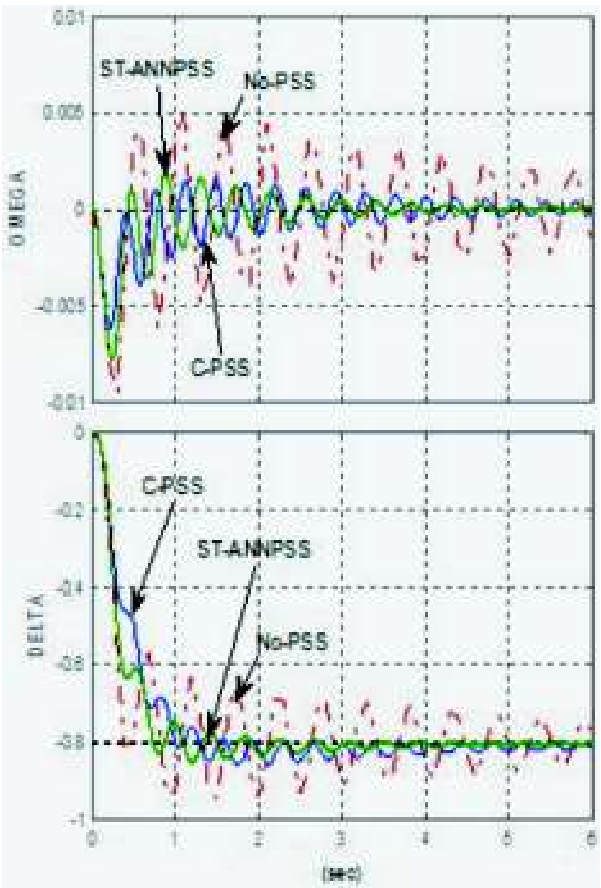

Figure 7 : Dynamic responses for ω, δ in the second operating point

overshoot also there is not undesirable transient oscillation in the response

The result imply the lack of the robustness in conventional PSS against the variation of the operational conditions, however the system dynamic performance with ST-ANNPSS is quite robust over the entire domain of loading.

Effects of changing generator real power on the parameters of the power system stabilizer

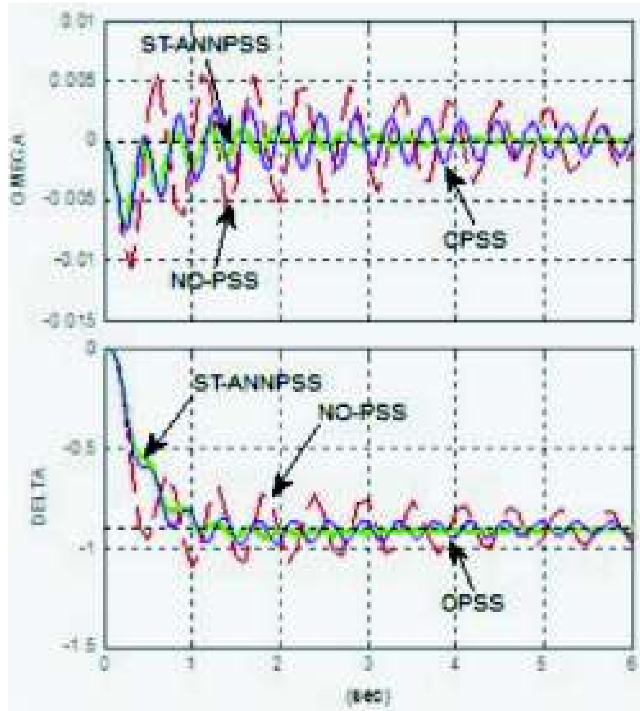

Figure 8 : Dynamic responses for ω, δ in the third operating point

In figure 9, 10 effects of changing generator real power of generator on K1 and K3 are shown. As seen, by increasing of the active power, K1 will be decreased smoothly, however k3 is constant..

In figure 11, 12 effects of changing active power of generator on K2 and K4 are depicted. As seen, by increasing of active power, K2 and K4 will be increased.

In figure13, 14 effects of changing active power of generator on K5 and K6 are shown. As seen, by increasing of active power, K5 and K6 will be decreased.

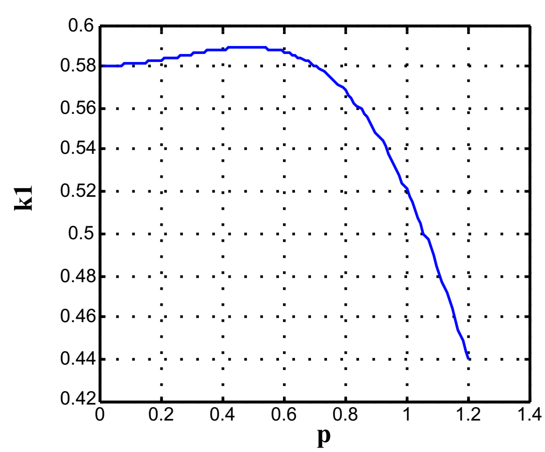

Figure 9 : Effect of changing generator real power on K1

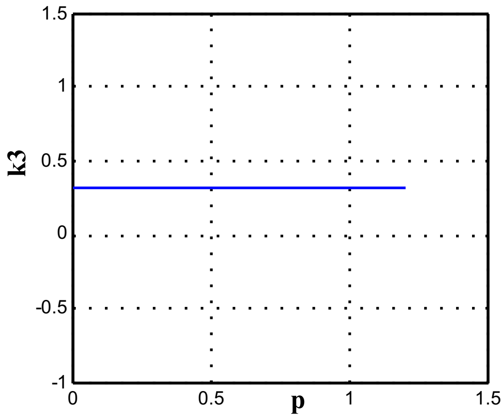

Figure 10 : Effect of changing generator real power on K3

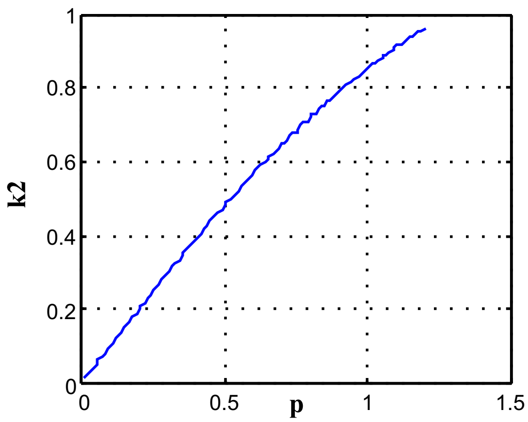

Figure 11 : Effect of changing generator real power on K2

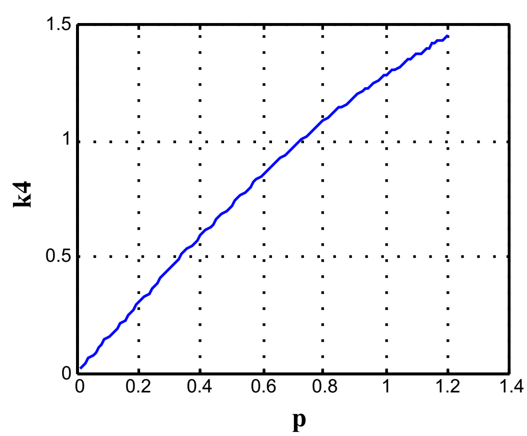

Figure 12 : Effect of changing generator real power on K4

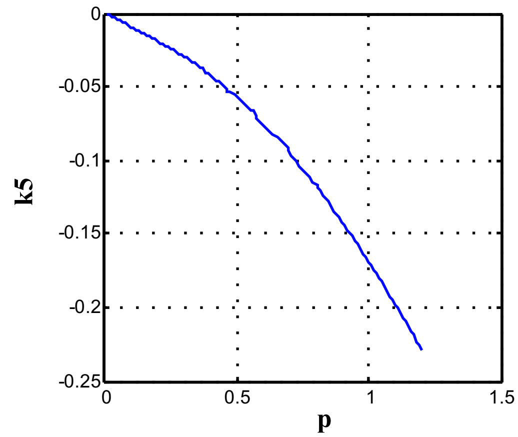

Figure 13 : Effect of changing generator real power on K5

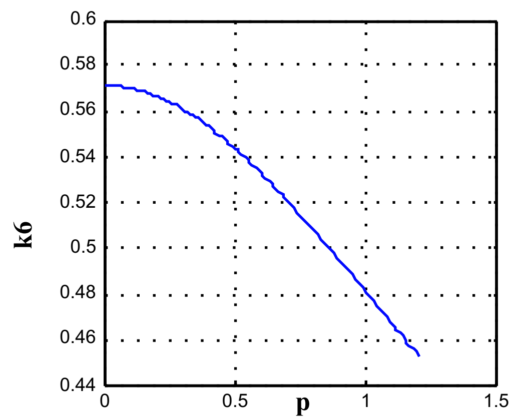

Figure 14 : Effect of changing active power of generator on K6

In figure 15 effect of changing active power of generator on rotor angle is depicted. As seen, by increasing of active power, the rotor angle increased significantly and

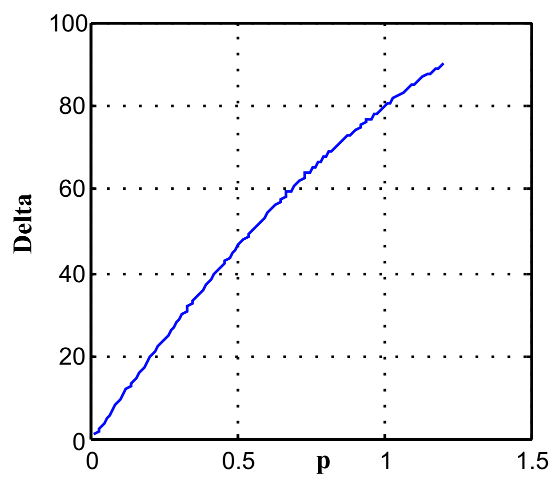

Figure 15: Effect of changing generator real power on K6

system will be instable.

CONCLUSION

A systematic approach for designing a ST-ANNPSS has been presented. Investigations show that ANN with one hidden layer comprising seven neurons is adequate and sufficient for ST-ANNPSS. Effects of changing generator real power on the parameters of the power system stabilizer are inspected. Studies show that the dynamic performance of ST-ANNPSS is quite superior to that of conventional PSS for the loading condition different from the nominal. Investigations also reveal that the performance of ST-ANNPSS is quite robust to a wide variation in loading condition.

Appendix

The nominal parameters of the system are given below. All data are in per unit, except M and the time constants. M and the time constants are expressed in seconds (Hsu and Chen; 1991).

M=2H=7.0, P=0.95, Vt=1.0, EB=1.0, Xd=1.81, Xq=1.76,Xd=0.3,Ladu=1.65, X1=0.16, Ra=0.003, Rfd=0.0006, Lfd=0.153, KA=50,TR=0.02, TA=0.05,Xe=0.65, Re=0.0, fo=60Hz

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