Dual Input Power System Stabilizer for Multi - Machine Infinite Bus System Using Neuro Fuzzy System

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Abstract: **This paper presents a new approach for real-time tuning of a dual input power system stabilizer using neuro-fuzzy system (NFS). Intelligent dual input power system stabilizer (IDIPSS) comprises of NFS and conventional dual input power system stabilizer. The NFS is a fuzzy inference system implemented in the framework of multi-layered feed forward adaptive network. NFS network is trained using hybrid training algorithm for real-time tuning of the dual input power system stabilizer. The generator real power *(Pe)*, reactive power *(Qe)*, and terminal voltage *(Vt)* characterizing the operating condition are input signals to the network while optimum DIPSS parameters *KS1* and *T1* are the outputs. Investigations have been carried out considering three, five and seven membership functions (MFs) of Triangular, Trapezoidal, and Gaussian shapes. Studies reveal that for real-time tuning of the dual input PSS, the NFS network with three MFs of any shape is adequate. The proposed IDIPSS exhibits quite a robust performance to wide variations in loading condition, system parameters, and large perturbations.**

Keywords— Intelligent Dual input power system stabilizer, Neuro-fuzzy system, Anfis system, intelligent controllers, Adaptive power system stabilizer, multi – machine system.

I. INTRODUCTION

Power system stabilizers (PSS) have been used for enhancing the overall stability of large power systems. Delta-Omega and Delta-P-Omega PSS (also known as dual input power system stabilizer) have been used. Delta-Omega PSS, when applied to turbo-generators, may cause excitation of torsional modes. Delta-P-Omega stabilizer uses a combination of electric power and speed deviations as input signals to the stabilizing signal and has been developed to overcome the problem of excitation of torsional modes [2]. Have dealt with the integral of the accelerating power type of PSS, which is in no way different from the IEEE type PSS2B model of dual input PSS [4].

Two basic problems associated with the application of PSS are:
1) The operating condition and parameters of a power system vary over a wide range.
2) The mathematical model of the power system is highly nonlinear and is not known precisely.

In the present work, an Intelligent Dual Input Power System Stabilizer (IDIPSS) is proposed which uses an NFS for real-time tuning of the dual input power system stabilizer. A maiden attempt has been made to arrive at a minimum number and shape of the MFs of the NFS for desired real-time tuning of the dual input power system stabilizer.

II. SYSTEM INVESTIGATED

A 4-generator, the 11-bus system is considered. A one-line diagram of the system is shown in Fig.1. It is assumed that all the 4 generators are provided with static excitation system IEEE Type STlA model of the static excitation systems is considered. A dual input PSS (IEEE type PSS2B model) has been considered for present investigations. The nominal parameters and operating condition are given in Appendix. The system investigated represents a two area system. The generators 1 and 2 are located in area I while the generators 3 and 4 are located in area II.

III.DUAL INPUT POWER SYSTEM STABILIZER

Fig. 2 shows the transfer function block diagram of the IEEE type PSS2B model of the dual input power system stabilizer [8]. The input signals to this PSS are speed deviation, Dv and electrical power deviation, *DPe* of the synchronous generator. The limits to the input signals, which represent the allowable ranges of the sensed values, depend on specific design parameters. For each input, two washout blocks can be represented (Twl — *Tw4)* along with transducer time constants (T6 and T7). A torsional filter (Time constants *T8* and *T9)* with indices m = 5 and n = 1 is provided. The VSMAX and VSMIN are, respectively, the maximum and minimum limits of the stabilizer output. FSMAX = 0.1-0.2 and VSMIN = —0.05 to —0.1 p.u. are used in practice [4]. The derived speed deviation signal, Dveq, has a relatively low level of torsional components and is fed to a pair of cascade connected lead-lag networks. A low value of *T2* = 0.05 s. is chosen from the consideration of practical realization. The gain setting *KS1* and time constant *T1* need to be tuned following variation in loading condition and system parameters.

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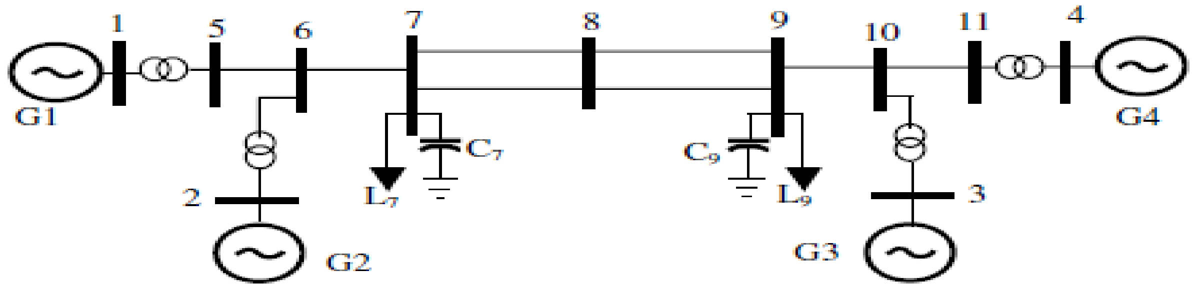

Fig. 1. One line diagram of 4 Machine 11 bus system

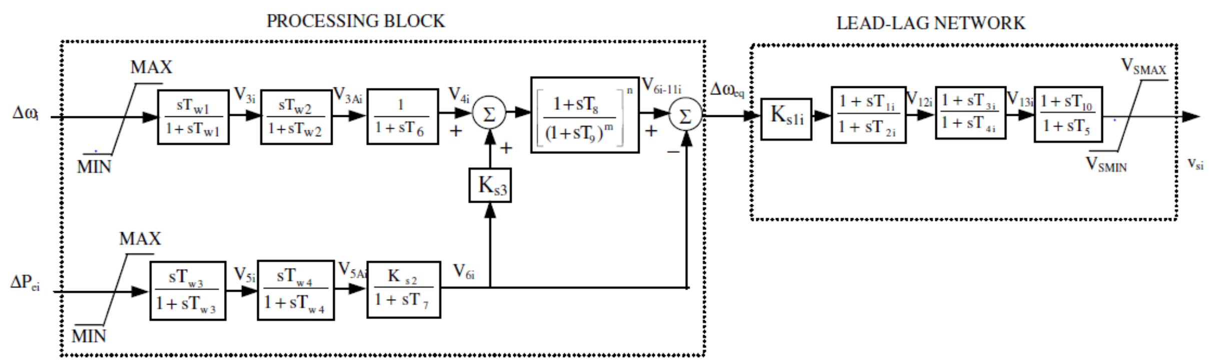

Fig. 2. Transfer function block diagram of DIPSS (IEEE type PSS2B model)

IV. NEURO-FUZZY SYSTEM

The functions and architecture of the nodes in each layer of the NFS in detail [6]. For the purpose of clarity of illustration, a two input and two output NFS are shown in Fig.3. The NFS has five layers. The nodes are denoted by two distinct symbols, i.e.

A square node has parameters, and these parameters are adapted during the training process. A circle node performs only a computation and has no parameters to be adapted during the training process [12]. The inputs to the NFS are denoted as x and y, and the outputs as z1 and z2. Three Gaussian MFs are chosen for each of the two inputs for illustration, i.e. A1, A2, and A3 for input x and B1, B2, and B3 for input y. With two inputs and three MFs for each of the inputs, the resulting Takagi-Sugeno type rule base is as follows:

Rule 1: If x is A1 and y is B1, then f11 = P11X+Q11Y+R11; H11=P21X+Q21Y+R21

Rule 9: If x is A3 and y is B3, then f19 = P19X+Q19Y+R19; H29=P29X+Q29Y+R29

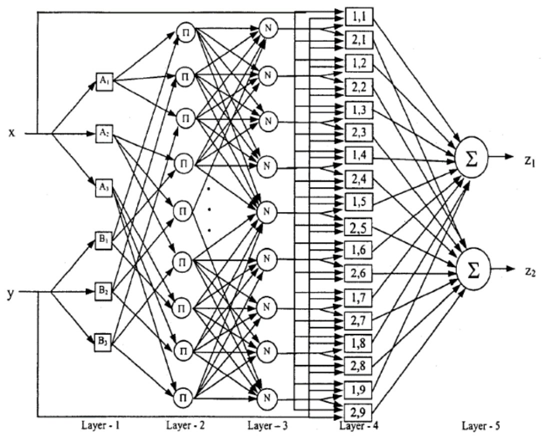

Fig. 3. Multi – layer network system

V. ANALYSIS

Power System Toolbox (PST) [6] and Fuzzy Logic Toolbox of the MATLAB software package has been used for all the investigations presented in this paper.

A. Optimization of parameters of DIPSS using ISE technique for a Multi-machine System

Integral of squared errors (ISE) technique is used in the present work for optimizing the parameters of dual input power system stabilizer (DIPSS) considering a performance index,

$$j = \int_0^\infty (\Delta\omega_1^2 + \Delta\omega_2^2 + \Delta\omega_3^2 + \Delta\omega_4^2)dt \qquad (1)$$

A quadratic performance index based on deviations in speed for all the generators has been considered since the minimization of such a performance index would provide the improved dynamic performance of the system.

B. Algorithm for designing

IDIPSS are designed considering 3 linguistic variables (i.e., membership functions) of Gaussian shape for all the three input signals. The UOD for all the three input signals is chosen as -3 to +3. An algorithm for designing IDIPSS is given below:

Step1: Generation of training patterns

For an MMIB system, the generator terminal complex power (Pe+jQe), generator terminal voltage (Vt), the equivalent reactance Xe and infinite bus voltage EB are related as,

$$E_B = V_t + jX_e\left(\frac{P_e - jQ_t}{V_T^*}\right) \qquad (2)$$

Let us consider EB as a reference phasor (i.e. EB = EB L0°, and Ft = Vtd+jVtq); from Eq. (2) by equating real and imaginary parts, we get:

$$E_B = V_{dt} - \frac{X_e(P_eV_t - Vt_d\ 2Q_e\ V_{Td}}{Vt} \qquad (3)$$

$$\sqrt{V_t^2 - V_{td}^2} + \frac{X_e(P_eV_{td} + \sqrt{V_t^2 - V_{td}^2}\,Q_{e)}}{V_t} = 0 \qquad (4)$$

The Eqs. (3) And (4) are two independent equations in terms of EB, Vt, Pe, Qe, Vtd and Xe. Assuming EB= 1.0 p.u., we are left with five variables and two equations. If three of these five variables are assumed, then other two can be determined. Since Pe, Qe and Vt are measurable at the terminals of the generator, these are chosen as the coordinates of the input space. A training pattern comprises of the input vector (i.e. Pe, Qe, and Vt) and output vector (i.e. KS1 and T1). The training patterns should be generated so that the complete domain of operation is covered. The Pe, Vt, and Xe are assumed to vary over the typical ranges given below for the present investigations,
Pe = 0.2 to 2.0 p.u and Vt = 0.9 to 1.1 p.u and Xe = 0.4 to 0.8 p.u

Step2: selection of UODs and normalization factors

The use of normalized domains, i.e. universes of discourse (UODs) requires a scale transformation which maps physical values of process variables into a normalized domain. The scaling factors which describe the particular input normalization play a role similar to that of the gain coefficient in a conventional controller. The maximum values of Pe, Qe, and Vt are 2.0, 1.3627 and 1.1 p.u. while their minimum values are 0.167, -0.0535 and 0.8961 p.u., respectively, in the 400 training patterns generated.

A scaling is done in order that the range of values of input variables is spread over the complete UOD. Upper limits of UODs for all the three variables i.e. Pe, Qe, and Vt, are chosen equal to 3, and hence the normalization or scaling factors Kp, Kv, and Kv are obtained as follows:

Kp= 1.5, Kq= 2.2015, Kv= 2.7273 (5)

Step3: Training of NFS network

The NFS is designed 3 Gaussian linguistic variables for all the three input signals. ANFIS Function of the Fuzzy Logic Toolbox of MATLAB software is used for training. Initializing the MFs are uniformly distributed and consequent parameters of the rule base are set to zero. The initial values of ci and si for MFs are selected using the following equations
C_i = lower value of UOD

$$C_i = a^{-1} + \frac{\text{upper value of uod} - \text{lower value of uod}}{(\text{number of MF} - 1)} \qquad (6)$$

$$a = \frac{1}{\sqrt{2\log(2)}} \times \left[\frac{upper\ value\ of\ uod - lower\ value\ of\ uod}{2(number\ of\ MF - 1)}\right] \qquad (7)$$

An equal value of s is assumed for all MFs of a variable. The NFS starts learning from zero and output during the training gradually learns to perform the desired function.
C. Dynamic performance of the system with IDIPSS
The dynamic performance of the system is obtained for the following three widely different loading conditions:
1. Nominal loading condition
2. Heavy loading condition (the loads are increased by 20 % from their nominal values).
3. Light loading condition (the loads are decreased by 20% from their nominal values)

A perturbation (i.e., step increase in VEf) is given at t = 0.1 sec. Examining the responses for $\Delta\omega_{13}$, and $\Delta\omega_{12}$, considering for ΔV_{ref3} = 0.05 p.u. with IDIPSS and conventional optimum DIPSS at nominal loading condition, it can be concluded that the IDIPSS provide slightly improved dynamic performance as compared to the one obtained with conventional optimum DIPS (responses are not shown because of 'space constraints). Figs. 6, 7 show the responses for $\Delta\omega_{13}$and $\Delta\omega_{12}$ at heavy loading condition considering ΔV_{ref3} = 0.05 p.u. with intelligent dual input PSS and conventional DIPSS (optimized at nominal loading condition).

VI. SIMULATION AND RESULT

In this section, the development of the Simulink model for the multi – machine infinite bus power system with and without the stabilizer is presented. The entire system modeled in Simulink is a closed loop feedback control system of the plants, controllers, comparators, feedback systems, the multiplexer, de – multiplexer, integrators, state

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– space models, sub – systems, transformers, the output sinks (scopes) and the input sources. The simulation model of the MMIB power system with HLA – PSS. It consists of gain block, signal washout block and lead – lag compensator.

The lower limit and upper limit of the UOD parameter ranges are given in m – file. The Simulink models are called in main m – file and by running m – file we get optimized values of the parameters. The electromechanical modes and the damping ratios obtained for different conditions, both with and without proposing stabilizers in the system are given in Table 2.

Modes	Eigenvalues	Frequency of the oscillatory modes (Hz)	ξ of the oscillatory modes
1,2	0.1310 ±j 3.6899	0.5873	-0.0355
3,4	-4.3109 ±j 0.4592	0.0731	0.9944
5,6	-5.0583 ±j 1.4179	0.2257	0.9629

Table. 1 Eigenvalues, damping ratios, and frequency of the oscillatory modes of multi-machine infinite bus system

S.No	Operating conditions	WITHOUT PSS	PSS	HLA – PSS
1	P=1, Q=0.1 and ΔP_d=0.01p.u	0.2966 ± 4.8628i	-0.0465 ± 4.8489i	-1.1551 ± 4.3497i
2	P=1, Q=0.1 and ΔP_d=0.02p.u, 20% increase in M and Tdo1	0.2803 ± 4.6255i	-0.0296 ± 4.6273i	-1.0970 ± 4.1349i
3	P=0.9, Q=0.15, and ΔP_d=0.015p.u, 20% increase in exciter gain and time constant	0.2302 ± 4.8184i	-0.0590 ± 4.7997i	-1.1966 ± 4.2590i

Table. 2. Closed loop Eigenvalues of without PSS, CPSS, and HLA-based PSS

The simulation results show that applying a hybrid learning algorithm based PSS signal, it greatly enhances the damping of low-frequency oscillations and the system becomes stable. Moreover, it can be seen that electromechanical mode controllability via HLA algorithm based PSS is higher than PSS. Table 3 show the percentage of settling time in dynamic response for speed deviation and power angle deviation. The simulation results under disturbance for various operating conditions are presented in Figure 4 to 6.

S. No	Operating conditions	PSS [Ks1, T1, T2]	HLA – PSS [Ks1, T1, T2]
1	P=1, Q=0.1 and ΔP_d=0.01p.u	7.2286 0.6287 0.1	1.20 1.05 0.12
2	P=1, Q=0.1 and ΔP_d=0.02p.u, 20% increase in M and Tdo1	7.5877 0.6714 0.10	1.3865 0.967 0.125
3	P=0.9, Q=0.15, and ΔP_d=0.015p.u, 20% increase in exciter gain and time constant	8.6290 0.5334 0.1	1.2082 0.888 0.12

Table. 3. Optimal parameters of the stabilizer

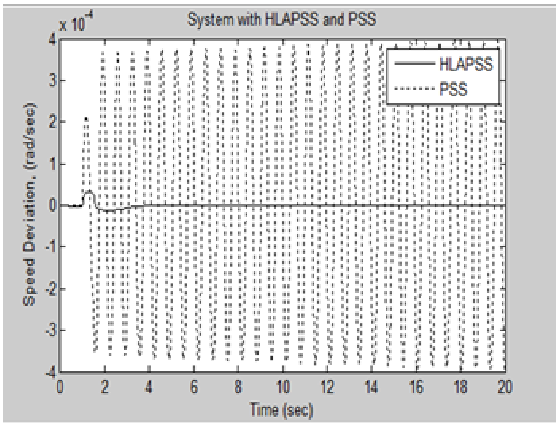

Fig. 4. System with HLA – PSS and PSS in speed deviation of P=1, Q=0.1, and Pd=0.02p.u, 20% increase in M and Tdo1

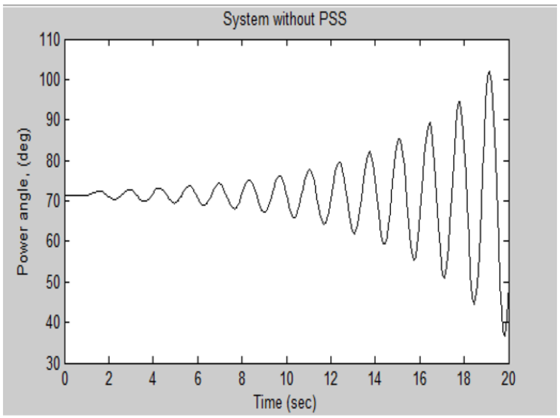

Fig. 5. System without PSS in Power angle of P=1, Q=0.1 and ΔPd=0.01p.u

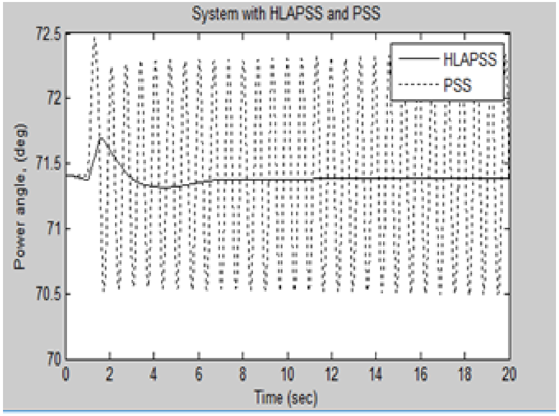

Fig. 6. System with HLA – PSS and PSS in Power angle of P=0.9, Q=0.15, and ΔPd=0.015p.u, 20% increase in exciter gain and time constant

It is clearly seen that the system becomes unstable with conventional DIPSS while the system responses are well damped with the IDIPSS.

VII. CONCLUSION

In this project, stability scrutiny, performance improvement by a PSS has been investigated. The stabilizers are tuned to simultaneously shift the undamped electromechanical modes of the machine to a prescribed zone. The design problem of the controller is converted into an optimization problem which is solved by a Hybrid Learning technique with the eigenvalue-based objective function. A multi – machine infinite bus power system installed with a PSS with disturbance has been assumed to demonstrate the ability of HLA-PSS instability enhancement via low-frequency oscillation damping. The eigenvalue analysis and non-linear time domain simulation results show that when there is a small perturbance in the power system, the proposed HLA-based PSS is effectively damping the oscillations.

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