TUNING OF A FUZZY LOGIC POWER SYSTEM STABILIZER USING GENETIC ALGORITHMS

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Abstract – A Hybrid Power System Stabilizer (HPSS) is presented in this paper. The proposed approach uses genetic algorithms (GA) to search for optimal or near optimal settings of fuzzy logic power system stabilizer (FLPSS) parameters. Incorporation of GA in FLPSSs design will add an intelligent dimension to these stabilizers and significantly reduce the time consumed in the design process. It is shown in this paper that the performance of FLPSS can be improved significantly by incorporating a genetic-based learning mechanism. The performance of the proposed HPSS under different disturbances and loading conditions is investigated. The results show the superiority and robustness of the proposed HPSS as compared to classical PSS and its capability to enhance system damping over a wide range of loading conditions.

1. INTRODUCTION

Due to increasing complexity of electrical power systems, there has been increasing interest in the stabilization of such systems. In the past two decades, the utilization of supplementary excitation control signals for improving the dynamic stability of power systems and damping out the low frequency oscillations due to disturbances has received much attention [1-4]. Nowadays, the conventional power system stabilizer (CPSS) - a fixed parameters lead-lag compensator - is widely used by power system utilities [3]. The gain settings of these stabilizers 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. Therefore, CPSS performance is degraded whenever the operating point changes from one to another because of fixed parameters of the stabilizer.

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, fuzzy logic power system stabilizers (FLPSSs) have been proposed [7-9]. FLPSSs appear to be the most suitable stabilizers due to their lower computation burden and robustness. Unlike the most classical methods, an explicit mathematical model of the system is not required to design a good FLPSS which makes it more suitable for on-line computer control. In addition, FLPSS can be easily set up using microcomputer with A/D and D/A converters [10].

Although fuzzy logic controllers showed promising results, they are subjective and somewhat heuristic. In addition, generation of membership functions, and the choice of scaling factors are done either iteratively, by trial-and-error, or by human experts. There is to-date no generalized method for the formulation of fuzzy control strategies, and design remains an ad hoc trial and error exercise. That makes the design of fuzzy logic controller a laborious and time-consuming task.

On the other hand, genetic algorithms (GA) are search algorithms based on the mechanics of natural selection and survival-of-the-fittest. The principles of GA were first introduced by Holland in his pioneering work in the theoretical development and adaptation in natural and artificial systems [11]. Recently, GA have been applied to various power system problems with promising results [12-14].

The recent approach is to integrate the use of GA and fuzzy logic systems in order to combine their different strengths and overcome each other's weaknesses [15-16]. In this paper, we use this approach to propose a hybrid power system stabilizer (HPSS). The proposed HPSS uses GA to search for optimal settings of FLPSS parameters. It is shown in this paper that the performance of FLPSS can be improved by incorporating a genetic-based learning mechanism.

2. GENETIC ALGORITHMS

GA are exploratory search and optimization procedures that were devised on the principles of natural evolution and population genetics. Unlike other optimization techniques, GA work with a population of individuals represented by bit strings and modify the

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population with random search and competition. The advantages of GA over other traditional optimization techniques can be summarized as follows:

- GA work on a coding of the parameters to be optimized, rather than the parameters themselves.
- GA search the problem space using a population of trials representing possible solutions to the problem, not a single point, i.e. GA have implicit parallelism. This property ensures GA to be less susceptible to getting trapped on local minima.
- GA use a performance index assessment to guide the search in the problem space.
- GA use probabilistic rules to make decisions.

Typically, the GA starts with little or no knowledge of the correct solution depending entirely on responses from interacting environment and their evolution operators to arrive at optimal or near optimal solutions. In general, GA include operations such as reproduction, crossover, and mutation. Reproduction is a process in which a new generation of population is formed by selecting the fittest individuals in the current population. Crossover is the most dominant operator in GA. It is responsible for producing new offsprings by selecting two strings and exchanging portions of their structures. The new offsprings may replace the weaker individuals in the population. Mutation is a local operator which is applied with a very low probability. Its function is to alter the value of a random position in a string.

3. FUZZY LOGIC CONTROL SCHEME

A single machine infinite bus system shown in Fig. 1 is considered. The system model and parameters are given in Appendix. The stabilizing signal u is added to the excitation loop as shown in Fig. 1. At time t, $u(t)$ is given by

$$u(t) = U(k) \qquad ; kT_s < t < (k+1)T_s \tag{1}$$

The value of $U(k)$ is determined at each sampling time based on fuzzy logic through the following steps:

Step 1: The speed deviation, $\Delta\omega(k)$, is measured at every sampling time, and the acceleration of the machine, $A(k)$, is calculated by

$$A(k) = [\, \Delta\omega(k) - \Delta\omega(k-1)\,] \,/\, T_s \tag{2}$$

Step 2: Compute the scaled acceleration, $A_s(k)$, using

$$A_s(k) = A(k) * F_a \tag{3}$$

Step 3: The generator condition is given by the point $C(k)$ where

$$C(k) = (\, \Delta\omega(k)\, ,\, A_s(k)\,) \tag{4}$$

Step 4: Calculate $R(k)$ and $\theta(k)$ using

$$R(k) = |\, C(k)\, | \tag{5}$$

and,

$$\theta(k) = \tan^{-1}(\, A_s(k) \,/\, \Delta\omega(k)\,) \tag{6}$$

Step 5: Compute the values of membership functions $N_s(\theta)$ and $P_s(\theta)$ defined as [7]

$$N_s(\theta) = \begin{cases} 1 - \Phi(x;\theta_i, \theta_{m1}, \theta_m)\, \forall x \le \theta_m \\ \Phi(x;\theta_m, \theta_{m2}, 2\pi)\, \forall x > \theta_m \end{cases} \tag{7}$$

and,

$$P_s(\theta) = \Psi(\, \theta, 2\pi - \theta_i, \theta_m\,) \tag{8}$$

where

$$\Phi(x;a,b,c) = \begin{cases} 0.0 \;\forall\; x \le a \\ 2[\frac{x-a}{c-a}]^2 \;\forall\; x \in\,]a,b] \\ 1 - 2[\frac{x-c}{c-a}]^2 \;\forall\; x \in\,]b,c[\\ 1.0 \;\forall\; x \ge c \end{cases} \tag{9}$$

$$\Psi(x;b,c) = \begin{cases} \Phi(x;c-b, c-b/2, c)\; \forall x \le c \\ 1 - \Phi(x;c, c+b/2, c+b)\; \forall x > c \end{cases} \tag{10}$$

$$\theta_m = (\, 2\pi + \theta_i\,) \,/\, 2 \tag{11}$$

$$\theta_{m1} = (\, \theta_i + \theta_m\,) \,/\, 2 \tag{12}$$

$$\theta_{m2} = (\, 2\pi + \theta_m\,) \,/\, 2 \tag{13}$$

It is worth mentioning that these continuous nonlinear membership functions are more suitable for power system stability problem [7].

Step 6: Determine the value of the gain function $G_c(k)$ defined as [8]

$$G_c(k) = \begin{cases} R(k) \,/\, D_r \;\forall R(k) \le D_r \\ 1.0 \;\forall R(k) > D_r \end{cases} \tag{14}$$

Step 7: Compute the stabilizing signal $U(k)$ using

$$U(k) = G_c(k)\, [\, N_s(\theta) - P_s(\theta)\,]\, U_{max} \tag{15}$$

Step 8: Increase k by 1 and return to step 1.

The main tuning parameters of FLPSS are θ_i, F_a, and D_r. For the optimal settings of these parameters, a quadratic performance index J is considered:

$$J = \sum_{k=1}^{L} [kT_s \Delta\omega(k)]^2 \tag{16}$$

In the above index, the speed deviation $\Delta\omega(k)$ is weighted by the respective time kT_s. The index J is selected because it reflects small settling time, small steady state error, and small overshoots. The tuning parameters are adjusted so as to minimize the index J.

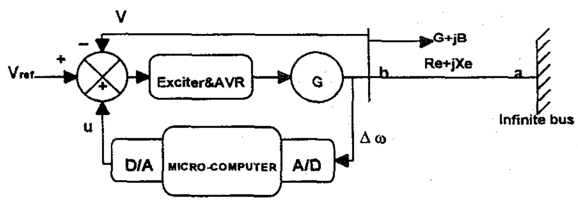

Fig. 1: Study system configuration.

4. THE PROPOSED HYBRID STABILIZER

Applying the GA to the problem of PSS design involves performing the following two steps.

1. The performance index value must be calculated for each of the strings in the current population. To do this, the tuning parameters must be decoded from each string in the population and the system is simulated to obtain the performance index value.
2. GA operations are applied to produce the next generation of the strings.

These two steps are repeated from generation to generation until the population has converged producing an optimal or near optimal parameter set.

The tuning parameters are coded in a binary string. The initial population is generated randomly. Population size, maximum number of generations, and crossover and mutation probabilities are chosen to be 60, 60, 0.75, and 0.001 respectively. Three operating points are used in the simulations to cover a wide range of operating conditions. They are (P_1,Q_1)=(1.1 pu, 0.4 pu), (P_2,Q_2)=(0.4 pu, 0.2 pu), and (P_3,Q_3)=(0.7 pu, -0.2 pu). The final values of the tuning parameters optimized at all operating points considered are given in Table 1. Fig. 2 shows the convergence rate of the performance index J for the operating point (P_1,Q_1).

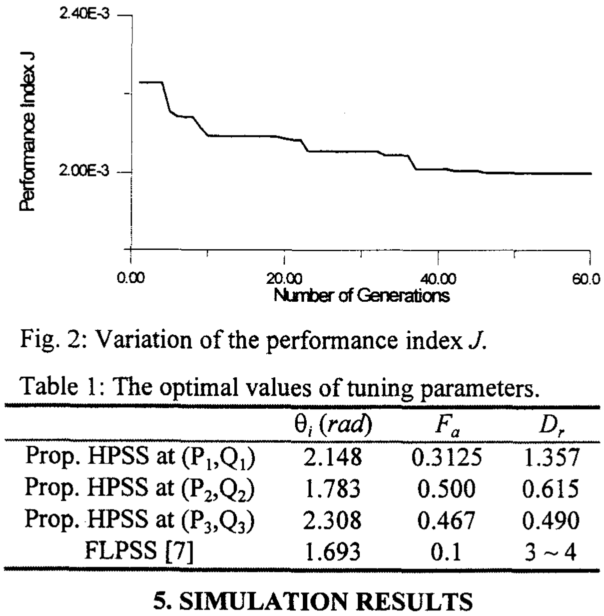

Fig. 2: Variation of the performance index J.

Table 1: The optimal values of tuning parameters.

	θ_i *(rad)*	F_a	D_r
Prop. HPSS at (P_1,Q_1)	2.148	0.3125	1.357
Prop. HPSS at (P_2,Q_2)	1.783	0.500	0.615
Prop. HPSS at (P_3,Q_3)	2.308	0.467	0.490
FLPSS [7]	1.693	0.1	3 ~ 4

5. SIMULATION RESULTS

A number of studies have been performed with the proposed HPSS. The performance of the proposed HPSS is compared to those of FLPSS [7] and CPSS [8]. A pulse in the input torque applied from t=1s to t=5s, and a three phase fault at the point 'a' (see Fig. 1) for 0.1s were considered as the disturbances in the following simulations.

5.1 Normal Operating Condition:

A pulse of 10% in input torque and a three phase fault disturbances were applied while the generator loading condition is (P_1,Q_1). Results of the study are shown in Figs. 3 and 4 respectively. It is obvious that, the system with the proposed HPSS returns to its previous operating point much faster. This is very helpful in the improvement of the disturbance tolerance ability of the system.

5.2 Light Load Operating Condition:

In this case, the generator operates in a light load condition specified by (P_2,Q_2). A 30% pulse in input torque and a three phase fault were applied. The results are shown in Figs. 5 and 6 respectively. It can be seen that the proposed HPSS provide very good damping to the system oscillations.

5.3 Leading Power Factor Operating Condition:

A 20% pulse in input torque and a three phase fault disturbances were applied while the generator loading condition is (P_3,Q_3). The simulation results are shown in Figs. 7 and 8 respectively. It can be concluded that the performance of the proposed HPSS is much better and the oscillations are damped out much quicker.

It is worth noting that all simulations above were carried out using the proposed HPSS with the tuning parameters optimized at operating point (P_1, Q_1). This indicates that although the proposed HPSS parameters are optimized at a single operating point, it can provide good damping to the system oscillations over a wide range of operating conditions.

5.4 Robustness of the Proposed HPSS:

With the operating point (P_1,Q_1), a 10% pulse in input torque and three phase fault were applied to the proposed HPSS with the three different settings of the tuning parameters given in Table 1. The simulation results are shown in Figs. 9 and 10 respectively. The results verify the robustness of the proposed HPSS and its ability to enhance the system damping.

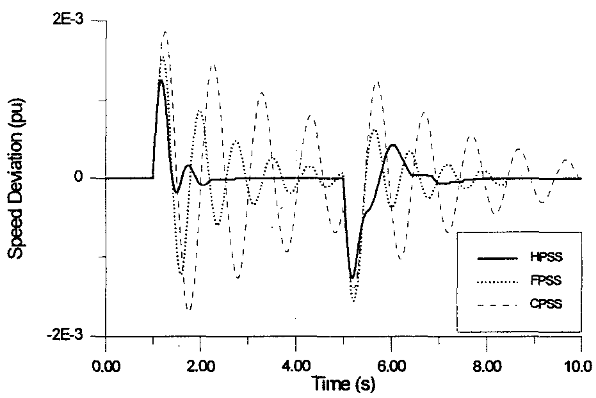

Fig. 3: Response to 10% pulse in torque for (P_1,Q_1).

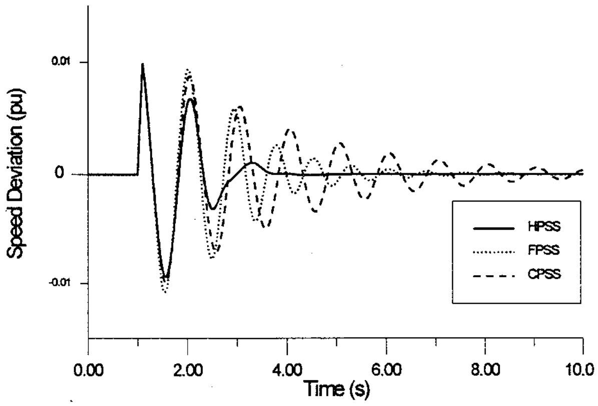

Fig. 4: Response to a three phase fault for (P_1,Q_1).

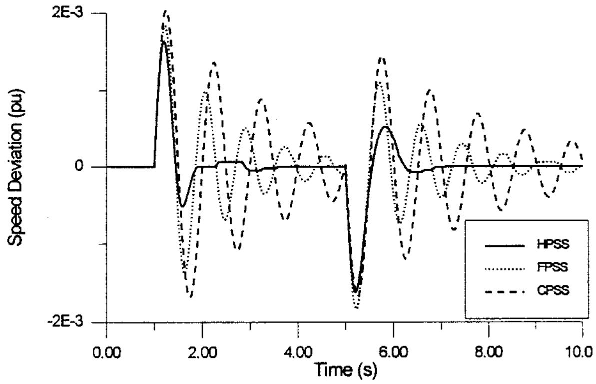

Fig. 5: Response to 30% pulse in torque for (P_2,Q_2).

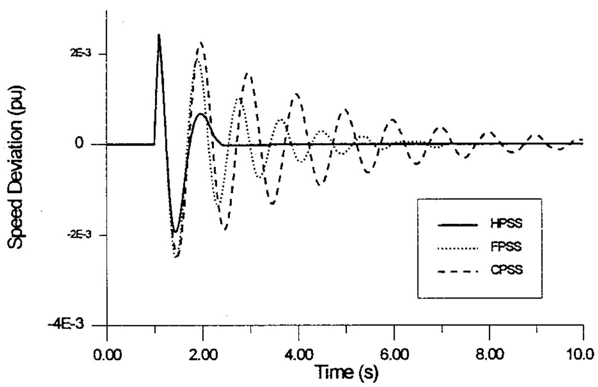

Fig. 6: Response to a three phase fault for (P_2,Q_2).

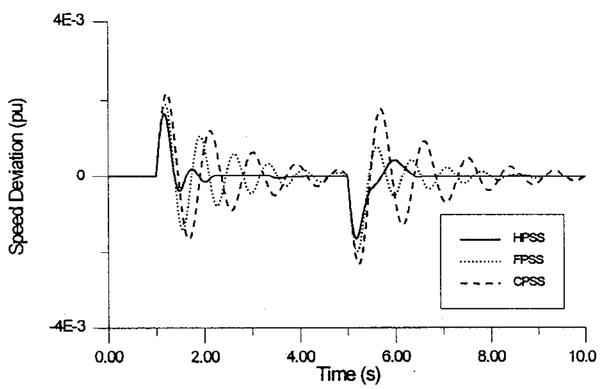

Fig. 7: Response to 20% pulse in torque for (P_3,Q_3).

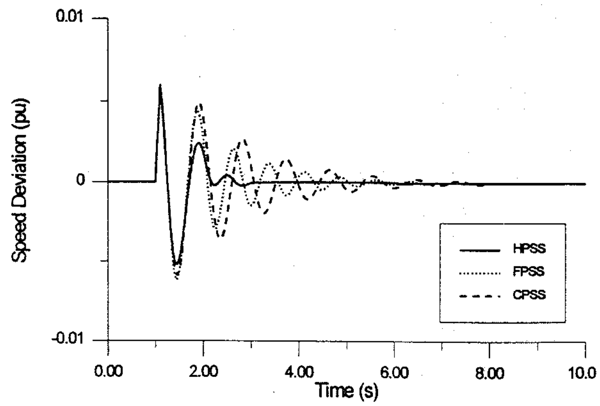

Fig. 8: Response to three phase fault for (P_3,Q_3).

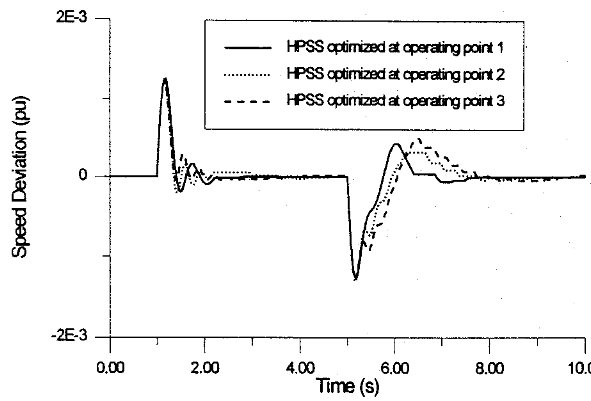

Fig. 9: Response to 10% pulse in torque for (P_1,Q_1).

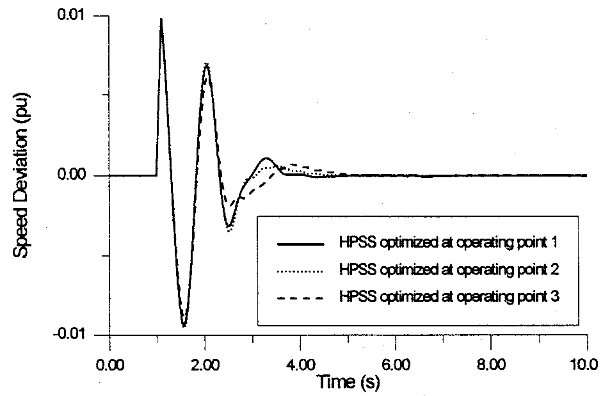

Fig. 10: Response to three phase fault for (P_1,Q_1).

6. CONCLUSION

In this study, a hybrid power system stabilizer is introduced. The proposed HPSS was designed by incorporation of GA to search for optimal settings of FLPSS tuning parameters. The simulation results show that the performance of FLPSS can be improved significantly by incorporating a genetic-based learning mechanism. It is shown that the proposed HPSS can provide good damping characteristics during transient conditions. In addition, the robustness of the proposed HPSS is demonstrated.

7. ACKNOWLEDGMENT

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9. APPENDIX

<u>System Model:</u>

$$\dot{\delta} = \omega_b(\omega - 1) \qquad (A.1)$$

$$\dot{\omega} = (T_m - T_e - D(\omega - 1)) / M \qquad (A.2)$$

$$\dot{E}'_q = (E_{fd} - (x_d - x'_d)i_d - E'_q) / T'_{do} \qquad (A.3)$$

$$\dot{E}_{fd} = (K_a(V_{ref} - V + U_c) - E_{fd}) / T_a \qquad (A.4)$$

$$V_d = V_b \sin\delta + R_e i_d - X_e i_q \qquad (A.5)$$

$$V_q = V_b \cos\delta + R_e i_q + X_e i_d \qquad (A.6)$$

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

$$T_e = E'_q i_q - (x'_d - x_q) i_d i_q \qquad (A.8)$$

<u>Parameters:</u>

M=9.26s, w_b=377rad/s, x_d=0.973, x_q=0.55, x'_d =0.19, R_e=0.03, X_e=0.6, D=0.01, T'_{do} =7.76, T_a=0.1, K_a=50, G=0.2, B=-0.1, $|E_{fd}| \leq 7.3$ pu, $|U| \leq 0.12$ pu.

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

NOMENCLATURE

δ	torque angle
$\omega, \Delta\omega$	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	transmission line resistance and reactance respectively
x_d, x_q	synchronous reactances in *d* and *q* axes
G,B	load conductance and susceptance respectively
x'_d	*d*-axis transient reactance
T'_{do}	time constant of excitation circuit
T_m, T_e	mechanical torque and electric torque respectively
K_a, T_a	regulator gain and time constant respectively
U	PSS control signal
T_s	sampling time
k	an integer
A, A_s	acceleration and scaled acceleration respectively
U_{max}	maximum value of the stabilizing signal
F_a	acceleration scaling factor
L	total data number
P_i, Q_i	active and reactive power at *i*th loading respectively