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Power System Stability Enhancement Through Optimal Design of PSS Employing PSO

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***Abstract*—Interconnected power systems are critically vulnerable to instability due to the disturbances in any one portion of the system. Even low-frequency oscillations and small disturbances may lead to an outage of the system. Properly tuned Power System Stabilizer (PSS) is an effective tool for the suppression of these oscillations. This paper proposes a novel approach to tune proportional-integral (PI), proportional-integral-derivative (PID) and lead-lag PSS for a single machine infinite bus (SMIB) network by using particle swarm optimization (PSO) to damp out low-frequency oscillations (LFOs). The effectiveness of PSO tuned PSS is investigated by comparing the simulation results with fixed gain conventional PSS. In addition, the eigenvalues and minimum damping ratios of the same network are compared with referenced work employing backtracking search algorithm (BSA) which provides confidence on the proposed approach.**

Keywords*—Eigenvalues; Low-frequency oscillations; Minimum damping ratio; Particle swarm optimization; Power system stabilizers; Single machine infinite bus.

I. Nomenclature

δ, ω = Machine's rotor angle and angular frequency
e_q', ΔE_{fd} = Generator's internal voltage and field excitation
P_m, P_e = Input mechanical and output electrical powers
P_D, M= System damping coefficient, and inertia coefficient
ω_o= Base angular frequency, u_{PSS} = Control input
i_d ,i_q = Direct and quadrature axes currents
v_d ,v_q = Direct and quadrature axes voltages
v_t, v_{tr} = Terminal and reference voltages
x_d, x_q = Direct and quadrature axes reactance
x_d', x_q' = Direct and quadrature axes transient reactance
T_w, T_A= Washout block's and excitation system's time constants
T_{do}'= Open circuit field time constant
K_1-K_6 = Fourth order model constants
K_C, K_A = Lead-lag controller's and excitation system's gains
T_1, T_2= Time constants for lead-lag controller
K_p, K_i, K_d = Proportional, integral and differential gains of the PI/PID controller

II. Introduction

Modern power systems are large interconnected systems of many power stations with complex transmission and distribution system and they are getting more sophisticated day by day through tremendous expansion with a view to meeting the ever-increasing demand for electricity. The stability of power system is of utmost importance for a reliable supply of power to the consumer. The term 'stability' for a power system is defined by the system's capability to bring back its operation to stable state within smallest amount of possible time after being subjected to some sort of transience or disturbance in the system [1]–[5]. Small signal stability is one of the prime stability problem faced by the synchronous machines of the electric network which causes LFOs due to disturbances. Two types of system oscillation are found in power systems which are inter-area mode oscillation and local mode oscillation where in inter-area mode oscillation, generators of one area are affected by the swinging of generators from other areas whereas local mode refers to swinging of generators in one particular area with respect to each other[4]. The use of high gain automatic voltage regulator (AVR) with synchronous generators to maintain constant voltage, sometimes decreases rotor damping torque and generates LFOs[6]. If these oscillations sustain for a longer period it may reduce the power transfer capability of the system even may lead towards network outage if no adequate damping is available [7]. So it is crucial for the power system to damp out these oscillations to maintain synchronism of the generators during disturbances [8]. Power System Stabilizers (PSS) can damp out these LFOs by generating a supplementary control signal for the generator excitation system. PSS works based on the principle of phase compensation technique and its performance to damp out the LFOs depends on the proper tuning of its crucial parameters [9].

A huge number of intelligent techniques generally based on evolutionary and swarm intelligence approaches have been found in the recent literature to design PSS to damp the small signal oscillations. Among those techniques, genetic algorithm [10], [11], bat search algorithm[12], bacterial foraging algorithm [13], backtracking search algorithm [14]–[16], artificial bee colonies [17], neural network [18], and support vector regression [19]are widely used to tune the parameters in power industry. For this purposes, industries also use some conventional techniques like fixed gain PSS but due to the better performances and robustness heuristic optimization techniques, these are getting more attention over conventional techniques but most of the heuristic techniques are exhaustive and does not guarantee the exactly optimized solution rather better solution with respect to others, so there is a chance to be trapped in local minima or to be converged in a premature stage. However, Eberhart and Kennedy developed a population based effective and diversified stochastic optimization approach called particle swarm optimization (PSO) which is inspired by social behavior of fish schooling or bird flocking [20]. PSO does not get trapped in local optima and can

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successfully figure out the global optimal solution. Consequently, it has been employed to solve many engineering problems including multi-objective optimization problem [21], optimal placement of phasor measurement units [22], distributed energy resources allocation [23], optimal reactive power dispatch[24], in power system networks.

In this paper, a swarm based intelligent technique called PSO is employed to tune the parameters of PSS. The performance of the PSO tuned PSS in damping out the LFOs in a single machine infinite bus (SMIB) network is compared with the results obtained from conventional fixed gain PSS. Moreover, the minimum damping ratio and eigenvalues of PSO tuned network are compared with the referenced work which employed another heuristic optimization approach called backtracking search algorithm (BSA).

III. POWER SYSTEM MODELING

A SMIB system has been considered which is comprised of a synchronous generator equipped with PSS, a local load as shown in the Fig. 1. A transmission line connects the generator to an infinite bus that represents the rest of the power system and the voltage magnitude and frequency of that bus remain constant.

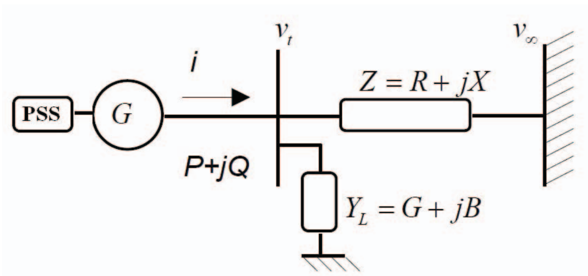

Fig.1 Single machine infinite bus system with PSS

In SMIB system the synchronous generator considered is of fourth order model which has Institute of Electrical and Electronics Engineers (IEEE)standard type excitation system as given below[1]–[4]:

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

$$\dot{\omega} = \frac{1}{M}(P_m - P_e - P_D) \tag{2}$$

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

$$\dot{E_{fd}} = \frac{1}{T_E}\left[K_A(v_{tr} - v_t + u_{PSS}) - E_{fd}\right] \tag{4}$$

The terminal voltage and the output power of the generator can be expressed in terms of the direct and quadrature axes quantities i.e. currents and voltages as given in the following equations.

$$v_t = v_d + jv_q \tag{5}$$

$$P_e = v_d i_d + v_q i_q \tag{6}$$

Where, the direct and quadrature axes voltages can be expressed with the following equations.

$$v_d = x_q' i_q \tag{7}$$

$$v_q = -x_d' i_d + e_q' \tag{8}$$

The Linearized model of the SMIB network is taken from [2] where the interaction among the variables is represented with six constants (K_1-K_6). The Linearized representation of the system of Fig.1 are as follows:

$$\Delta\dot{\delta} = \omega_b \Delta\omega \tag{9}$$

$$\Delta\dot{\omega} = -\frac{K_1}{M}\Delta\delta - \frac{D}{M}\Delta\omega - \frac{K_2}{M}\Delta e_q' \tag{10}$$

$$\Delta\dot{e_q'} = -\frac{K_4}{T_{do}'}\Delta\delta - \frac{1}{K_3 T_{do}'}\Delta e_q' + \frac{1}{T_{do}'}\Delta E_{fd} \tag{11}$$

$$\Delta\dot{E}_{fd} = -\frac{K_A K_5}{T_A}\Delta\delta - \frac{K_A K_6}{T_A}\Delta e_q' - \frac{1}{T_A}\Delta E_{fd} + \frac{K_A}{T_A}u_{pss} \tag{12}$$

IV. POWER SYSTEM STABILIZER

Figs. 2 to 4 show proportional-integral (PI), proportional-integral-derivative (PID) and lead-lag controller based PSS respectively. Here the PSSs take the change in generator angular frequency ($\Delta\omega$) as the inputs and return back control signals (u_{PSS}) as outputs. The washout/rest blocks deactivate the controller during steady state operation of the power system and the limiter blocks limit the amplitude of the control signals. The states vectors obtained for the SMIB system after connecting the PSS are $\Delta\delta, \Delta\omega, \Delta e_q', \Delta E_{fd}, x_5$ and u_{pss}.

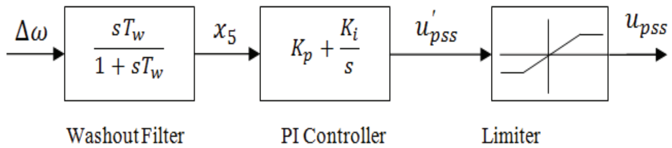

Fig. 2 Structure of PI-PSS

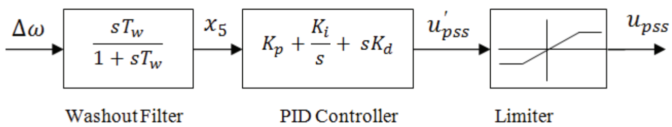

Fig. 3 Structure of PID-PSS

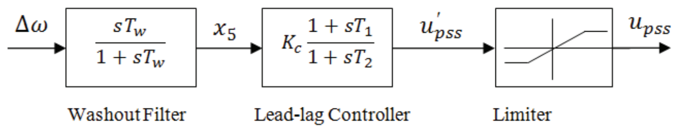

Fig. 4 Structure of lead-lag PSS

The detail state space model of the single machine infinite bus (SMIB) power network with PI, PID and lead-lag controller based PSS can be found in [15]. In addition, the associated parameters values were taken from references [14], [15].

V. PROPOSED OPTIMIZATION PROBLEM

To enhance the overall damping of the electric network, the objective function of the optimization problem can be formulated by aiming to maximize the minimum damping ratio as given below:

$$J = \text{maximize } (\zeta) \quad (13)$$

where ζ is the minimum damping ratio obtained from eigenvalues of one set of population. The value of the damping ratio can be calculated from the real part (σ) and imaginary part (ω) of the eigenvalues as follows:

$$\zeta = -\frac{\sigma}{\sqrt{\sigma^2 + \omega^2}} \quad (14)$$

The eigenvalues are calculated from the system matrix obtained from equations (9) -(12) as well as augmented system equations coming from the structure of the PSS used.

However, the design problem of PI controller based PSS has the following constraints

$$K_{pmin} \le K_p \le K_{pmax}$$
$$K_{imin} \le K_i \le K_{imax}$$

The design problem of PID controller based PSS has the following constraints

$$K_{pmin} \le K_p \le K_{pmax}$$
$$K_{imin} \le K_i \le K_{imax}$$
$$K_{dmin} \le K_d \le K_{dmax}$$

The design problem of lead-lag controller based PSS has the following constraints

$$K_{cmin} \le K_c \le K_{cmax}$$
$$T_{1min} \le T_1 \le T_{1max}$$
$$T_{2min} \le T_2 \le T_{2max}$$

The parameters of the constraints presented above are optimized through backtracking search algorithm.

VI. PARTICLE SWARM OPTIMIZATION (PSO)

Initially, PSO starts with a population of random solutions and then searches for global optimal solution though continuous upgradation of populations. The following parts of this section briefly demonstrate the steps of PSO technique [21]–[25]:

Step a: Initialization

PSO generates random positions and velocities for the particles from the search spaces by using the following equations.

$$x_{i,j} = U\left(x_j^{min}, x_j^{max}\right); \quad \forall\, i \,\&\, j \quad (15)$$
$$v_{i,j} = U\left(v_j^{min}, v_j^{max}\right); \quad \forall\, i \,\&\, j \quad (16)$$

Where, i and j are the size of the particles and the dimension of the problem, respectively. U is the uniform distribution, x^{min} and x^{max} represent the lower and upper boundaries of the constraints parameters. The minimum and maximum values of velocities for each particle are determined by using the following equations:

$$v_j^{max} = \frac{x_j^{max} - x_j^{min}}{NN} \text{ and } \quad v_j^{min} = -v_j^{max} \quad (17)$$

Where, NN=10 has been selected for this paper through a systematic trial and error method.

Step b: Fitness test and storing/updating the best solution

The fitness of all particles are evaluated and based on fitness the individual and global best positions are updated and stored and finally, the global best position is chosen as the optimal solution.

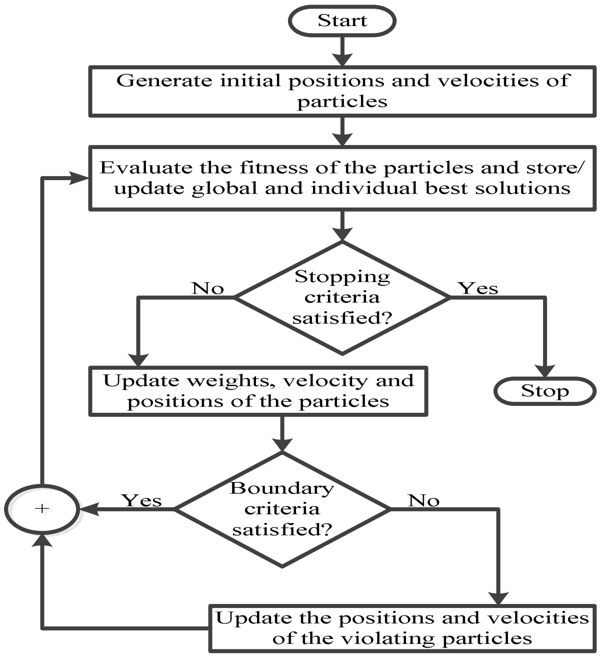

Fig. 5 Flowchart of particle swarm optimization (PSO)

Step c: Weight, velocity and position updating

To update the weight, velocity, and positions of the particles the following formulas have been used. If the positions and the velocities of the particles violate their minimum or maximum limits, then they are set to the minimum or maximum values, respectively.

$$w(t) = \alpha w(t-1) \quad (18)$$

$$v_{i,j}(t) = w(t)\, v_{i,j}(t-1) + c_1 r_1 [x_{i,j}^{*}(t-1) - x_{i,j}(t-1)] + c_2 r_2 [x_{i,j}^{**}(t-1) - x_{i,j}(t-1)] \quad (19)$$

$$x_{i,j}(t) = v_{i,j}(t) + x_{i,j}(t-1) \quad (20)$$

Where c_1=c_2=2, α =0.99 are chosen for this paper and r_1, r_2 are random numbers in [0, 1] based on the references [21]–[25] and through systematic trial and error basis.

Additionally, $x_{i,j}^{*}(t-1)$ =local best position and $x_{i,j}^{**}(t-1)$ = global best position of generation (t-1).

Step d: Checking the termination criteria

To avoid premature convergence, termination criteria is started checking after 230 generations and if the objective functions remain same for another 270 generations or the program reaches its pre-specified maximum number of generations, the program stops generating further positions and velocities for particles and eventually terminates the algorithm. The Fig. 5 provides the complete flowchart of particle swarm optimization approach.

VII. SIMULATION RESULTS AND DISCUSSIONS

A. Eigenvalues and minimum damping ratio analyses

Fig. 6 shows the variations of the objective function (minimum damping ratio) for seven different runs with respect to a pre-specified number of iterations while optimizing lead-lag controller based PSS. The graph provides the confidence on the proposed PSO approach as each run stops at a certain value (~0.6966) of the objective function. Consequently, it can be concluded that despite initial population, the PSO was able to find out the global optimal solution which ensures the robustness of the proposed approach. However, the variations of objective functions for PI and PID controller based PSS are not presented for brevity's sake.

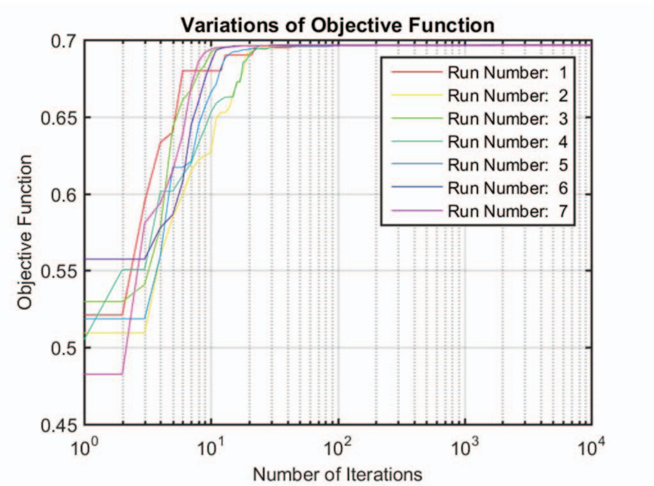

Fig. 6 Variations of objective function for seven different runs

Table I. Damping ratio and eigenvalues for without PSS and PI-PSS

Item	Fourth Order Linear Model (No PSS)	Proposed PI controller based PSS	PI PSS of Ref. [15]
Minimum Damping Ratio	-0.0594	0.5262	0.5262
Eigenvalues	0.2951 ± j4.9596	-1.8226 ± j1.1023	-1.82257 ± j1.10234
	-10.3930 ± j3.2837	-2.1829 ± j3.5278	-2.18296 ± j3.52788
	--	-3.84e-14	-1.23e-14
	--	-12.5179	-12.518

The eigenvalues with a minimum damping ratio of the linearized model without PSS and with different types of controller based PSS tuned with PSO are summarized in Tables I and II. In addition, the obtained results of referenced work employing BSA for the same network and parameters are also included in Table I and Table II. The proposed PSO and referenced BSA approaches ended up with exactly same minimum damping ratio for the PI controller based PSS as can be seen from the Table I and the achieved damping ratio is very high compared to the system without PSS. As can be observed from Table II, the achieved minimum damping ratio for PID controller based PSS with proposed approach is slightly lower than that of referenced work. However, the proposed PSO approach achieved better minimum damping ratio for the lead-lag controller based PSS over referenced BSA approach.

Table II. Damping ratio and eigenvalues for PID and lead-lag PSS

Item	PID controller based PSS	PID PSS of Ref. [15]	Lead-lag controller based PSS	Lead-lag PSS of Ref. [15]
Minimum Damping Ratio	0.6530	0.6929	0.6966	0.6931
Eigenvalues	-3.3098 ± j3.8392	4.7504 ± j4.9219	-4.9582 ± j5.1068	-4.6302 ± j4.8154
	-6.7781 ± j7.8618	-5.3376 ± j5.5394	-5.0871 ± j5.2396	-5.3937 ± j5.6096
	-3.09e-15	-8.45e-15	-0.3617	-0.361607
	-0.3530	-0.3530	-992.0026	-642.3245

As can be observed from both Tables I & II, the proposed PSO approach achieved the best minimum damping ratio for lead-lag controller based PSS over other controllers and referenced work. Consequently, the performance of the power system network after being subjected to any external disturbances considered only PSO optimized lead-lag controlled based PSS in the following subsection for brevity's sake.

B. Performance of the proposed approach after being subjected to a disturbance

Damping capability of a SIMBelectric network after being subjected to an external disturbance has been analyzed with fixed gain conventional and PSO optimized lead-lag controller based PSS with a view to investigating the superiority of PSO tuned PSS. A 10% pulse input of mechanical torque from 1.0s to 1.1s has been applied and corresponding system responses have been recorded and plotted. PSO tuned PSS witnessed the better performance in time domain simulation than that of fixed gain conventional one. The state variables for the linearized model without any PSS and with fixed gain conventional and PSO tuned lead-lag controller based PSS are displayed in the following graphs.

Fig. 7 shows the behavior of the machine rotor angle for SMIB system. From the Fig.7, it can be depicted that the linear model without any PSS grows beyond the limit and make the system unstable due to the disturbance applied to the electric network. On the other hand, both fixed gain conventional and PSO tuned lead-lag PSS stabilize the system after experiencing the disturbance (accelerating power) but the percentage of overshoot, as well as the settling time for conventional one, is greater than the PSO tuned PSS which illustrate the superiority of PSO tuned PSS over the conventional one. As can be seen from Fig. 8 that both conventional and PSO tuned PSS stabilize the machine angular frequency of the SMIB system after experiencing an external disturbance and the PSO tuned PSS exhibits better and faster response than that of the conventional one.

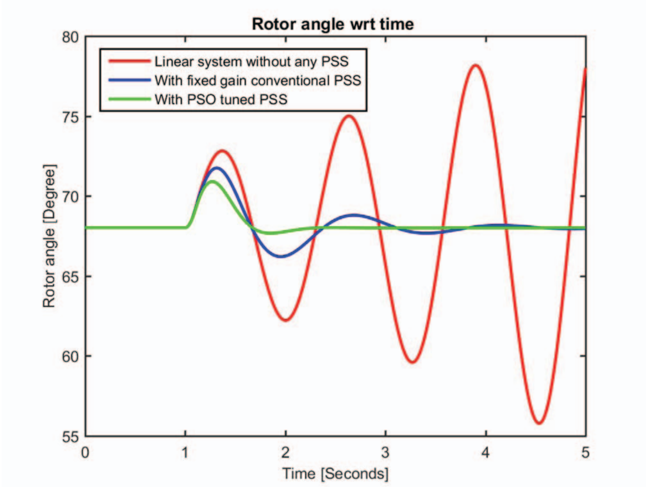

Fig. 7 Rotor angle with respect to time

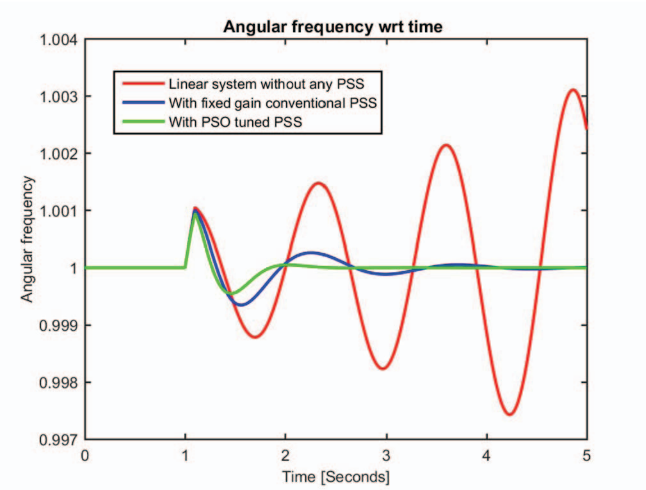

Fig. 8 Angular frequency in pu with respect to time

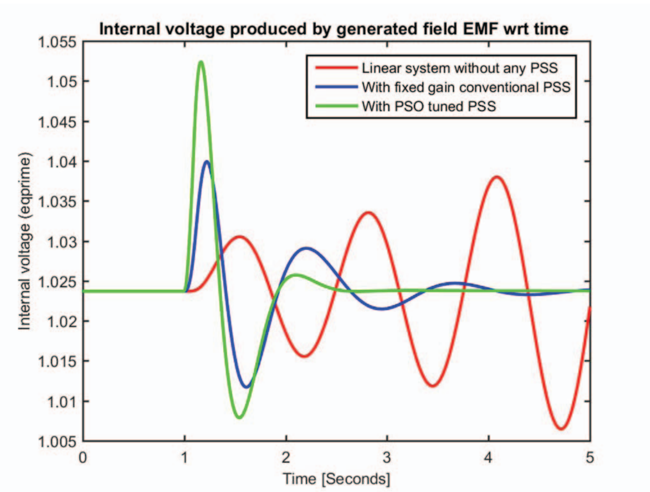

Fig.9 Internal voltage produced by generated field EMF in pu wrt time

The behavior of internal voltage has been presented in Fig.9. In this figure, the percentage of overshoot is greater for the PSO tuned controller whereas the settling time for conventional PSS is higher. If the decision makers are interested in stabilizing the system quickly (lower settling time) then the performance of the PSO based controller is better. Fig.10 shows the control signals for conventional and PSO based PSS. Though the amplitude of the PSO tuned PSS is higher, it settles system oscillations down earlier by maintaining the control signal's amplitude within a pre-specified limit (~ 0.1 pu).

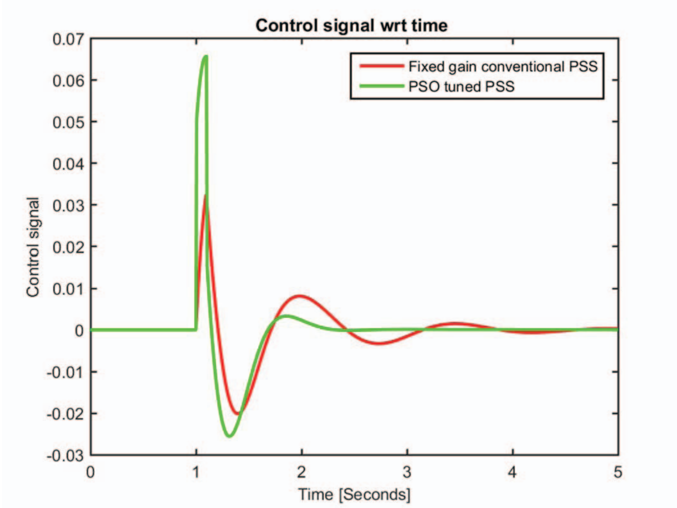

Fig. 10 Control signal in pu with respect to time

VIII. Conclusions

PSSs generally enhances the stability of electric networks by damping out the LFOs after being subjected to any kind of disturbances. In this paper, a stochastic optimization approach called PSO has been employed for designing PI, PID, and lead-lag controller based PSS to damp out the LFOs in a SMIB electric network. The robustness of the proposed approach has been proven through its capability to achieve the optimal design of the PSSs despite the initial guess. Additionally, the comparison of damping ratio with BSA tuned PSS of the referenced work provide the compatibility of the proposed approach. The efficacy of the proposed approach has been verified through different analyses including analysis of eigenvalues, damping ratio, and time domain simulation results.

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