

# Robust Power System Stabilizer Design using Particle Swarm Optimization Technique

Sidhartha Panda, N. P. Padhy

**Abstract**—Power system stabilizers (PSS) are now routinely used in the industry to damp out power system oscillations. In this paper, particle swarm optimization (PSO) technique is applied to design a robust power system stabilizer (PSS). The design problem of the proposed controller is formulated as an optimization problem and PSO is employed to search for optimal controller parameters. By minimizing the time-domain based objective function, in which the deviation in the oscillatory rotor speed of the generator is involved; stability performance of the system is improved. The non-linear simulation results are presented under wide range of operating conditions; disturbances at different locations as well as for various fault clearing sequences to show the effectiveness and robustness of the proposed controller and their ability to provide efficient damping of low frequency oscillations. Further, all the simulations results are compared with a conventionally designed power system stabilizer to show the superiority of the proposed design approach.

**Keywords**—Particle swarm optimization, power system stabilizer, low frequency oscillations, power system stability.

## I. INTRODUCTION

LOW frequency oscillations are observed when large power systems are interconnected by relatively weak tie lines. These oscillations may sustain and grow to cause system separation if no adequate damping is available [1]. Power system stabilizers (PSS) are now routinely used in the industry to damp out oscillations. An appropriate selection of PSS parameters results in satisfactory performance during system disturbances [2].

The problem of PSS parameter tuning is a complex exercise. A number of conventional techniques have been reported in the literature pertaining to design problems of conventional power system stabilizers namely: the eigenvalue assignment, mathematical programming, gradient procedure for optimization and also the modern control theory [3]. Unfortunately, the conventional techniques are time consuming as they are iterative and require heavy computation burden and slow convergence. In addition, the search process is susceptible to be trapped in local minima and the solution

obtained may not be optimal [4]. Most of the proposals on PSS parameter tuning are based on small disturbance analysis that required linearization of the system involved. However, linear methods cannot properly capture complex dynamics of the system, especially during major disturbances. This presents difficulties for tuning the PSS in that the controller tuned to provide desired performance at small signal condition do not guarantee acceptable performance in the event of major disturbances. In order to overcome the above short comings, this paper uses three-phase non-linear models of power system components and to optimally tune the PSS parameters.

Also, the controller should provide some degree of robustness to the variations loading conditions, and configurations as the machine parameters change with operating conditions. A set of controller parameters which stabilize the system under a certain operating condition may no longer yield satisfactory results when there is a drastic change in power system operating conditions and configurations [5].

The evolutionary methods constitute an approach to search for the optimum solutions via some form of directed random search process. A relevant characteristic of the evolutionary methods is that they search for solutions without previous problem knowledge. Recently, Particle Swarm Optimization (PSO) technique appeared as a promising algorithm for handling the optimization problems. PSO is a population based stochastic optimization technique, inspired by social behaviour of bird flocking or fish schooling [6]. PSO shares many similarities with Genetic Algorithm (GA); like initialization of population of random solutions and search for the optimal by updating generations. However, unlike GA, PSO has no evolution operators such as crossover and mutation. One of the most promising advantages of PSO over GA is its algorithmic simplicity as it uses a few parameters and easy to implement. In PSO, the potential solutions, called particles, fly through the problem space by following the current optimum particles [7]. In view of the above, PSO is employed in the present work to optimally tune the parameters of the PSS.

In this paper, a comprehensive assessment of the effects of PSS-based damping controller has been carried out. The design problem of the proposed controller is transformed into an optimization problem. The design objective is to improve the stability of a single-machine-infinite-bus (SMIB) power

Sidhartha Panda is a research scholar in the Department of Electrical Engineering, Indian Institute of Technology, Roorkee, Uttaranchal, 247667, India. (e-mail: speeddee@iitr.ernet.in, panda\_sidhartha@rediffmail.com).

N.P.Padhy is with Department of Electrical Engineering, IIT, Roorkee, India. (e-mail: nppeefee@iitr.ernet.in).

system, subjected to severe disturbances. PSO based optimal tuning algorithm is used to optimally tune the parameters of the PSS. The proposed controller has been applied and tested on a weakly connected power system under wide range of operating conditions; disturbances at different locations as well as for various fault clearing sequences to show the effectiveness and robustness of the proposed controller and their ability to provide efficient damping of low frequency oscillations. To show the superiority of the proposed design approach, all the simulations results are compared with a conventionally designed power system stabilizer.

This paper is organized as follows. In Section II, the power system under study, which is a SMIB power system is presented. The proposed controller structure and problem formulation is described in Section III. A short overview of PSO is presented in Section IV. Simulation results are provided and discussed in Section V and conclusions are given in Section VI.

## II. POWER SYSTEM UNDER STUDY

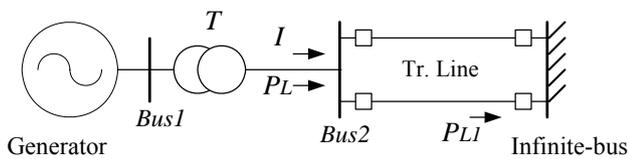


Fig. 1 Single-machine infinite-bus power system

The SMIB power system with SSSC controller, as shown in Fig. 1, is considered in this study. The system comprises a generator connected to an infinite bus through a step-up transformer and a SSSC followed by a double circuit transmission line. In the figure T represents the transformer;  $V_T$  and  $V_B$  are the generator terminal and infinite bus voltage respectively;  $I$  is the line current and  $P_L$  is the real power flow in the transmission lines. The generator is equipped with hydraulic turbine & governor (HTG), excitation system and a power system stabilizer. All the relevant parameters are given in appendix.

## III. THE PROPOSED APPROACH

### A. Structure of Power System Stabilizer

The structure of PSS, to modulate the excitation voltage is shown in Fig. 2. The structure consists of a sensor, a gain block with gain  $K_P$ , a signal washout block and two-stage phase compensation blocks as shown in Fig. 2. The input signal of the proposed controller is the speed deviation ( $\Delta\omega$ ), and the output is the stabilizing signal  $V_S$  which is added to the reference excitation system voltage. The signal washout block serves as a high-pass filter, with the time constant  $T_W$ , high enough to allow signals associated with oscillations in input signal to pass unchanged. From the viewpoint of the washout function, the value of  $T_W$  is not critical and may be in the range of 1 to 20 seconds [1]. The phase compensation

block (time constants  $T_1$ ,  $T_2$  and  $T_3$ ,  $T_4$ ) provides the appropriate phase-lead characteristics to compensate for the phase lag between input and the output signals.

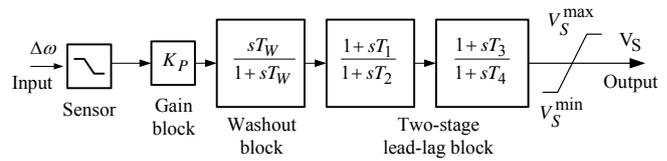


Fig. 2 Structure of power system stabilizer

### B. Problem Formulation

In case of above lead-lag structured PSS, the sensor and the washout time constants are usually specified. In the present study, a sensor time constant  $T_{SN} = 15$  ms and washout time constant  $T_W = 10$ s are used. The controller gain  $K_P$  and the time constants  $T_1$ ,  $T_2$ ,  $T_3$  and  $T_4$  are to be determined.

It is worth mentioning that the PSS is designed to minimize the power system oscillations after a large disturbance so as to improve the power system stability. These oscillations are reflected in the deviations in power angle, rotor speed and line power. Minimization of any one or all of the above deviations could be chosen as the objective. In the present study, an integral time absolute error of the speed deviations is taken as the objective function expressed as follows:

$$J = \int_{t=0}^{t=t_{sim}} [ |\Delta\omega| ] \cdot t \cdot dt \quad (1)$$

In the above equations,  $\Delta\omega$  denotes the rotor speed deviation for a set of controller parameters (note that here the controller parameters represent the parameters to be optimized;  $K_P$ ,  $T_1$ ,  $T_2$ ,  $T_3$  and  $T_4$ ; the parameters of the PSS), and  $t_{sim}$  is the time range of the simulation. For objective function calculation, the time-domain simulation of the power system model is carried out for the simulation period. It is aimed to minimize this objective function in order to improve the system response in terms of the settling time and overshoots.

## IV. OVERVIEW OF PARTICLE SWARM OPTIMIZATION (PSO)

The PSO method is a member of wide category of Swarm Intelligence methods for solving the optimization problems. It is a population based search algorithm where each individual is referred to as particle and represents a candidate solution. Each particle in PSO flies through the search space with an adaptable velocity that is dynamically modified according to its own flying experience and also the flying experience of the other particles. In PSO each particles strive to improve themselves by imitating traits from their successful peers. Further, each particle has a memory and hence it is capable of remembering the best position in the search space ever visited by it. The position corresponding to the best fitness is known

as *pbest* and the overall best out of all the particles in the population is called *gbest* [6]-[7].

The features of the searching procedure can be summarized as follows [8]-[9]:

- Initial positions of *pbest* and *gbest* are different. However, using the different direction of *pbest* and *gbest*, all agents gradually get close to the global optimum.
- The modified value of the agent position is continuous and the method can be applied to the continuous problem. However, the method can be applied to the discrete problem using grids for XY position and its velocity.
- There are no inconsistency in searching procedures even if continuous and discrete state variables are utilized with continuous axes and grids for XY positions and velocities. Namely, the method can be applied to mixed integer nonlinear optimization problems with continuous and discrete state variables naturally and easily.
- The above concept is explained using only XY axis (2 dimensional space). However, the method can be easily applied to n dimensional problem.

The modified velocity and position of each particle can be calculated using the current velocity and the distance from the *pbest<sub>j,g</sub>* to *gbest<sub>g</sub>* as shown in the following formulas [10]:

$$v_{j,g}^{(t+1)} = w * v_{j,g}^{(t)} + c_1 * r_1 * (pbest_{j,g} - x_{j,g}^{(t)}) + c_2 * r_2 * (gbest_g - x_{j,g}^{(t)}) \quad (2)$$

$$x_{j,g}^{(t+1)} = x_{j,g}^{(t)} + v_{j,g}^{(t+1)} \quad (3)$$

where  $j = 1, 2, \dots, n$  and  $g = 1, 2, \dots, m$

$n$  = number of particles in a group;  
 $m$  = number of members in a particle;  
 $t$  = number of iterations (generations);  
 $v_{j,g}^{(t)}$  = velocity of particle  $j$  at iteration  $t$ ,

$$\text{with } v_g^{min} \leq v_{j,g}^{(t)} \leq v_g^{max};$$

$w$  = inertia weight factor;  
 $c_1, c_2$  = cognitive and social acceleration factors respectively;  
 $r_1, r_2$  = random numbers uniformly distributed in the range (0, 1);

$x_{j,g}^{(t)}$  = current position of  $j$  at iteration  $t$ ;

$pbest_j$  = *pbest* of particle  $j$ ;

$gbest$  = *gbest* of the group.

The  $j$ -th particle in the swarm is represented by a  $g$ -dimensional vector  $x_j = (x_{j,1}, x_{j,2}, \dots, x_{j,g})$  and its rate of position change (velocity) is denoted by another  $g$ -dimensional vector  $v_j = (v_{j,1}, v_{j,2}, \dots, v_{j,g})$ . The best previous

position of the  $j$ -th particle is represented as  $pbest_j = (pbest_{j,1}, pbest_{j,2}, \dots, pbest_{j,g})$ . The index of best particle among all of the particles in the group is represented by the  $gbest_g$ . In PSO, each particle moves in the search space with a velocity according to its own previous best solution and its group's previous best solution. The velocity update in a PSO consists of three parts; namely momentum, cognitive and social parts. The balance among these parts determines the performance of a PSO algorithm. The parameters  $c_1$  &  $c_2$  determine the relative pull of *pbest* and *gbest* and the parameters  $r_1$  &  $r_2$  help in stochastically varying these pulls. In the above equations, superscripts denote the iteration number. Fig. 3 shows the velocity and position updates of a particle for a two-dimensional parameter space. The computational flow chart of PSO is shown in Fig. 4.

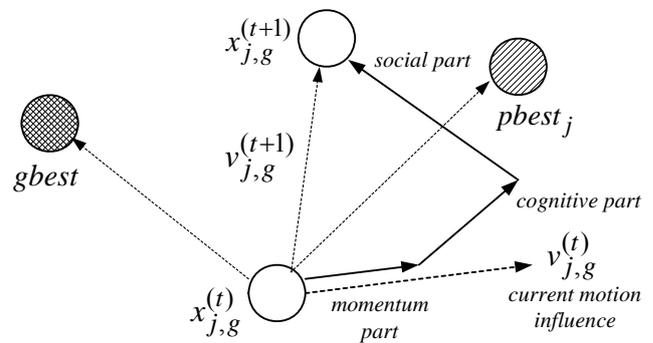


Fig. 3 Description of velocity and position updates in particle swarm optimization technique

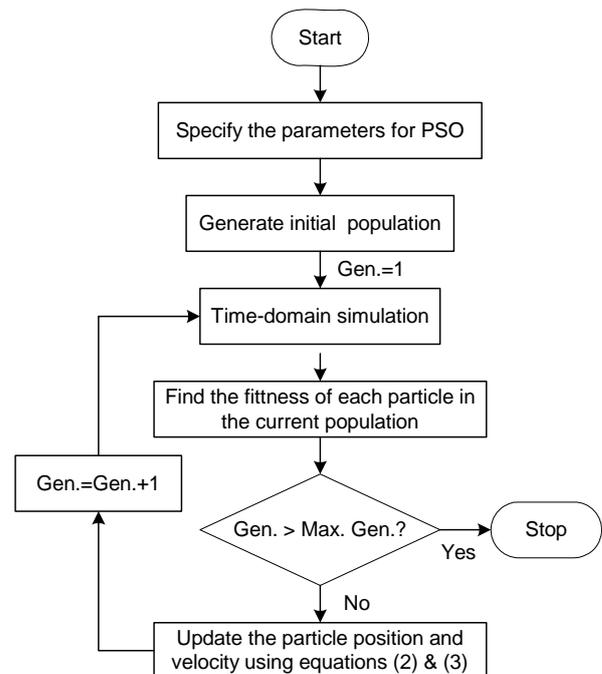


Fig. 4 Flowchart of particle swarm optimization algorithm

Tuning a controller parameter can be viewed as an optimization problem in multi-modal space as many settings of the controller could be yielding good performance. Traditional method of tuning doesn't guarantee optimal parameters and in most cases the tuned parameters needs improvement through trial and error. In PSO based method, the tuning process is associated with an optimality concept through the defined objective function and the time domain simulation. The designer has the freedom to explicitly specify the required performance objectives in terms of time domain bounds on the closed loop responses. Hence the PSO method yields optimal parameters and the method is free from the curse of local optimality.

## V. RESULTS AND DISCUSSIONS

The SimPowerSystems (SPS) toolbox is used for all simulations and SSSC-based damping controller design. SPS is a MATLAB-based modern design tool that allows scientists and engineers to rapidly and easily build models to simulate power systems using Simulink environment. The SPS's main library, *powerlib*, contains models of typical power equipment such as machines, governors, excitation systems, transformers, and transmission lines. The library also contains the Powergui block that opens a graphical user interface for the steady-state analysis of electrical circuits. The Load Flow and Machine Initialization option of the Powergui block performs the load flow and the machines initialization [11].

In order to optimally tune the parameters of the PSS, as well as to assess its performance and robustness under wide range of operating conditions with various fault disturbances and fault clearing sequences, the test system depicted in Fig. 1 is considered for analysis. The model of the example power system shown in Fig. 1 is developed using SimPowerSystems blockset. The system consists of a of 2100 MVA, 13.8 kV, 60Hz hydraulic generating unit, connected to a 300 km long double-circuit transmission line through a 3-phase 13.8/500 kV step-up transformer and a 100 MVA SSSC. The generator is equipped with Hydraulic Turbine & Governor (HTG) and Excitation system. All the relevant parameters are given in appendix.

### A. Application of PSO

For the purpose of optimization of equation (1), routines from PSO toolbox [12] are used. The objective function is evaluated for each individual by simulating the example power system, considering a severe disturbance. For objective function calculation, a three phase short-circuit fault in one of the parallel transmission lines is considered. The fitness function comes from time-domain simulation of power system model. Using each set of controllers' parameters, the time-domain simulation is performed and the fitness value is determined.

While applying PSO, a number of parameters are required to be specified. An appropriate choice of these parameters

affects the speed of convergence of the algorithm. Table I shows the specified parameters for the PSO algorithm. Although the chances of PSO giving a local optimal solution are very few, sometimes getting a suboptimal solution is also possible. For different problems, it is possible that the same parameters for PSO do not give the best solution, and so these can be changed according to the situation. One more important point that affects the optimal solution more or less is the range for unknowns. For the very first execution of the programme, a wider solution space can be given and after getting the solution one can shorten the solution space nearer to the values obtained in the previous iteration. Optimization is terminated by the prespecified number of generations. The optimization was performed with the total number of generations set to 100. The convergence rate of objective function  $J$  for  $g_{best}$  with the number of generations is shown in Fig. 5. Table II shows the optimal values of PSS parameters obtained by the PSO algorithm.

TABLE I  
 PARAMETERS USED FOR PSO ALGORITHM

PSO parameters	Value/Type
Swarm size	20
No. of Generations	100
$c1, c2$	2.0, 2.0
$w_{start}, w_{end}$	0.9, 0.4

TABLE II  
 OPTIMIZED PSS PARAMETERS

$K_P$	$T_1$	$T_2$	$T_3$	$T_4$
46.3616	0.0574	0.0139	3.8946	5.2275

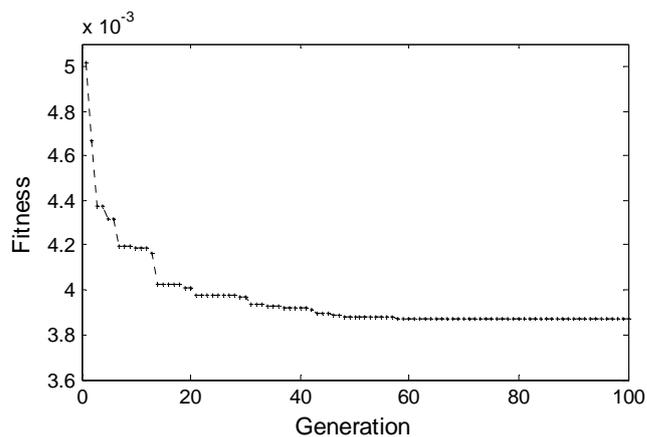


Fig. 5 Convergence of fitness value

### B. Simulation Results

To assess the effectiveness and robustness of the proposed controller, simulation studies are carried out for various fault disturbances and fault clearing sequences. The behavior of the proposed controller under transient conditions is verified by applying various types of disturbances under different

operating conditions. In the Figs., the response without control (no control) is shown with legend NC; the response with conventionally designed power system stabilizer [1] is shown with legend CPSS and the response with proposed PSO optimized PSS is shown with legend PSOPSS respectively. The following cases are considered:

*Case I: Nominal loading:*

A 3-phase fault is applied at the nominal operating conditions ( $P_e = 0.75$  pu,  $\delta_0 = 41.48^\circ$ ), at Bus 2 at  $t = 1$  s. The fault is cleared after 3-cycles and the original system is restored after the fault clearance. The system response under this severe disturbance is shown in Figs. 6-8. It is clear from the Figs. that, the system is critically stable without control under this disturbance. Stability of the system is maintained and power system oscillations are effectively suppressed with the application of conventional power system stabilizer. It is also clear from Figs. that, the proposed PSO optimized PSS out perform the conventional PSS from dynamic performance point of view. The power system oscillations are quickly damped out with the application of proposed PSS.

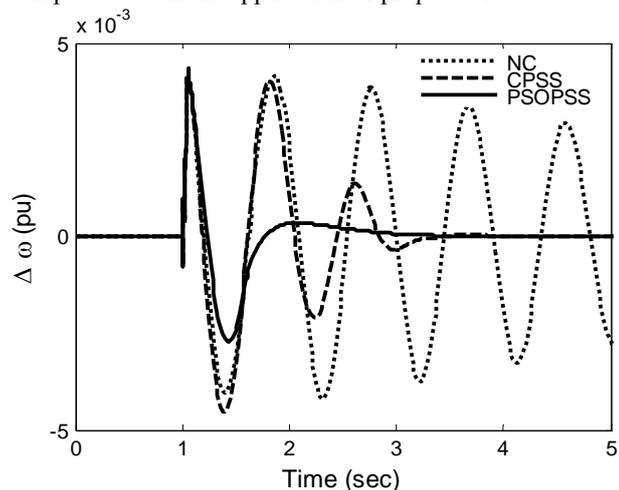


Fig. 6 Speed deviation response of for 3-cycle 3-phase fault disturbance at Bus 2 with nominal loading condition.

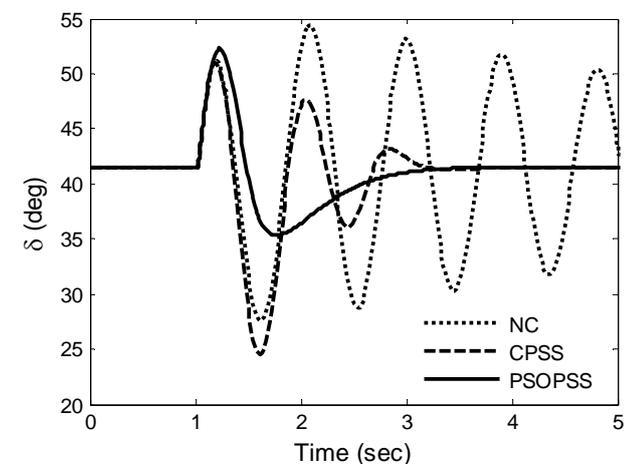


Fig. 7 Power angle response of for 3-cycle 3-phase fault disturbance at Bus 2 with nominal loading condition.

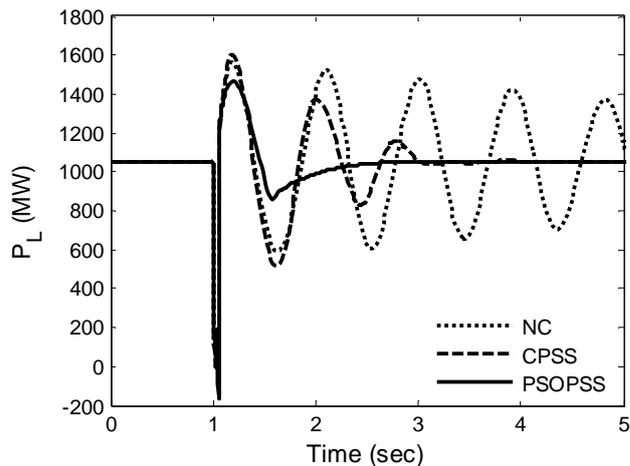


Fig. 8 Tie-line power response of for 3-cycle 3-phase fault disturbance at Bus 2 with nominal loading condition.

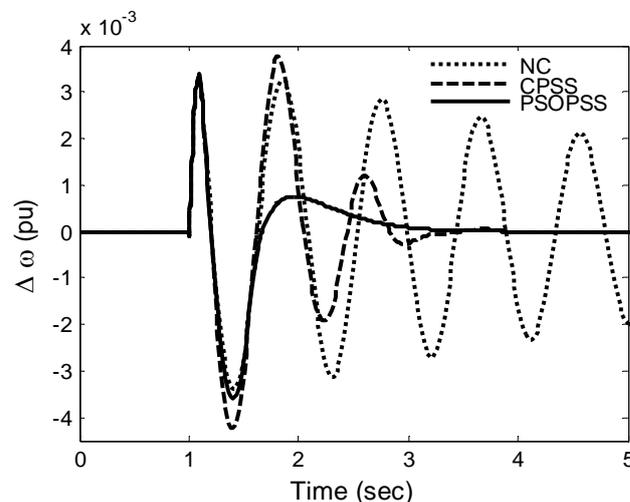


Fig. 9 Speed deviation response of for 3-cycle 3-phase fault at middle of transmission line with nominal loading condition.

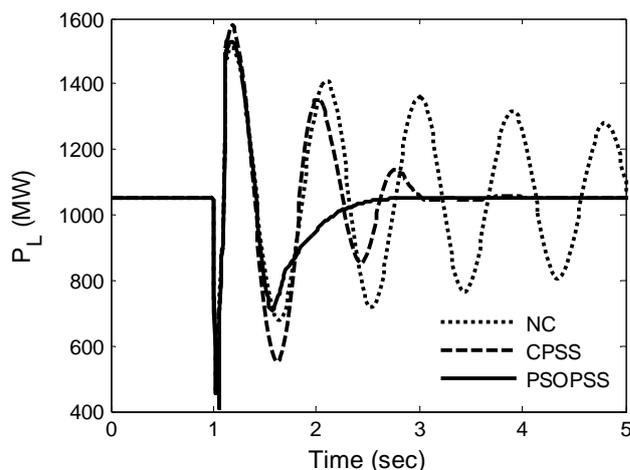


Fig. 10 Speed deviation response of for 3-cycle 3-phase fault at middle of transmission line with nominal loading condition.

Another severe disturbance is considered at this loading condition. A 3-cycle 3-phase fault is applied at the middle of one transmission line. The fault is cleared by tripping of the faulty line and the line is reclosed after 3-cycles. The original system is restored after the line reclosure. The system response for the above contingency is shown in Figs. 9-10. It is evident from Figs. 9-10 that the proposed PSS is robust to fault location and provides efficient damping to power system oscillations. The dynamic performance of the proposed PSS is also superior to that of conventional PSS.

In order to show the robustness of the proposed PSS to type of disturbance, one of the parallel transmission line is permanently tripped out at  $t = 1$  s. Figs. 11-12 shows the system response for the above severe disturbance. It is clear from the Figs. that, the system is oscillatory without control under this disturbance. Stability of the system is maintained and power system oscillations are effectively suppressed with the application of conventional power system stabilizer and proposed PSS. It is also clear from Figs. that, the proposed PSO optimized PSS outperform the conventional PSS from dynamic performance point of view.

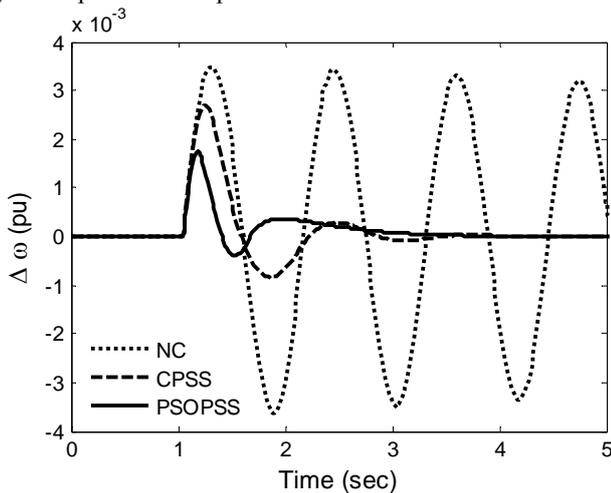


Fig. 11 Speed deviation response of for permanent line outage disturbance with nominal loading condition

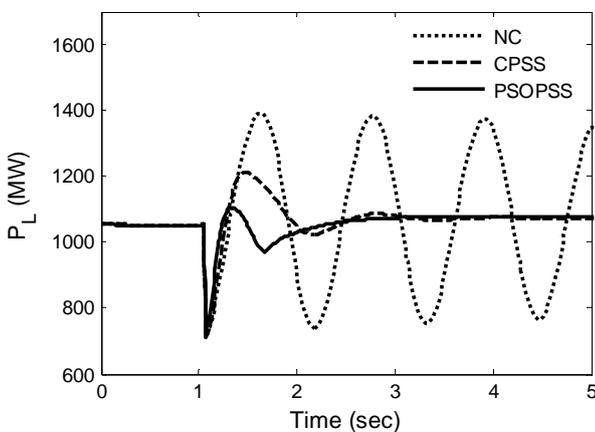


Fig. 12 Tie-line power flow response of for permanent line outage disturbance with nominal loading condition

**Case II: Heavy loading:**

To test the robustness of the controller to operating condition and fault clearing sequence, the generator loading is changed to heavy loading condition ( $P_e = 1.0$  pu,  $\delta_0 = 60.7^\circ$ ), and a 3-cycle, 3-phase fault is applied at Bus2. The fault is cleared by opening both the lines. The lines are reclosed after 3-cycles and original system is restored. The system response for the above severe disturbance is shown in Figs. 11-13. It can be clearly seen from Figs. 13-15 that, for the given operating condition and contingency, the system is unstable without control. Stability of the system is maintained and power system oscillations are effectively damped out with the application of conventional PSS. The proposed PSS provides the best performance and outperform the conventional PSS by minimizing the transient errors and quickly stabilizes the system.

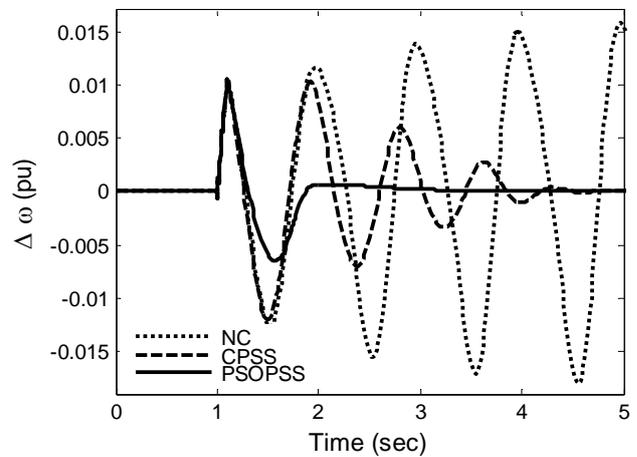


Fig. 13 Speed deviation response of for 3-cycle 3-phase fault disturbance at Bus 2 cleared by both line tripping with heavy loading

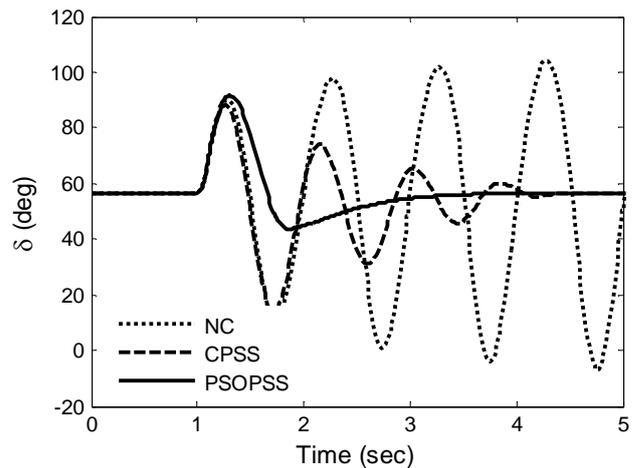


Fig. 14 Power angle response of for 3-cycle 3-phase fault disturbance at Bus 2 cleared by both line tripping with heavy loading

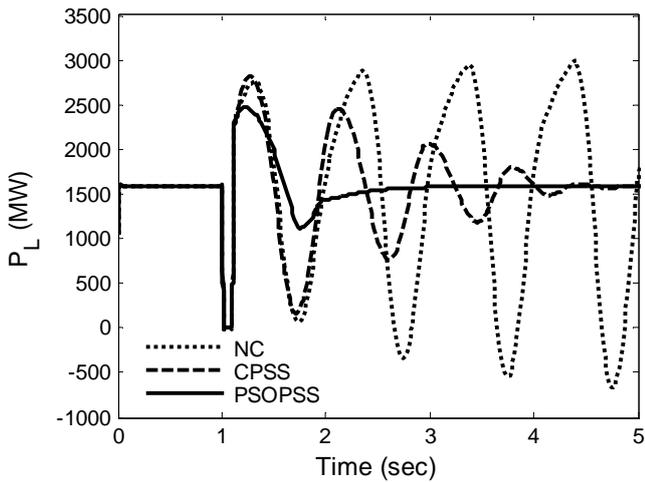


Fig. 15 Tie-line power flow response of for 3-cycle 3-phase fault disturbance at Bus 2 cleared by both line tripping with heavy loading

*Case III: Light loading:*

The effectiveness and robustness of proposed PSS is also verified under light loading condition ( $P_e = 0.5$  pu,  $\delta_0 = 22.9^\circ$ ). A 3-cycle 3-phase fault is applied at Bus 2 at  $t=1.0$  s. the fault is cleared by opening both the lines. One of the lines is reclosed after 3-cycles and the other is reclosed after 5 sec. The system response to this disturbance is shown in Fig. 16-17. These Figs. show the robustness of proposed PSS to operating conditions and fault clearing sequence. It can be seen from the Figs. that, without control, the system is stable but oscillations are poorly damped. Power system oscillations are effectively damped out with the application of conventional PSS. It is also clear that, the proposed PSS provides the best dynamic performance and outperform the conventional PSS by minimizing the transient errors and quickly stabilizes the system.

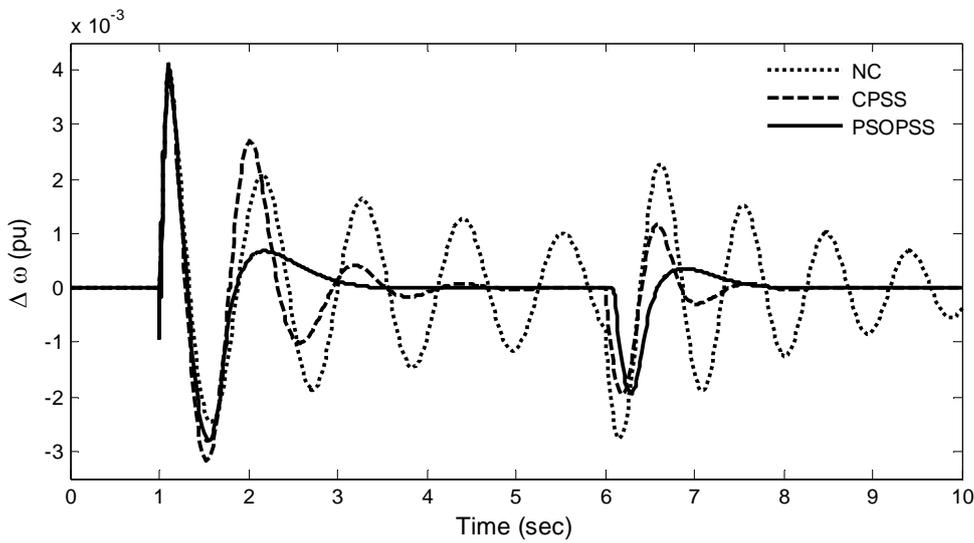


Fig. 16 Speed deviation response of for 3-cycle 3-phase fault cleared by both line tripping and reclosing with light nominal loading

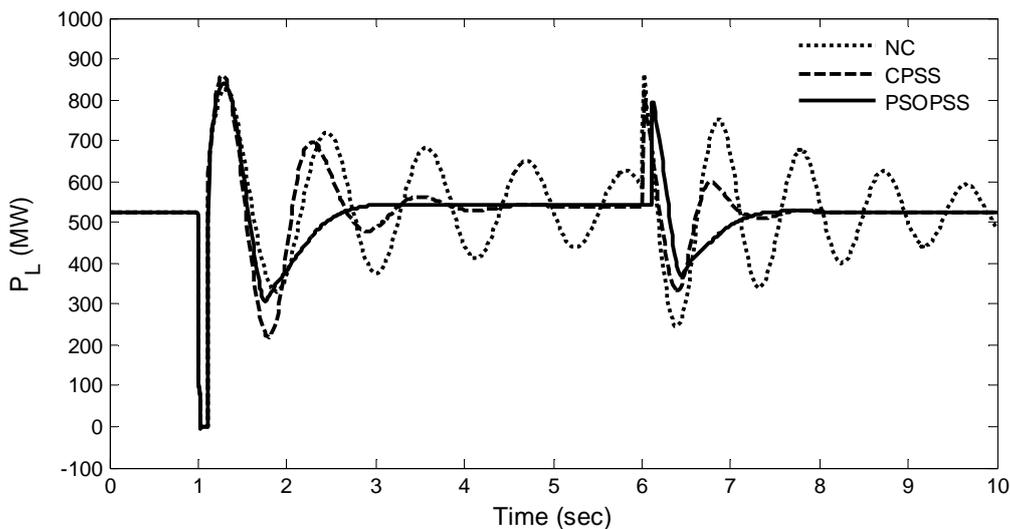


Fig. 17 Tie-line power flow response of for 3-cycle 3-phase fault cleared by both line tripping and reclosing with light nominal loading

## VI. CONCLUSION

In this paper, power system stability enhancement by power system stabilizer is presented. For the proposed controller design problem, a non-linear simulation-based objective function to increase the system damping was developed. Then, the particle swarm optimization technique is implemented to search for the optimal controller parameters. The effectiveness of the both the proposed controller, for power system stability improvement, is demonstrated by a weakly connected example power system subjected to different severe disturbances. The dynamic performance of proposed PSS has also been compared with a conventionally designed PSS to show its superiority. The non-linear simulation results presented under wide range of operating conditions; disturbances at different locations as well as for various fault clearing sequences, show the effectiveness and robustness of the proposed PSO optimized PSS controller and their ability to provide efficient damping of low frequency oscillations.

## APPENDIX

A complete list of parameters used appears in the default options of SimPowerSystems in the User's Manual [15]. All data are in pu unless specified otherwise.

### Generator

$S_B = 2100$  MVA,  $H = 3.7$  s,  $V_B = 13.8$  kV,  $f = 60$  Hz,  $P_{eo} = 0.75$ ,  $V_{to} = 1.0$ ,  $\delta_o = 41.51^\circ$ ,  $R_S = 2.8544 \times 10^{-3}$ ,  $X_d = 1.305$ ,  $X_d' = 0.296$ ,  $X_d'' = 0.252$ ,  $X_q = 0.474$ ,  $X_q' = 0.243$ ,  $X_q'' = 0.18$ ,  $T_d = 1.01$  s,  $T_d' = 0.053$  s,  $T_{qo} = 0.1$  s.

### Hydraulic Turbine and Governor

$K_a = 3.33$ ,  $T_a = 0.07$ ,  $G_{min} = 0.01$ ,  $G_{max} = 0.97518$ ,  $V_{gmin} = -0.1$  pu/s,  $V_{gmax} = 0.1$  pu/s,  $R_p = 0.05$ ,  $K_p = 1.163$ ,  $K_i = 0.105$ ,  $K_d = 0$ ,  $T_d = 0.01$  s,  $\beta = 0$ ,  $T_w = 2.67$  s

### Excitation System

$T_{LP} = 0.02$  s,  $K_a = 200$ ,  $T_a = 0.001$  s,  $K_e = 1$ ,  $T_e = 0$ ,  $T_b = 0$ ,  $T_c = 0$ ,  $K_f = 0.001$ ,  $T_f = 0.1$  s,  $E_{fmin} = 0$ ,  $E_{fmax} = 7$ ,  $K_p = 0$

### Transformer

2100 MVA, 13.8/500 kV, 60 Hz,  $R_1 = 0.002$ ,  $L_1 = 0$ ,  $D_1/Y_g$  connection,  $R_m = 500$ ,  $L_m = 500$

### Transmission line

3-Ph, 60 Hz, Length = 300 km each,  $R_1 = 0.02546 \Omega/\text{km}$ ,  $R_0 = 0.3864 \Omega/\text{km}$ ,  $L_1 = 0.9337 \times 10^{-3}$  H/km,  $L_0 = 4.1264 \times 10^{-3}$  H/km,  $C_1 = 12.74 \times 10^{-9}$  F/km,  $C_0 = 7.751 \times 10^{-9}$  F/km

### Conventional power system stabilizer

Sensor time constant = 15 ms,  $T_w = 10$  s,  $T_1 = 0.05$  s,  $T_2 = 0.02$  s,  $T_3 = 3$  s,  $T_4 = 5.4$  s, Output limits of  $V_S = \pm 0.15$

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**Sidhartha Panda** received the M.E. degree in Power Systems Engineering from University College of Engineering, Burla, Sambalpur University, India in 2001. Currently, he is a Research Scholar in Electrical Engineering Department of Indian Institute of Technology Roorkee, India. He was an Associate Professor in the Department of Electrical and Electronics Engineering, VITAM College of Engineering, Andhra Pradesh, India and Lecturer in the Department of Electrical Engineering, SMIT, Orissa, India. His areas of research include power system transient stability, power system dynamic stability, FACTS, optimization techniques, distributed generation and wind energy.

**Narayana Prasad Padhy** received the electrical engineering degree and Master's degrees in power systems engineering (with distinction) in 1990 and 1993, respectively, from the Institution of Engineers, Calcutta and Thiagarajar College of Engineering, Madurai, Tamilnadu, India, and the Ph.D. degree in electrical engineering from Anna University, Chennai, India. He joined Birla Institute of Technology and Science (BITS) as Assistant Professor in Electrical Engineering Department in 1997. He is presently an Associate Professor in the Department of Electrical Engineering, Indian Institute of Technology, Roorkee (IITR), India. His fields of interest include power system privatization, restructuring, and deregulation, artificial intelligence applications to power system operation and optimization problems, unit commitment, power system wheeling, and FACTS.