



Design of Damping Lead Lag (PSS) for SMIB Power System Using Particle Swarm Optimization Algorithm

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Abstract - This paper presents PSS (Power system stabilizer) design using Particle Swarm Optimization PSO method. The design is considered for single-machine power systems. The main motivation for this design is to damp electromechanical oscillations, and stabilize low-frequency oscillations of power systems. Firstly, the problem is formulated to optimize a composite set of objectives. The lead-lag PSS parameters are tuned; the problem is converted to an optimization problem which is solved by the PSO algorithm, to reach optimal global stability. Finally, the proposed PSO based PSSs is tested on a single-machine power system (SMIB) under different operating conditions and disturbances and different loads.

Keywords: Lead-lag PSS, Dynamic stability, Single-machine, Particle Swarm Optimization Algorithm.

I. Introduction

Stability of power systems has mainly depended on the stability of their generators, introducing the automatic voltage regulator (AVR) to stabilize the voltage, consequently this choice affect the dynamic stability of the power system , the device placed in excitation system, the Power System Stabilizers (PSSs) are used to generate supplementary control signals for the excitation system in order to damp the low frequency inter-area and intra-area oscillations [1, 2, 3].

The parameters of CPSS (Conventional Power System Stabilizer) are determined based on a linearized model of the power system around a nominal operating point where they can provide good performance [3]. Because power systems are highly nonlinear systems, with configurations and parameters that change with time, the CPSS design based on the linearized model of the power systems cannot guarantee its performance in a practical operating environment [1]. To improve the performance of CPSS, numerous techniques have been proposed for their design [1, 3, 4] such us using intelligent optimization methods.

In recent years, several heuristic search algorithms such as genetic algorithms (GA), ant colony optimization (ACO) and simulated annealing algorithms have been applied to the problem of PSS design. Other optimization techniques, GA are a population-based search algorithm, which works with a population of strings; consequently, heuristic methods are widely used for global optimization problems [5; 6].

Metaheuristics are a new family of stochastic algorithms which aim at solving difficult optimization problems. Used to solve various applicative problems, these methods have the advantage to be generally efficient on a large amount of problems. Among the metaheuristics, Particle Swarm Optimization (PSO) is a new class of algorithms proposed to solve continuous optimization problems [7, 8, 9].

The Particle Swarm Optimizer was introduced by James Kennedy and Russell Eberhart in 1995. Inspired by social behavior and movement dynamics of insects, birds and fish, it is also related, however, to evolutionary Computation, and has links to both genetic algorithms and evolution strategies. The Performance is comparable to Genetic algorithms.

The problem of PSS design is as an optimization problem with mild constraints. Then, PSO algorithm is employed to solve this optimization problem.

Simulation results have been carried out to assess the effectiveness of the proposed PSS under different disturbances and loading conditions [5, 7, 8].

II. Power System modeling

A. Power system model

The complex nonlinear model related to an n-machine interconnected power system [6, 10], can be described by a set of differential-algebraic equations. This steady single-machine-infinite-bus power system (SMIB) is considered in (Fig. 1). The system parameters are given in Appendix.

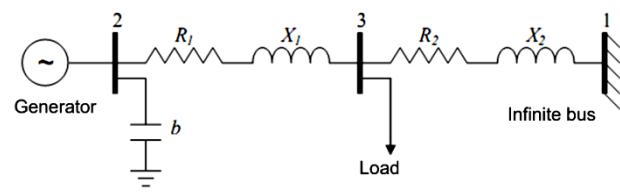


Fig. 1: Machine-infinite-bus power system (SMIB)

For a given operating condition, the single-machine power system is linearized around the operating point.

The closed loop eigenvalues of the system are computed and the desired objective functions are formulated using only the unstable or lightly damped electromechanical eigenvalues, keeping the constraints of all the system modes stable under any condition [1, 3]. For multi-machine power system of n generators the state forms are written as follows [11, 12, 13]:

$$\frac{d\mathbf{X}(t)}{dt} = A\mathbf{X}(t) + B\mathbf{U}(t) + \Gamma\mathbf{P}(t) \quad (1)$$

Where, $\mathbf{X}(t)$, $\mathbf{U}(t)$ et $\mathbf{P}(t)$ are the state variables, the control and the disturbance vectors respectively, with:

$$\mathbf{X}(t) = [\Delta\omega_1 \Delta\omega_2 \cdots \Delta\omega_n \Delta\delta_1 \Delta\delta_2 \cdots \Delta\delta_n \Delta E'_{q1} \Delta E'_{q2} \cdots \Delta E'_{qn} \Delta E_{fd1} \Delta E_{fd2} \cdots \Delta E_{fdn}]^T \quad (2)$$

$$\mathbf{U}(t) = [\Delta U_1 \Delta U_2 \cdots \Delta U_n]^T \quad (3)$$

$$\mathbf{P}(t) = [\Delta P_{m1} \Delta P_{m2} \cdots \Delta P_{mn}]^T \quad (4)$$

For a single machine system $n=1$ these equations can be written as:

$$\mathbf{X}(t) = [\Delta\omega, \Delta\delta, \Delta E'_q, \Delta E_{fd}]^T \quad (5)$$

Where:

III. PSO Concept

A. Overview

Metaheuristics are a new family of stochastic algorithms which aim at solving “difficult” optimization problems. Used to solve various applicative problems, these methods have the advantage to be generally efficient on a large amount of problems [9]. Among the metaheuristics, Particle Swarm Optimization (PSO) is a new class of algorithms proposed to solve continuous optimization problems. PSO was chosen for these advantages [8]:

- Simple implementation.
- Easily parallelized for concurrent processing.
- Very few algorithm parameters.
- Very efficient global search algorithm.
- Insensitive to scaling of design variables.

Known for their efficiency, metaheuristics show the drawback of comprising too many parameters to be tuned. Indeed, according to the values given to the parameters of the algorithm. So, it is important, for each problem, to find the parameter set which gives the best performance of the algorithm [9].

B. PSO Algorithm

The particle swarm optimization based on a set of individuals originally randomly arranged and homogeneous, therefore we call it particles, which move in the hyperspace of research and are each a potential solution. Each particle has a memory about his best seen as the ability to communicate with the particles forming around it. From this information, the particle will follow a trend made, from one side, willingness to return to its optimal solution, and from the other side, his mimicry in relation to the solutions found in its vicinity. From local optima and empirical, all particles will normally converge to the global optimum solution of the addressed problem [17].

The process of finding the particles is based on two rules:

- 1) Each particle has a memory that can store the best point by which it has already passed and it tends to return to this point.
- 2) Each particle is informed of the best known point in its neighborhood and it will tend to move towards this point.

Each particle moves according to a compromise between the 3 following trends:

- Repeat its previous motion;

- Move towards its best previous position;
- Move towards the best position (past) its group of informants.

Each agent tries to modify its position based on the following information [18]:

- Current positions (x, y),
- Current velocities (v_x, v_y),
- Distance between the current position and p_{best} ,
- Distance between the current position and g_{best} ,

The speed of each agent is defined as follows (18):

$$v_i^{k+1} = wv_i^k + c_1 \text{rand}_1(p_{best} - S_i^k) + c_2 \text{rand}_2(g_{best} - S_i^k) \quad (14)$$

The position of the particle S_i^k is modified from the current position and a new speed calculated v_i^{k+1}

$$S_i^{k+1} = S_i^k + v_i^{k+1} \quad (15)$$

The weight w is given by the following equation:

$$w = w_{max} - \frac{w_{max} - w_{min}}{iter_{max}} iter \quad (16)$$

The following figure shows the general flowchart of PSO

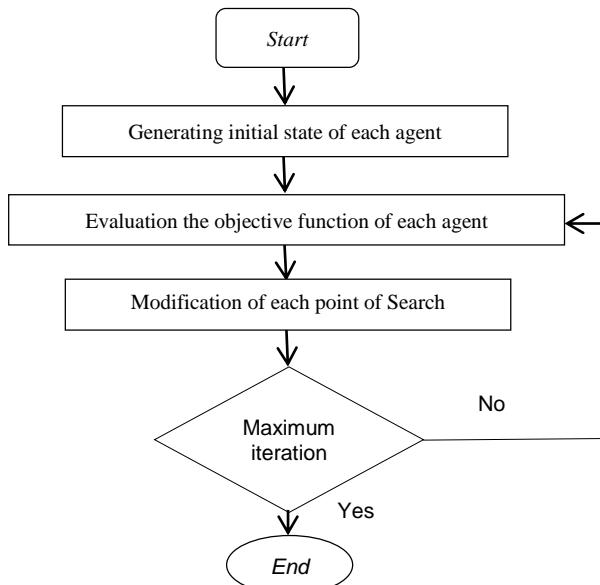


Fig. 4 : General flowchart of the PSO algorithm

The steps involved in Algorithmic Optimization of the Particle Swarm are as follows [5, 17, 18]:

Step1: Select several parameters of PSO.

Step2: Initialize a population of particles with random positions and velocities in the problem space.

Step3: Evaluate the ability of optimization for desired personal touch to each particle.

Step4: For each individual particle, compare the value of the particle with its ability $pbest$. If the current value is better than the evaluated $pbest$, then set this as $pbest$ for agent i .

Step5: Identify the particle that has the most good value fitness. The value of its fitness function is identified as $gbest$.

Step6: Calculate the new speed and position of particles using Eq. 14 and Eq. 15.

Step7: Repeating steps 3-6 until the stopping criterion is met.

IV. Simulation results

In this part of study, a single machine is connected to infinite bus through a transmission line, and operating at different loading conditions [10], is considered.

Details of the system data are given in Fig. 1 and Table 5.

The optimized parameters are K_c , T_1 and T_2 . These parameters are optimized for several operating points by the PSO algorithm, three different cases are considered for the dynamic study, normal, light and heavy load Table 3.

Determining the parameters of the PSO algorithm are chosen after several trials, they are shown in Table 1.

Table 1 : PSO algorithm Parameters

Parameter	Value
size of the swarm	50
c_1 and c_2	1.5
w_{max} et w_{min}	0.9 - 0.5

After several tests, we found that the best objective function value is obtained for 60 generations, see

Table 2:

Table 2 Choice of the number generations

Number of Generation	Objective Function
10	0.5446
20	0.5261
40	0.5579
60	0.5619
80	0.5486
100	0.5591
150	0.5615
200	0.5614

A. Eigenvalue Analysis

To evaluate the efficiency of the proposed PSOPSS over a wide range of loading and operating conditions, the generator output ranging from 0.2 to 1.2 pu and power factor ranging from 0.80 lead to 0.45 lag, variations of the voltage generator for 0.95 to 1.05 pu generates a database of 3000 operating points by the PSO algorithm.

The Location of eigenvalues without PSS and with the PSOPSS is given in Fig. 5.

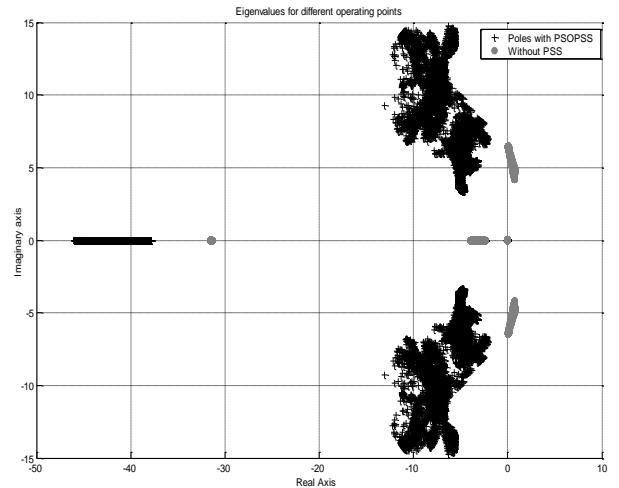


Fig. 5 : Eigenvalues for different operating points
"With and without PSS"

It is obvious that the system damping with the proposed PSOPSS is greatly improved and enhanced. The shift of the poles to the left is clearly visible, which greatly improves system stability.

B. Dynamic stability studies

To give an idea of the dynamic response of the system, we considered the three mentioned cases.

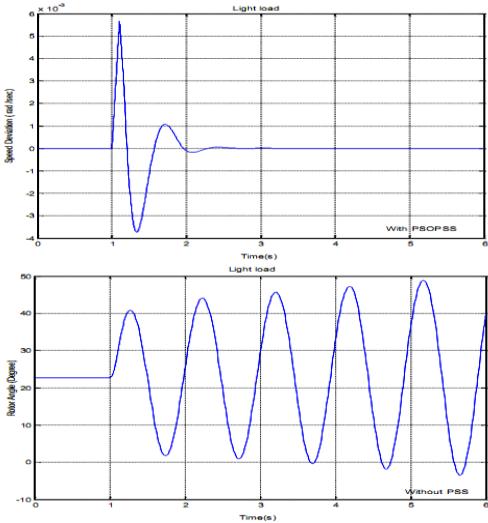
In the study of the robustness of the system, we will consider the following scenario:

- A three-phase short circuit near the generator (node-2) at $t = 1$ second,
- Opening of the line after $t = 1.05$ second.
- Closing the line after $t = 1.1$ seconds.

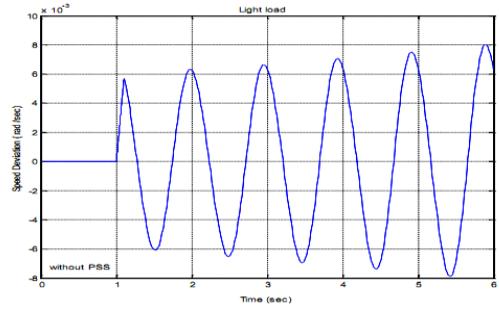
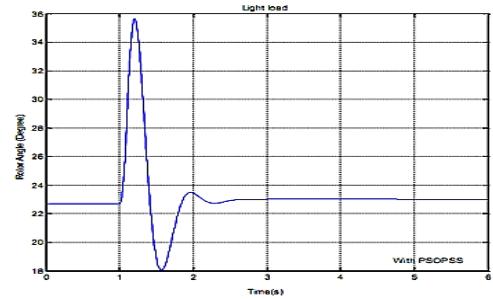
Simulation time 6 seconds.

Table 3: Three load cases considered Results of PSSPSO parameters optimized

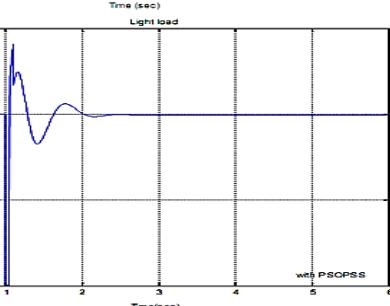
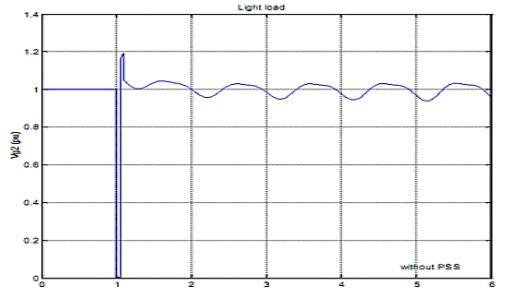
System base 100 MVA				
Type	V_{g2} (pu)	K_c	T_1 (s)	T_2 (s)
	$P_{g2} + iQ_{g2}$ (pu)	$0.45 + i 1.071$	$0.9 + i 0.287$	$1.2 + i 0.276$
	Light	Normal	Heavy	



a) Speed deviation signal

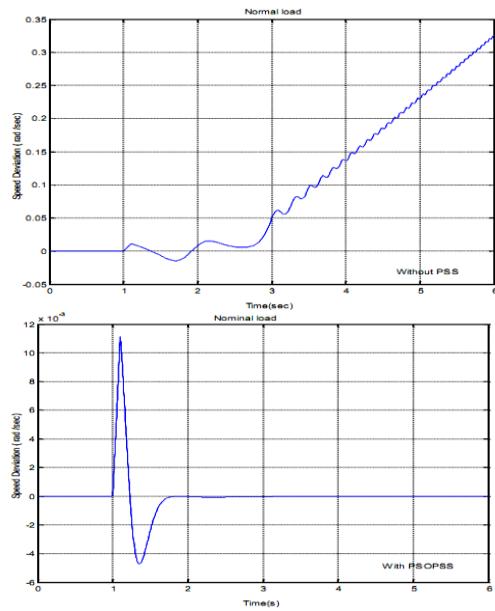


b) Rotor angle signal

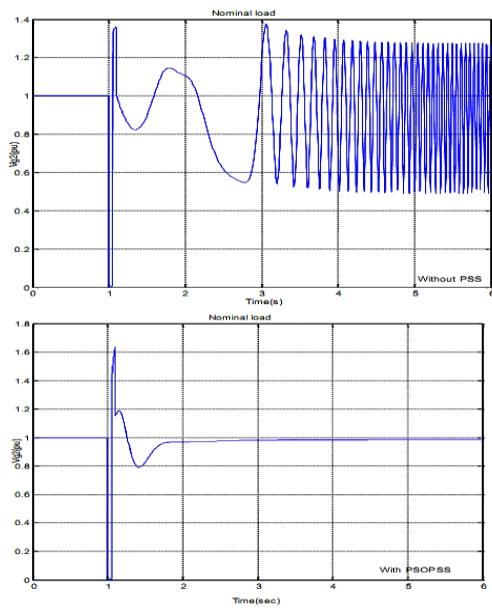


a) Voltage signal

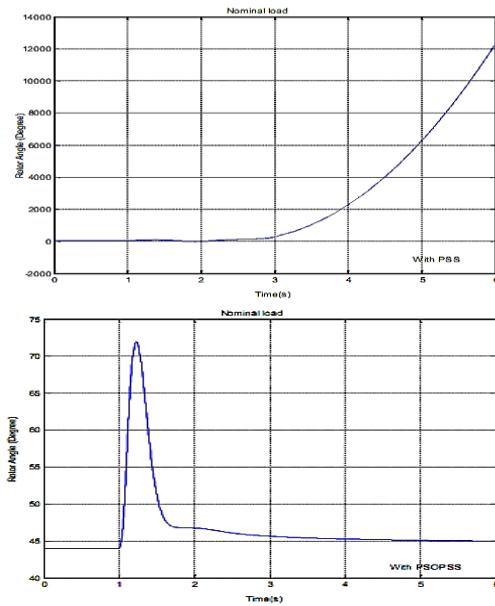
Fig. 6: Dynamic response for small Perturbation at Light load



a) Speed deviation signal

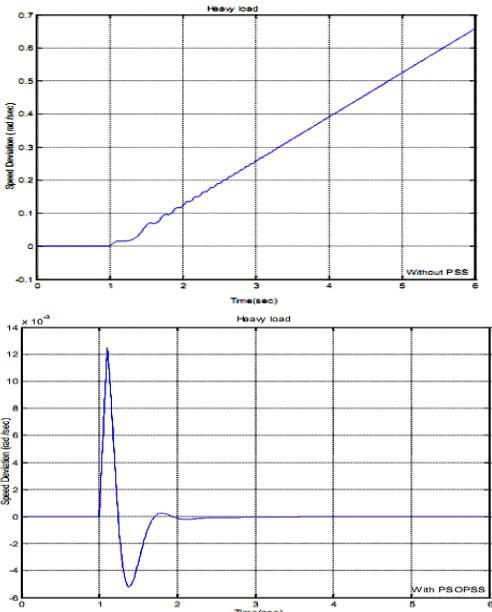


c) Voltage signal

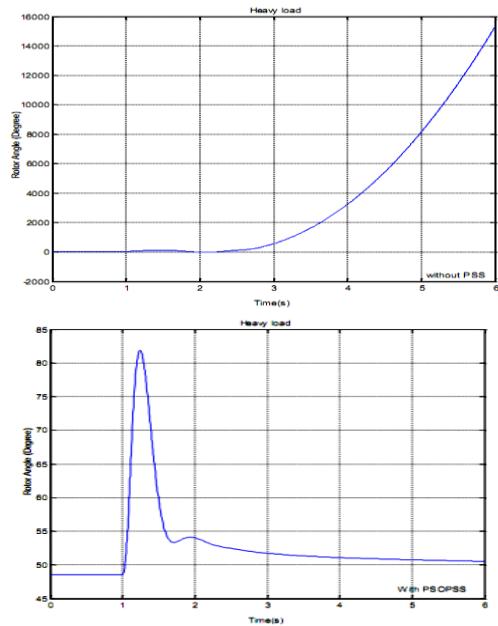


b) Rotor angle signal

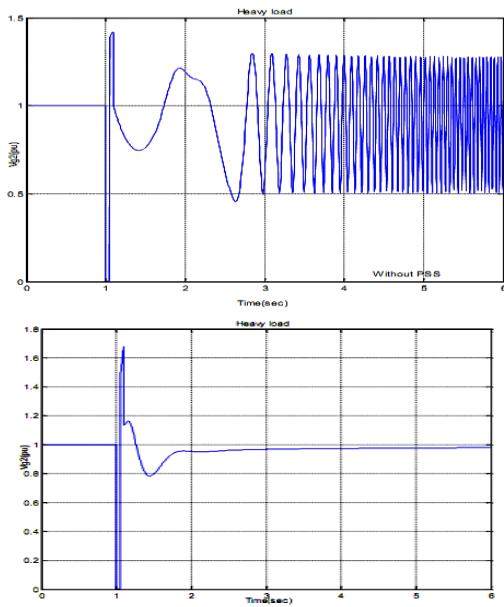
Fig. 7: Dynamic response for small Perturbation at nominal load



a) Speed deviation signal



b) Rotor angle signal



c) Voltage signal

Fig. 8: Dynamic response for small perturbation at heavy load

The simulation results obtained with the PSOPSS, given in Fig. 6, Fig. 6 and Fig. 6, show the response of speed deviation, variation of the angle rotor and the generator voltage during a short circuit at node 2 for different loads, these are also compared with the system without PSS. It can be observed that the proposed PSOPSS provides a better response and robustness against disturbances. The results clearly reveal that the PSOPSS is quite robust to wide variations in loading

conditions for large perturbations. The results clearly show the robustness of the PSOPSS and its ability to work over a wide range of operating conditions under small and large perturbations, thereby improving system stability.

V. Conclusion

The PSO algorithm is a powerful technique capable of handling the problems of stability of most complex networks.

In this study, swarm optimization based approach to optimal design for a single machine infinite bus system has been presented. Simulation of the response to small and large disturbances has demonstrated the effectiveness of this robust algorithm. It is shown that the proposed robust optimization provides good damping characteristics and enhances the dynamic stability of the system. The simulation results of various parameter optimization techniques can be compared for multi-machine system and its effectiveness can be studied.

APPENDIX

Table 4: Meaning Symbols

Symbol	Meaning
Γ	Disturbance matrix
A	State matrix,
B	Command matrix
n	Number of generator.
P	Disturbance vector
U	Vector Control
H	Inertia constant in (second)
D	Damping constant (p.u)
ω_0	Synchronous angular velocity in (rad / s)

Table 5: Power System Data

Data line				
R1 (p.u)	X1 (p.u)	R2 (p.u)	X2 (p.u)	b (p.u)
0.012	0.3	0.012	0.3	0.066
Data generator				
X_d	X'_d	X_q	T'_{d0}	
1.72 (pu)	0.45 (pu)	0.45 (pu)	6.30(sec)	
H	f	K_A	T_A	
4.00 (sec)	60 (Hz)	20	0.03 (sec)	

Table 6 : PSO algorithm symbol

v_i^{k+1}	Speed of the agent iteration k+1
w	Weight function
c	Weighing factor
$rand$	Random number between 0 and 1
S_i^k	Current position of agent i at iteration k
p_{best}	The best position of the agent she met in the (past)
g_{best}	The best solution found by the swarm particles
w_{min}	Minimum weight
w_{max}	Maximum weight
$iter$	Number of iteration
$iter_{max}$	Maximum number of iteration

VI. References

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