Performance Evaluation of a PBIL-Based Power System Damping Controller

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Abstract— **Recently Population-Based Incremental Learning (PBIL) algorithm has been applied to a range of problems in engineering with promising results. However, in most of the literature the standard PBIL with fixed learning rate has been used. It has been shown that when applied to dynamic environment as the one encountered in power systems, adaptive learning rate is more appropriate to use. In this paper, Population-Based Incremental Learning (PBIL) algorithm with adaptive learning rate is used to tune the parameters of a power system controller for damping power oscillations in a multi-machine power system. The optimization of controller's parameters has been performed over pre-specified range of system operating conditions. Robustness Evaluation of the proposed controller based on eigenvalue analysis and time domain simulation shows that the proposed controller is more robust than the conventional controller over the range of operating conditions considered.**

I. Introduction

THE occurrence of dynamic instability in power system due to poorly damped power oscillations has been a problem for power utilities worldwide. This has led to a wide application of power system damping controller commonly known as power system stabilizers (PSSs) [1-2]. A power system stabilizer operates through the exciter, generator and transmission system, whose characteristics change with changes in load, network configuration, etc. Therefore, the conventional way of designing PSS based on a single nominal operation condition is inadequate [3]. Conventional controllers designed for optimal performance at the nominal operating conditions do not guarantee the system stability and performance under off-nominal operating conditions. It is therefore important that multiple operating conditions of the power system be considered when designing the PSSs. Also, in multi-machine power system the various PSSs in the system interact with each other, and should be coordinated. With the conventional way of designing the controller one at the time, proper coordination may be difficult to achieve [3]. To achieve a good coordination, it is important that the parameters of the PSSs be tuned simultaneously.

The need for robust control design and adequate coordination of the controller in multi-machine power system has led researchers to the exploration of optimization techniques such as Simulated Annealing [4] , Evolutionary Algorithms (EA) [5], H_∞ optimal control [6] etc. Application of H_∞ optimal control theory to power system stabilizer design has been researched extensively in the past 20 years or so [6]-[8]. However, practical issues related to the selection of appropriate weighting functions, the inability to adequately model parametric uncertainties, and the high order of H_∞ controllers have made the power industry reluctant to use this type of controller.

In recent years, Evolutionary Algorithms (EA) has received increasing attention. The most widely used EA for controller design is Genetic Algorithms (GAs) [9]-[11]. Genetic algorithms (GAs) are stochastic global search algorithms that use models based on natural biological evolution [10], [11]. They operate on a population of potential solutions applying the principle of survival of the fittest [11]. Although GAs provide robust and powerful adaptive search mechanism, they still have several drawbacks such as ―genetic drift" which prevents GAs from maintaining diversity in its population. Other drawbacks are (a) the difficulty to optimally select the genetic operators (e.g. , population size, crossover and mutation rates), and (b) the slow convergence of the algorithm when complex problems are to be solved [20], [21].

To cope with the above limitations, many variant of GAs have been suggested often tailored to specific problems [11]. In the last few years, Particle Swarm Optimization (PSO) has been proposed as an alternative to GAs for PSS design [12], [13].

In this paper, a newly introduced EA called Population-Based Incremental Learning (PBIL) algorithm is proposed to tune the parameters of the PSSs. Population-Based Incremental Learning (PBIL) algorithm was first proposed by Baluja [14]-[15], and was subsequently improved by Green [16]-[17]. In PBIL, the crossover operator of GAs is abstracted away and the role of population is redefined. PBIL works with a probability vector (PV) which controls the random bitstrings generated by PBIL and is used to create other individuals through learning. Learning in PBIL consists of using the current probability distribution to create *N* individuals. These individuals are evaluated according to the objective function. The best individual is used to update

This work was supported in part by NSF grants: CAREER ECCS #0348221 and EFRI # 0836017.

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978-1-4244-8126-2/10/$26.00 ©2010 IEEE

the probability vector, increasing the probability of producing solutions similar to the current best individuals. As a result, PBIL is simpler, faster and more effective than the standard GAs [14]-[17].

PBIL was used in [20] to design PSS for a three-machine, nine bus system. However, standard PBIL with fixed learning rate was used. In addition, the power system in [20] does not have inter-area modes. In this paper, Population-Based Incremental Learning (PBIL) algorithm with adaptive learning rate as proposed in [21] is used to tune the parameters of a power system controller for damping power oscillations in a two-area power system model that possesses both local and inter-area modes. It should be mentioned that in [22], PBIL with fixed learning rate was compared with three population based evolutionary algorithms, namely, Modified Clonal Selection Algorithm (MCSA), Differential Evolution based Particle Swarm Optimization (DEPSO), Small Population based Particle Swarm Optimization (SPPSO). It has been shown in [22] that PBIL gives the almost the same or better performance compared to other algorithms. The objective of this paper is to evaluate the robustness of the proposed new approaches. Therefore, comparison with other population based algorithms is not provided.

The rest of the paper is organized as follows. The system model is described in section 2. Section 3 gives the overview of the PBIL. The problem formulation is described in section 4. Robustness evaluation is discussed in section 5 and the conclusions are given in section 6.

II. Power System Model

The system considered in this paper is the two-area four machine system as shown in Fig. 1. The system consists of two similar areas connected by a tie-line. Each area consists of two coupled units, each having a ratio of 900 MVA and 20 kV. There is a transfer of power from Area 1 to Area 2 of 400 MW at the nominal condition. The line and transformer parameters can be found in [1]. Each machine is represented by the detailed six order differential equations. The machines are equipped with a simple AVR as given in [1]. The loads are modeled as constant impedance. The dynamics of the system are described by a set of nonlinear differential equations. However, for the purpose of controller design these equations are linearized around the nominal operating conditions as given in (1) [2]-[3]:

$$\begin{aligned} \dot{x} &= A_o x + B_o u \\ y &= C_o x + D_o u \end{aligned} \quad (1)$$

where, the state variables are x, the system output is y and the signal u represents the control input. A_o, B_o, C_o, D_o are constant matrices of appropriate dimensions.

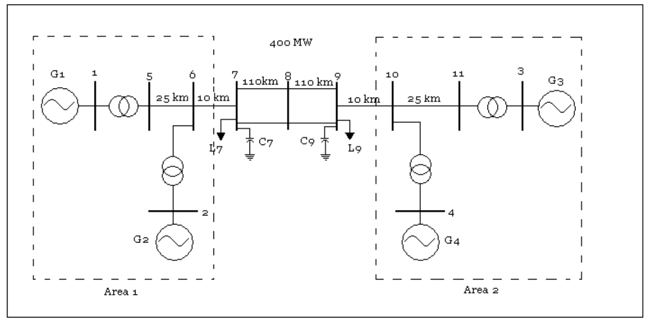

Fig. 1 Power system configuration

III. Overview of PBIL

A. Standard PBIL

PBIL is a technique that combines aspects of Genetic Algorithms and simple competitive learning derived from Artificial Neural Networks [13]-[16].

The three main operators of PBIL used in this paper are: probability vector (PV), Learning rate (LR) and mutation. Unlike the mechanisms inherent to GAs, where operations are defined on the population, in PBIL, the operations take place directly on the probability vector. During the search the values in the probability vector are updated to represent those in high evaluation vectors. The probability vector also guides the search, which produces the next sample point from which learning take place. The learning rate determines the speed at which the probability vector is shifted to resemble the best solution vector. In other words, a higher learning rate would ensure a faster convergence to an optimal solution; however, the whole function space will not be search. This could result in premature convergence. The role of the mutation is to maintain the diversity in the trial solutions.

The individuals are evaluated according to the objective function. The ―best" individual is used to update the probability vector so as to produce solutions similar to the current best individuals. Initially, the values of the probability vector are set to 0.5 to ensure that the probability of generating 0 or 1 is equal. As the search progresses, the values in the probability vector are moved away from 0.5, towards either 0.0 or 1.0.

It has been shown that PBIL outperforms standard GAs approaches on a variety of optimization problems including commonly used benchmark problems [15],[16]. In [22], PBIL was compared with three population based evolutionary algorithms, namely, Modified Clonal Selection Algorithm (MCSA), Differential Evolution based Particle Swarm Optimization (DEPSO), Small Population based Particle Swarm Optimization (SPPSO). It has been shown in [22] that PBIL gives the almost the same performance as MCSA and slightly better performance compared to DEPSO and SPPSO.

A summary of the PBIL used in the paper is given below [16]-[17]:

Step 1. Initialize element of the probability vector (PV) to 0.5 to ensure uniformly-random bitstrings.

Step2. Generate a population of uniformly-random bitstrings and comparing it element-by-element with the PV. Wherever an element of the PV is greater than the corresponding random element, a ―1' is generated, otherwise a ‗0' is generated.

Step 3. Interpret each bitstring as a solution to the problem and evaluate its merit in order to identify the "Best".

Step 4. Adjust *PV* by slightly increasing *PV* (*i*) to favor the generation of bitstrings which resemble ―Best", if Best (*i*) = 1 and decrease PV(*i*) if Best(*i*) = 0.

Step 5. Apply the mutation and generate a new population reflecting the modified distribution. Stop if satisfactory solution is found. Otherwise, go to step 3.

The mutation used in this paper is slightly different from the ―mutation" operator used by Baluja [12]-[13]. That is, a forgetting factor is used to relax the probability vector toward neutral value of 0.5 [16]-[17].

The algorithm flow chart is shown in Fig. 3

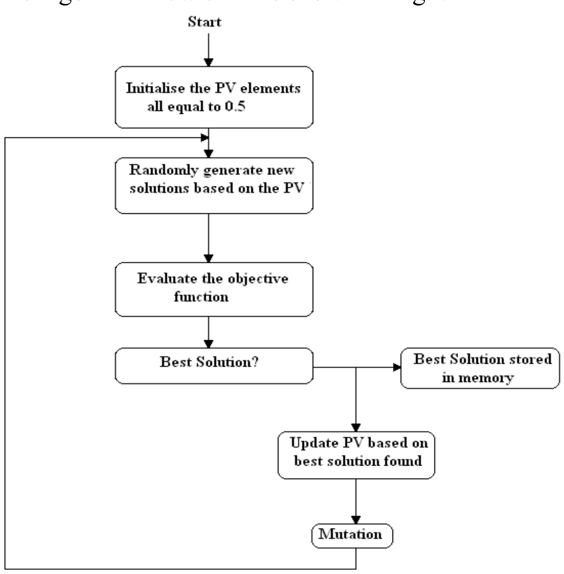

Fig. 3 PBIL Algorithm Flow Diagram

B. Adaptive PBIL

As discussed previously, the learning rate in the standard PBIL is fixed to a specific value. This may not be adequate if the environment is dynamic and changes as it is the case in power systems. To deal with this, adaptive learning rate schemes have been investigated in [21] and one of these scheme is used in this paper. We start with a very small value of LR (LR≈ 0), and increases the learning rate linearly with the generation to the final LR value according to the following equation:

$$LR(i) = LR\frac{G(i)}{G\max} \qquad (2)$$

where

LR(i) is the learning rate at the i^{th} generation

LR is the final learning rate (in this paper LR = 0.2)

G(i) is the *ith* generation

Gmax: is the maximum generation allowed (2000 for this study and a population of 30 individuals)

IV. PROBLEM FORMULATION

A. Operating Conditions

Four operating conditions, namely, nominal operating condition, light load, heavy load, and weak-tie line conditions have been considered during the design of the PSSs. Under nominal operating condition (case 1), 400 MW is transmitted from area 1 to area 2; under light load conditions (case 2), the nominal values of the loads at buses 7 and 9 were decreased by 50% and bout 209 MW power is transferred from area 1 to area 2. For the heavy load condition (case 3), the nominal values of the loads at buses 7 and 9 were increased by 30%; therefore approximately 500 MW is transmitted from area 1 to area 2. For the weak tie-line condition (case 4), one of the transmission lines between buses 7- 9 is removed, while 400 MW of power was transmitted from area 1 to area 2.

To investigate the robustness of the PSS, three more operating conditions (cases 5-7) that have not been considered during the design are investigated. All these three cases are considered under weak tine-line, while the power transferred from are 1 to area to is varied from 106 MW for case 5, to 437 MW for case 7 as shown in Table I.

TABLE I
SELECTED OPERATING CONDITION FOR CONTROLLER DESIGN

Case	P7-9	Line 7-9
1	400 MW	double
2	209 MW	double
3	500 MW	double
4	400 MW	single
5	106 MW	single
6	305 MW	single
7	437 MW	single

All the values are given in per-unit.

B. PSS Structure and Objective Function

PBIL with adaptive learning rate is applied to tune the parameters of a fixed structure ($\Delta\omega$ input) PSS of the form

$$K(s) = K_p \left(\frac{T_w s}{1+T_w s}\right)\left(\frac{1+T_1 s}{1+T_2 s}\right)\left(\frac{1+T_3 s}{1+T_4 s}\right) \qquad (3)$$

where, K_p is the gain, T_1-T_4 represent suitable time constants. T_w is the washout time constant needed to prevent steady-state offset of the voltage.

The conventional PSS is also of form (3) and has been designed based on the nominal operating condition as given in [1].

Since power oscillations are generally poorly damped and dominate the time response of the system, it is expected that by maximizing the minimum damping ratio, a set of system models could be simultaneously stabilized over a wide range of operating conditions [20]-[21]. The following objective function used to achieve the above requirements is:

$$J = \max\left(\min \zeta_{i,j}\right) \qquad (4)$$

where $i = 1, 2 \ldots n$, and $j = 1, 2, \ldots m$

and $\zeta_{i,j} = \dfrac{-\sigma_{i,j}}{\sqrt{\sigma_{i,j}^{2} + \omega_{i,j}^{2}}}$ is the damping ratio of the i-th eigenvalue in the j-th operating condition. σ_{ij} is the real part of the eigenvalue and the ω_{ij} is the frequency. n denotes the total number eigenvalues and m denotes the number of operating conditions.

V. Robustness Evaluation

A. Eigenvalue Analysis

The eigenvalues of the open-loop system and the closed-loop system equipped with the CPSS and the APBIL-PSSs for all seven cases are listed in Tables II-VIII.

Table II listed the eigenvalues of the nominal system (case 1) with and without the PSSs. It can be seen from the open-loop eigenvalues shown in the Table that there are two local oscillation modes and one inter-area mode. Without PSSs, the inter-area mode is unstable and the two local modes are poorly damped. The introduction of the PSSs stabilizes the system. However, the APBIL-PSS provides the best damping for the local modes (almost the double of that provided by the CPSS) and slightly better damping for the inter-area modes.

Table III shows the eigenvalues of the system for the light load condition (case 2). It can be seen that the PSSs have improved the damping of the modes. Again, The APBIL-PSS provides the best damping for both the local and inter-area modes.

Table IV shows the eigenvalues of the system for the heavy load condition (case 3). Without the PSSs, the inter-area mode is unstable, whereas the local modes are poorly damped. The CPSS provides a better damping for the inter-area than the APBIL-PSS but at the expense of the local modes. The PBIL-PSS is seen to provide the best damping for the local modes.

Table V shows the eigenvalues of the system for the weak tie-line condition (case 4). It can be seen that without the PSS, the damping of the inter-area mode has further deteriorated as compared to the nominal condition (case 1), while the damping and frequency of oscillations of the local modes have not changed much. However, the frequency of oscillations of the inter-area has decreased. The CPSS provides a better damping for the inter-are mode, whereas the APBIL-PSS provides the best damping ratio for the locale modes.

Tables VI, VII, VIII show the eigenvalues for cases 5, 6 and 7, respectively. These cases were introduced to investigate the robustness of the PSSs. They were not used during the design of the APBIL-PSS.

Table VI shows that without the PSSs, the inter-area mode for case 5 is poorly damped, while the local modes are relatively well-damped. It can be seen that the CPSS provides a slightly better damping for the inter-area modes, whereas the APBIL-PSS gives better damping for both local modes. Overall, the APBIL-PSS, provide the best damping to the oscillation modes.

Table VII shows the eigenvalues of the system for case 6. The CPSS provides better damping for the inter-area whereas the PBIL-PSS is seen to provide the best damping for the local modes.

Table VIII shows the eigenvalues of the system for case 7. It can be seen that without the PSSs, the inter-area mode is unstable, while the two local modes are poorly damped. The introduction of the PSSs stabilizes the system, with the CPSS providing a better damping for the inter-are mode, whereas the APBIL-PSS provides the best damping ratio for the locale modes. The overall performance of the system can only be judged using time domain simulations as will be described below.

TABLE II
EIGENVALUES OF THE NOMINAL SYSTEM-WITH AND WITHOUT PSSS

	Inter-area	Area 1 local	Area 2 local
	λ (ζ)	λ (ζ)	λ (ζ)
NO PSS	0.0142±*j*3.8277 (-0.0038)	-0.6604±*j*7.2287 (0.0916)	-0.6585±*j*7.3991 (0.0887)
APBIL-PSS	-0.6632±*j*3.3069 (0.1966)	-2.9599- ±*j*3.7959 (0.6149)	-3.1857±*j*4.6988 (0.5612)
CPSS	-0.7135±*j*3.7938 (0.1848)	-2.1531±*j*8.2370 (0.2529)	-2.2356±*j*8.5884 (0.2519)

λ: eigenvalue, ζdamping ratio

TABLE III

EIGENVALUES FOR CASE 2 WITH AND WITHOUT THE PSSS

	Inter-area	Area 1 local	Area 2 local
	λ (ζ)	λ (ζ)	λ (ζ)
NO PSS	-0.3291±*j*3.8692 (0.08475)	-1.4271±*j*6.55670 (0.2124)	-1.45±*j*6.7500 (0.2103)
APBIL-PSS	-0.7796±*j*3.5483 (0.2158)	-3.8552±*J*3.4001 (0.7500)	-3.2547±*j*4.9433 (0.5500)
CPSS	-0.7688±*j*3.8682 (0.1949)	-2.5879±*j*7.2541 (0.3360)	-2.6401±*j*7.4653 (0.3334)

λ: eigenvalue, ζdamping ratio

TABLE IV

EIGENVALUES FOR CASE 3 WITH AND WITHOUT THE PSSS

	Inter-area	Area 1 local	Area 2 local
	λ (ζ)	λ (ζ)	λ (ζ)
NO PSS	0.1059±*j* 2.4638 (-0.0430)	-0.2633±*j*7.1528 (-0.03679)	-0.1821±*j*7.4241 (-0.0245)
APBIL-PSS	-0.4480±*j* 1.9234 (0.2268)	-2.7370±*j*5.1200 (0.4714)	-2.3859±*j* 5.4068 (0.4037)
CPSS	-0.7945±*j*2.3363 (0.3220)	-1.5234±*j*7.8240 (0.1911)	-1.5534±*j*8.2134 (0.1858)

λ: eigenvalue, ζ damping ratio

TABLE V

EIGENVALUES FOR CASE 4 WITH AND WITHOUT THE PSSS

	Inter-area	Area 1 local	Area 2 local
	λ (ζ)	λ (ζ)	λ (ζ)
NO PSS	0.0113± *j*1.9335 (-0.0058)	-0.6614±*j*7.1123 (0.0926)	-0.6189±*j*7.3485 (0.0839)
APBIL-PSS	-0.4250±*j*1.4522 (0.2690)	-3.2221±*J*3.9128 (0.6357)	-3.0067±*j*4.7753 (0.5328)
CPSS	-0.7074±*j*1.7970 (0.3663)	-2.0977±*j*8.0445 (0.2523)	-2.1463±*j*8.3895 (0.2479)

λ: eigenvalue, ζdamping ratio

TABLE VI

EIGENVALUES FOR CASE 5 WITH AND WITHOUT THE PSSS

	Inter-area	Area 1 local	Area 2 local
	λ (ζ)	λ (ζ)	λ (ζ)
No PSS	-0.2711± *j*3.0847 (-0.0875)	-1.7188±*j*6.1613 (0.2687)	-1.7347±*j*6.3503 (0.2635)
APBIL-PSS	-0.4453±*j*2.9338 (0.1501)	-4.0029±*J*5.5970 (0.5817)	-2.9064±*J*5.3476 (0.4775)
CPSS	-0.4817±*j*3.0805 (0.1545)	-2.4187±*j*6.5154 (0.3480)	-2.4446±*j*6.7078 (0.3424)

λ: eigenvalue, ζdamping ratio

TABLE VII

EIGENVALUES FOR CASE 6 WITH AND WITHOUT THE PSSS

	Inter-area	Area 1 local	Area 2 local
	λ (ζ)	λ (ζ)	λ (ζ)
No PSS	-0.03500± *j*2.5609 (0.01367)	-1.0070±*j*6.8474 (0.1455)	-0.9947±*j*7.0492 (0.1397)
APBIL-PSS	-0.3922±*j*2.2403 (0.1724)	-3.4014±*J*3.7707 (0.6698)	-2.9823±*j*4.9422 (0.5167)
CPSS	-0..5564±*j*2.5080 (0.2166)	-2.2950±*j*7.6077 (0.2888)	-2.3190±*j*7.8328 (0.2839)

λ: eigenvalue, ζdamping ratio

TABLE VIII

EIGENVALUES FOR CASE 7 WITH AND WITHOUT THE PSSS

	Inter-area	Area 1 local	Area 2 local
	λ (ζ)	λ (ζ)	λ (ζ)
No PSS	0.0080± *j*1.9062 (-0.0042)	-0.5116±*j*7.2463 (0.0926)	-0.63786±*j*7.4308 (0.0855)
APBIL-PSS	-0.4231±*j*1.5052 (0.2706)	-3.1840±*J*3.8264 (0.6396)	-3.3108±*j*4.4205 (0.5995.)
CPSS	-0.6730.±*j*1.7947 (0.3511)	-2.0376±*j*8.3462 (0.2372)	-2.2853.±*j*8.7342 (0.2531)

λ: eigenvalue, ζdamping ratio

B. *Time Domain Simulations*

Time domain simulations have been performed to evaluate the performance and the robustness of the PSSs under the various cases discussed previously. For all the following simulations, a 50% step disturbance was applied to the V_{ref} of generator 3. The output power responses are shown in Figs 4-10.

Figs. 4-7 show the electrical power responses for cases 1-4. It can be seen that for all the responses, the APBIL-PSS is seen to give the smallest overshoots and undershoots with less oscillations than the CPSS. The performance of the APBIL-PSS is therefore better than that of the CPSS.

Figs. 8-10 show the electrical power responses for cases 5-7. The overall trend is similar to the previous cases 1-4, where the APBIL is seen to produce the smallest overshoots and undershoots with less oscillations. It can be said that overall, the APBIL-PSS is more robust in damping the oscillations.

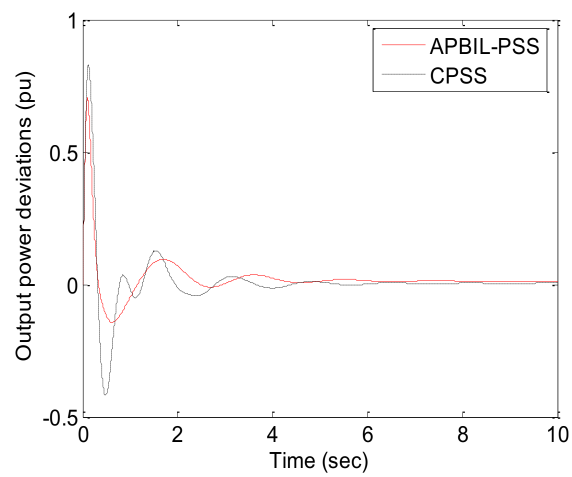

Fig. 4 Step responses of G3 output power for case 1

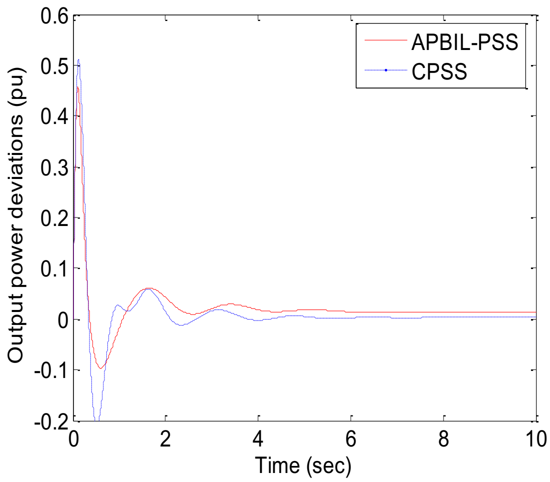

Fig. 5 Step responses of G3 output power for case 2

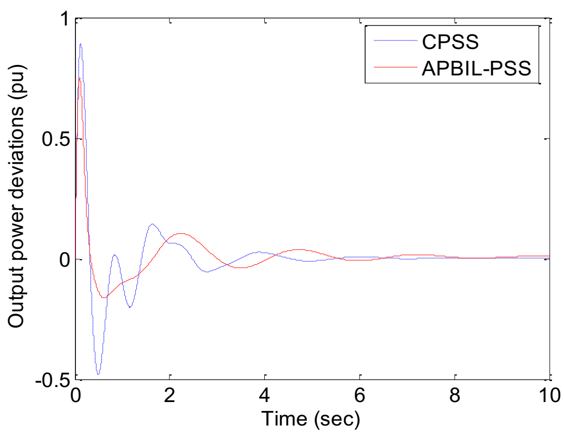

Fig. 6 Step responses of G3 output power for case 3

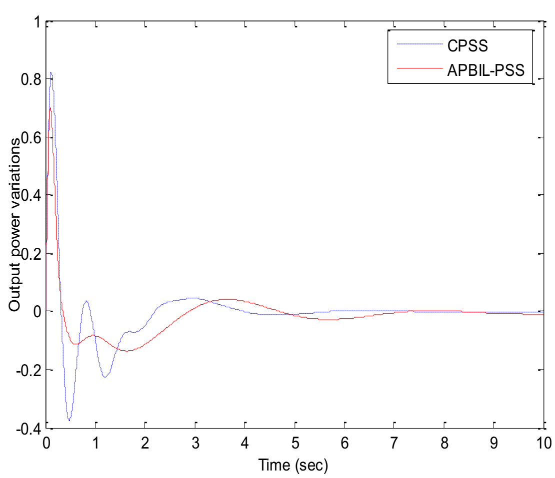

Fig. 7 Step responses of G3 output power for case 4

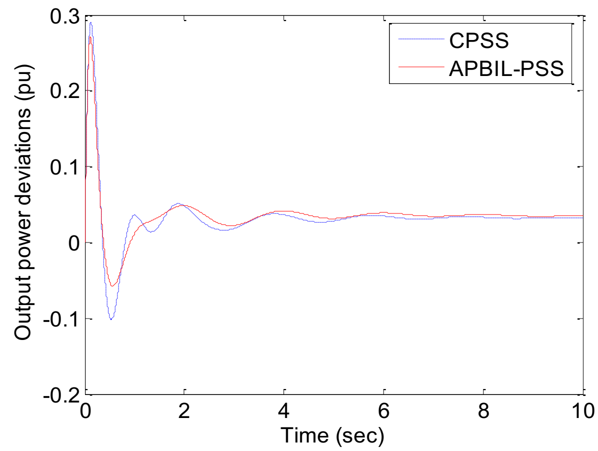

Fig. 8 Step responses of G3 output power for case 5

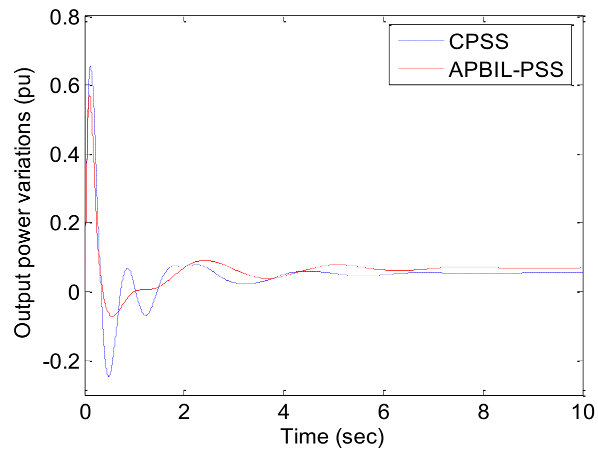

Fig. 9 Step responses of G3 output power for case 6

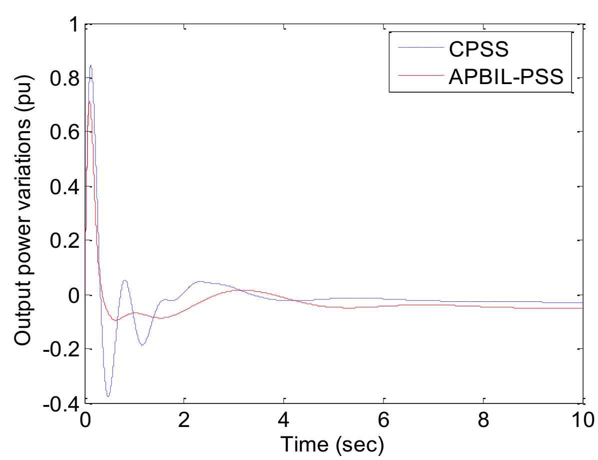

Fig. 10 Step responses of G3 output power for case 7

VI. Conclusion

PBIL with adaptive learning rate has been used in this paper to tune the parameters of power system stabilizers for a multi-machine power system that exhibits both local and inter-area oscillations. To guarantee controller robustness, the parameters of the PSSs are optimized over a pre-specified range of operating conditions. Eigenvalue analysis shows that overall the APBIL-PSS provide better damping than the conventional PSS. Time domain simulations show that with the APBIL-PSS, the overshoots and undershoots are smaller, and the oscillations are lesser for the entire range of operating conditions considered.

The main advantage of PBIL is that it is computationally simple and has fewer genetic operators compared to GA. PBIL requires few parameters than GA, therefore non-experts users can easily apply it to solve optimizations problems. There is no crossover or selection in PBIL. It requires less CPU memory as only two solutions are stored (the current best solution and the solution being evaluated) and the probability vector, while in GA, the whole population is stored. Thus, it is very attractive for online implementation.

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