Tuning of Power System Stabilizers in a Multi-Machine Power System using C-Catfish PSO

M. H. Moradi, S. M. Moosavi, A. R. Reisi

Abstract—The main objective of this paper is to investigate the enhancement of power system stability via coordinated tuning of Power System Stabilizers (PSSs) in a multi-machine power system. The design problem of the proposed controllers is formulated as an optimization problem. Chaotic catfish particle swarm optimization (C-Catfish PSO) algorithm is used to minimize the ITAE objective function. The proposed algorithm is evaluated on a two-area, 4-machines system. The robustness of the proposed algorithm is verified on this system under different operating conditions and applying a three-phase fault. The nonlinear time-domain simulation results and some performance indices show the effectiveness of the proposed controller in damping power system oscillations and this novel optimization algorithm is compared with particle swarm optimization (PSO).

Keywords—Power system stabilizer, C-Catfish PSO, ITAE objective function, Power system control, Multi-machine power system

I. INTRODUCTION

IN 1950s and to 1960s, many power-generating plants were equipped with continuously acting automatic voltage regulators (AVRs). As the number of power plants with AVRs grew, it became apparent that the high performance of these voltage regulators had a destabilizing effect on the power system. Power oscillations of small magnitude and low frequency often persisted for long periods of time. Since the development of interconnected large electric power systems, there have been spontaneous system oscillations at very low frequencies in order of 0.2–3.0 Hz. Once started, they would continue for a long period of time. In some cases, they continue to grow, causing system separation if no adequate damping is available. Moreover, low frequency oscillations present limitations on the power-transfer capability. In some cases, this presented a limitation on the amount of the power to be transmitted within the system [1]. Power system stabilizers (PSSs) are auxiliary control devices on synchronous generators, used in conjunction with their excitation systems to provide control signals toward enhancing the system damping and extending power transfer limits.

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Thus, maintaining reliable operation of the power system [2]. Several approaches based on modern control theory have been applied to power system stabilizer design problems. These include optimal control, adaptive control, variable structure control and intelligent control [3]–[5]. Novel intelligent control design methods such as fuzzy logic controllers [6] and artificial neural network controllers [7] have been used as the PSSs. Unlike other classical control methods, fuzzy logic and neural network controllers are model-free controllers; i.e. they do not require an exact mathematical model of the controlled system. Moreover, speed and robustness are the most significant properties in comparison to other classical schemes. H_∞ optimization techniques [8] have been also applied to the robust PSS design problem. However, the importance and difficulties in the selection of weighting functions of the H_∞ optimization have been reported. Recently, intelligent optimization techniques like genetic algorithms (GA) [9]–[12], Tabu search [13], simulated annealing [14], evolutionary programming [15] and rule based bacteria foraging [16] have been applied for PSS parameter optimization. These evolutionary algorithms are heuristic population-based search procedures that incorporate random variation and selection operators. Although, these methods seem to be good methods for the solution of PSS parameter optimization problem, However, when the system has a highly epistatic objective function (i.e. where parameters being optimized are highly correlated), and number of parameters to be optimized is large, then they have regarded efficiency to obtain global optimum solution and also simulation process use a lot of computing time. An algorithm for computerized automatic tuning of power system stabilizers has been presented in [17]. Particle swarm optimization [18] has been applied for PSSs parameter optimization in 3-machines power system. In this paper, a comprehensive assessment of the effects of the coordinated design of PSSs stabilizers on power system stability enhancement has been carried out in multi-machine power system. Chaotic catfish particle swarm optimization (C-Catfish PSO) algorithm is used to minimize the ITAE objective function for a two-area, 4-machines system under different operating conditions and applying a three-phase fault. Unlike the other heuristic techniques, C-Catfish PSO has a flexible and well-balanced mechanism to enhance the global and local exploration abilities. The nonlinear time-domain simulation results and some performance indices show the effectiveness of the proposed controller in damping power system oscillations.

II. C-CATFISH PSO ALGORITHM

PSO is one of the optimization techniques and belongs to evolutionary computation techniques [19]. The method has been developed through a simulation of simplified social models. The features of the method are as follows:

1) The method is based on researches on swarms such as fish schooling and bird flocking.

2) It is based on a simple concept. Therefore, the computation time is short and it requires few memories.

According to the research results for bird flocking, birds are finding food by flocking (not by each individual). It leaded the assumption that information is owned jointly in flocking. According to observation of behavior of human groups, behavior pattern on each individual is based on several behavior patterns authorized by the groups such as customs and the experiences by each individual (agent). The assumptions are basic concepts of PSO.

The PSO starts with a population of random solutions "particles" in a D-dimension space. The i_{th} particle is represented by $X_i=(x_{i1}, x_{i2}, ..., x_{iD})$. Each particle keeps track of its coordinates in hyperspace, which are associated with the fittest solution it has achieved so far. The value of the fittest for particle i (P_{best}) is also stored as $P_i=(P_{i1}, P_{i2}, ..., P_{iD})$. The global version of the PSO keeps track of the overall best value (g_{best}), and its location, obtained thus far by any particle in the population. PSO consists of changing the velocity of each particle toward its P_{best} and g_{best}, at each step according to (1). The velocity of particle i is represented as $V_i=(v_{i1}, v_{i2}, ..., v_{iD})$. Acceleration is weighted by a random term, with separate random numbers being generated for acceleration toward P_{best} and g_{best}. The position of the i_{th} particle is then updated according to (2) [20] and [21].

$$V_{id} = W \times V_{id} + C_1 \times r_1 \times (P_{id} - X_{id}) + C_2 \times r_2 \times (P_{gd} - X_{id}) \qquad (1)$$

$$x_{id} = x_{id} + cv_{id} \qquad (2)$$

Where P_{id} and P_{gd} are P_{best} and g_{best}. Several modifications have been proposed in literature to improve the PSO algorithm speed and convergence toward the global minimum. One modification is to introduce a local-oriented paradigm (I_{best}) with different neighborhoods.

It is concluded that g_{best} version performs best in terms of median number of iterations to converge. However, P_{best} version with neighborhoods of two is most resistant to local minima. The positive constants C_1 and C_2 are the cognitive and social components that are the acceleration constants responsible for varying the particle velocity towards P_{best} and g_{best}, respectively. Variables r_1 and r_2 are two random functions based on uniform probability distribution functions in the range [0,1]. The inertia weight w is responsible for dynamically adjusting the velocity of the particles, so it is responsible for balancing between local and global searches and hence requiring less iteration for algorithm to converge. The following inertia weight is used in (1):

$$W = W_{max} - \frac{W_{max} - W_{min}}{iter_{max}} iteration \qquad (3)$$

Where $iter_{max}$ is the maximum number of iterations and iteration is the current number of iteration. (3) presents that the inertia weight is updated, considering W_{max} and W_{min} are the initial and final weights, respectively. The underlying idea for the development of Catfish PSO was derived from the catfish effect observed when catfish were introduced into large holding tanks of sardines [22]. The catfish in competition with the sardines, stimulate renewed movement amongst the sardines. Similarly, the introduced catfish particles stimulate a renewed search by the other ''sardine'' particles in Catfish PSO. In other words, the catfish particles can guide particles trapped in a local optimum onto a new regions of the search space, and thus to potentially better particle solutions.

In Catfish PSO, a population is randomly initialized in a first step, and the particles are distributed over the D-dimensional search space. The position and velocity of each particle are updated by (1)–(3). If the distance between g_{best} and the surrounding particles is small, each particle is considered a part of the cluster around g_{best} and will only move a very small distance in the next generation. To avoid this premature convergence, catfish particles are introduced and replace the 10% of original particles with the worst fitness values of the swarm.

In PSO, the parameters w, r_1 and r_2 are the key factors affecting the convergence behavior. The inertia weight controls the balance between the global exploration and the local search ability. A large inertia weight favors the global search, while a small inertia weight favors the local search. For this reason, an inertia weight that linearly decreases from 0.9 to 0.4 throughout the search process is usually used [23]. Since logistic maps are frequently used chaotic behavior maps and chaotic sequences can be quickly generated and easily stored, there is no need for storage of long sequences [24]. In C-PSO, sequences generated by the logistic map substitute the random parameters r_1 and r_2 are modified by the logistic map based on the following equation.

$$Cr_{(t+1)} = k \times Cr_{(t)} \times (1 - Cr_{(t)}) \qquad (4)$$

In (4), $Cr_{(0)}$ is generated randomly for each independent run, with $Cr_{(0)}$ not being equal to {0, 0.25, 0.5, 0.75, 1} and k equal to 4. The driving parameter k of the logistic map, controls the behavior of $Cr_{(t)}$ (as t goes to infinity) [25]. The velocity update equation for C-PSO can be formulated as:

$$V_{id} = W \times V_{id} + c_1 \times Cr \times (P_{id} - X_{id}) + c_2 \times (1 - Cr) \times (P_{gd} - X_{id}) \qquad (5)$$

In (5), Cr is a function based on the results of the logistic map with values between 0.0 and 1.0.

In C-Catfish PSO, a logistic map is embedded into Catfish PSO, which updates the parameters r_1 and r_2 based on (4) [26]. The logistic map improves the search capability of Catfish PSO significantly. The particle velocities are updated according to (5).

This new approach features many advantages; it is simple, fast and easy to be coded. Also, its memory storage requirement is minimal. Another advantage of C-Catfish PSO

is that the initial population of the PSO is maintained, and so there is no need for applying operators to the population, a process that is time and memory-storage-consuming. It is shown in [26] that better solutions can be found by guiding the whole swarm to more promising regions in the search space. C-Catfish PSO achieved far better performance than PSO, C-PSO, Catfish PSO and several other advanced PSO algorithms.

The proposed algorithm will proceed as follows:

01: Begin
02: Randomly initialize particles swarm
03: Randomly generate $Cr_{(0)}$
04: while (number of iterations, or the stopping criterion is not met)
05: Evaluate fitness of particle swarm
06: for n = 1 to number of particles
07: Find p_{best}
08: Find g_{best}
09: for d = 1 to number of dimension of particle
10: update the Chaotic Cr value by (4)
11: update the position of particles by (5) and (2)
12: next d
13: next n
14: if fitness of g_{best} is the same Seven times then
15: Sort the particle swarm via fitness from best to worst
16: for n = number of Nine-tenths of particles to number of particles
17: for d = 1 to number of dimension of particle
18: Randomly select extreme points at Max or Min of the search space
19: Reset the velocity to 0
20: next d
21: next n
22: end if
23: update the inertia weight value by (3)
24: next generation until stopping criterion
25: end

III.   STUDY SYSTEM MODELING

A. Power system model

A four-machine, two-area study system, shown in Fig. 2, is considered for the damping control design. Each area consists of two generator units. The rating of each generator is 900 MVA and 20 kV. Each of the units is connected through transformers to the 230 kV transmission line. There is a power transfer of 400MW from area 1 to area 2. Each synchronous generator of the multi-machine power system is simulated using a third-order model. The detailed bus data, line data, and the dynamic characteristics for the machines, exciters and loads are given in [27]. The loads are modeled as constant impedances. On the basis of participation factors [28], two PSSs are installed in generators 1 and 3. The dynamics of the machines are given in the Appendix A.

B. PSS structure

A first order model of a static type AVR was used and the structure of the AVR equipped with the PSS is presented in Fig. 3. The operating function of a PSS is to produce a proper torque on the rotor of the machine involved in such a way that the phase lag between the exciter input and the machine electrical torque is compensated. The supplementary stabilizing signal considered is one proportional to speed. In Fig.3, V_t is the terminal bus voltage and V_{ref} is the reference voltage for the AVR. Limits of +5.0 p.u and -5.0 p.u, for the field voltage were used in the simulations.

Whereis $\Delta\omega_i$ the deviation in speed from the synchronous speed. This type of stabilizer consists of a washout filter, a dynamic compensator. The output signal is fed as a supplementary input signal, U_i , to the regulator of the excitation system. The washout filter, which essentially is a high pass filter, is used to reset the steady state offset in the output of the PSS. The value of the time constant, T_w is usually not critical and it can range from 0.5 to 20 s. In this study, it is fixed to 10 s. The dynamic compensator is made up to two lead–lag stages and an additional gain

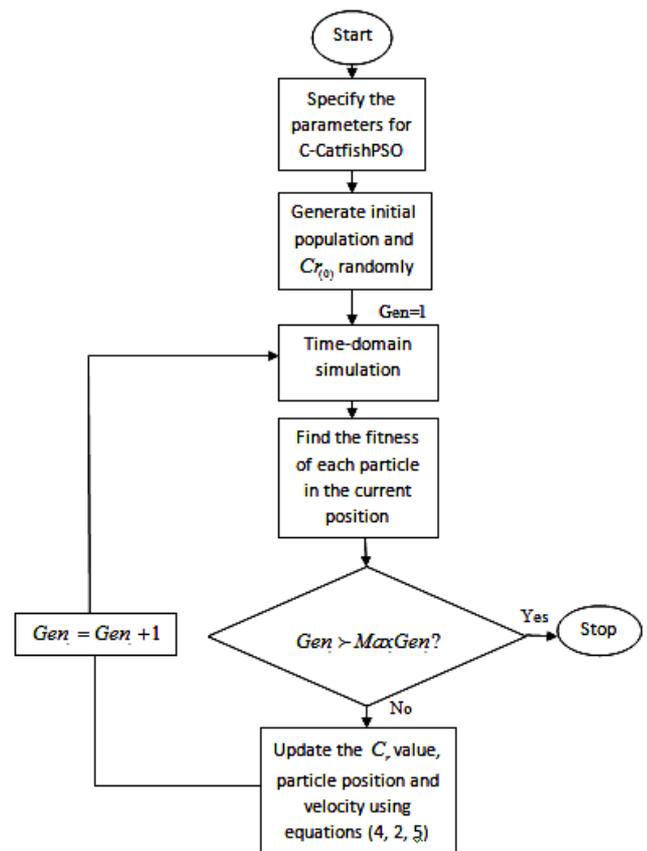Fig. 1 The computational flow chart of PSO algorithm is shown in
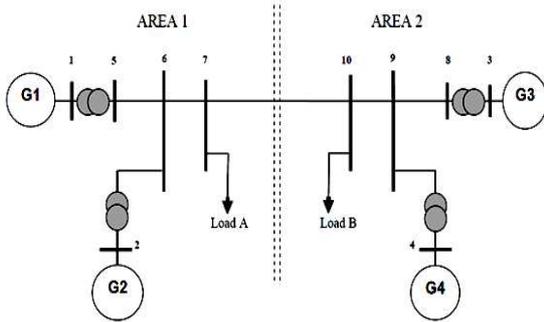

Fig. 1 Flowcharts of C-Catfish PSO algorithm

Fig. 2 Multi-machine power system

The transfer function of the i_{th} PSS is:

$$U_i = K_i \frac{sT_w}{1+sT_w} \left[\frac{(1+sT_{1i})(1+sT_{3i})}{(1+sT_{2i})(1+sT_{4i})} \right] \Delta \omega_i(s) \qquad (6)$$

The adjustable PSS parameters are the gain of the PSS, K_i, and the time constants, T_{1i}-T_{4i}. The lead–lag block present in the system provides phase lead compensation for the phase lag that is introduced in the circuit between the exciter input and the electrical torque. The required phase lead can be derived from the lead–lag block even if the denominator portion consisting of T_{2i} and T_{4i} gives a fixed lag angle. Thus, to reduce the computational burden in this study, the values of T_{2i} and T_{4i} are kept constant at a reasonable value of 0.05 s and tuning of T_{1i} and T_{3i} are undertaken to achieve the net phase lead required by the system.
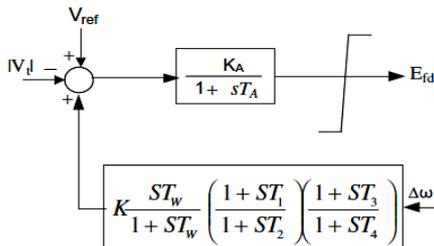

Fig. 3 Block diagram of the AVR equipped with PSS

C. Simultaneous coordinated design using C-Catfish PSO

The proposed controller must be able to work well under different operating conditions, while the improvement for the damping of the critical modes is necessary. Since the selection of the PSS parameters is a complex optimization problem. Thus, to acquire an optimal combination, this paper employs the C-Catfish PSO algorithm to improve the optimization synthesis and find the global optimum value. A performance index based on the system dynamics after an impulse disturbance alternately occurs in the system is organized and used as the objective function for the design problem. In this study, an ITAE is taken as the objective function. Since the operating conditions in the power systems are often varied, a performance index for three different operating points is defined as follows [30]:

$$J = \int_0^{t_{sim}} t \cdot \left(|w_1 - w_2| + |w_1 - w_3| + |w_1 - w_4| + |w_3 - w_4| \right) dt \qquad (7)$$

$$F = \sum_{i=1}^{3} J_i \qquad (8)$$

Where t_{sim} is the time range of the simulation. It is aimed to minimize this objective function in order to improve the system response in terms of the settling time and overshoots. To reduce the computational burden in this study, the values of T_{21PSS}, T_{41PSS}, T_{23PSS} and T_{43PSS} are kept constant at a reasonable value of 0.05 s. Thus, the design problem can be formulated as constrained optimization problem shown in table I.

TABLE I
CONSTRAINS OF PSSs PARAMETERS

	K_{1PSS}	T_{11PSS}	T_{31PSS}	K_{3PSS}	T_{13PSS}	T_{33PSS}
min	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
max	50	1	1	50	1	1

The proposed approach employs C-Catfish PSO technique to solve this optimization problem and search for optimal or near optimal set of PSS parameters.

It is emphasized that with this procedure, robust stabilizer, enable to operate satisfactorily over a wide range of the operating conditions, are obtained. The flowchart of the optimization based coordinated designing is depicted in Fig. 4. The optimization of the PSSs controller parameters is carried out by evaluating the objective cost function as given in (8) which considers a multiple of the operating conditions (OP). The operating conditions are given in Table II. In order to acquire better performance, number of particle, particle size, number of iterations, c_1, c_2, and c are chosen as 50, 6, 100, 2, 2 and 1, respectively. It should be noted that the C-Catfish PSO algorithm is run several times and then optimal set of coordinated controller parameters is selected. The final values of the optimized parameters are given in Table III. Also, Fig. 5 shows the minimum fitness value evaluating process.

TABLE II
THREE OPERATING CONDITION

CONDITION	OP_1	OP_2	OP_3
P_1	0.7778	0.5556	0.9911
Q_1	0.2056	0.2056	0.1722
P_2	0.2885	0.5556	0.6283
Q_2	-0.1084	0.2611	0.5836
P_3	0.8020	0.5597	0.0095
Q_3	0.0697	0.2217	0.0712
P_4	0.8889	0.5556	1.1110
Q_4	0.2244	0.2244	0.2222

TABLE III
OPTIMAL PSSs PARAMETERS USING PSO AND C-CATFISH PSO TECHNIQUE

	PSO			C-Catfish PSO		
	K	T_1	T_3	K	T_1	T_3
G_1	10.6354	1.0000	0.0801	12.0528	0.0001	1.0000
G_3	12.4578	1.0000	0.0001	14.0424	0.0001	1.0000

IV. NONLINEAR TIME-DOMAIN SIMULATION

The effectiveness and robustness of the performance of the proposed controller under transient conditions is verified by applying
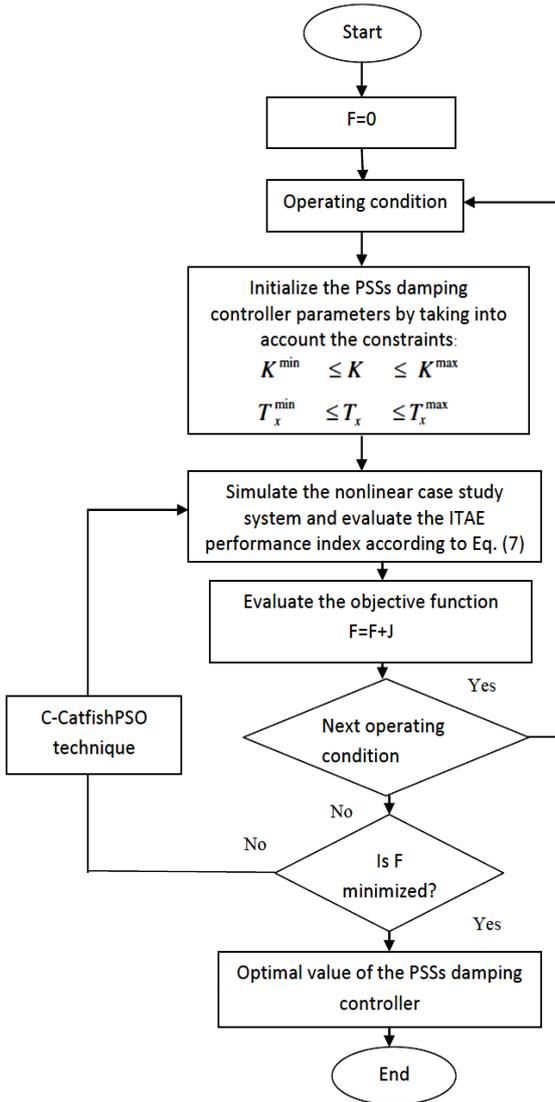
Fig. 4 Flowchart of optimization based coordinated designing

Fig. 5 Variations of objective function

a three-phase fault of 100 ms duration at the middle of one of the transmission lines between bus-7 and bus-10. PSO algorithm has been also used in this paper to minimize the ITAE objective function and these two algorithms are compared according to nonlinear time-domain simulation for different operating conditions. The inter-area and local mode of oscillations with coordinated design of the controllers using PSO and C-Catfish PSO algorithms are shown in Figs (6-8) for different operating conditions. In C-Catfish PSO, a chaotic map was embedded to determine the PSO parameters r_1 and r_2. The PSO parameters r_1 and r_2 cannot ensure optimal ergodicity in the search space because they are absolutely random i.e. the r_1 and r_2 are generated by a linear congruential generator (LCG) with a random seed. The generated sequence of LCG consists of pseudo-random numbers that have periodic characteristics.

Furthermore, the generated sequence of a logistic map also consists of pseudo-random numbers, but there are no fixed points, periodic orbits, or quasi-periodic orbits in the behavior
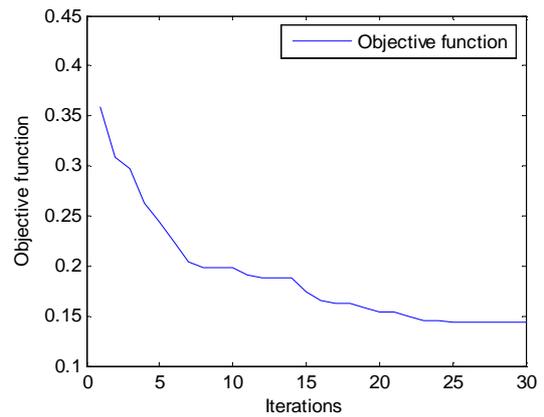
of the chaos system. In PSO, each particle only relies on its individual p_{best} value and the global best position g_{best} to update its position at each generation. If g_{best} is trapped in a local optimum, the particles cluster together and lose their ability to explore the search space in later generations. In order to avoid such a scenario, the worst 10% of the swarm are replaced by Catfish particles when g_{best} has not changed for a certain number of generations. After the catfish particles are introduced, they initialize a renewed search from extreme points of the search space, and thus find the better solutions by guiding the entire swarm to promising new regions. They also improve the search efficiency of the swarm. The catfish particles not only allow the swarm to discover better solutions within the area of the swarm itself, but also to obtain better solutions located outside the swarm area.

Now it is clear from the figures (6-8) that the PSSs which are tuned by C-Catfish PSO, are more effective than the ones tuned by PSO in damping the low frequency oscillations and improves the stability performance of the example power system.

To demonstrate the performance and robustness of the proposed method, two performance indices: the ITAE and FD based on the system performance characteristics are defined as [31]:

$$ITAE = 1000 \int_0^{t_{sim}} t \cdot (|w_1 - w_2| + |w_1 - w_3| + |w_1 - w_4| + |w_3 - w_4|) dt \qquad (9)$$

$$FD = (OS \times 5000)^2 + (us \times 5000)^2 + T_s^2$$

Where w is the speed rotor, overshoot (OS), undershoot (US) and settling time of Δw_{13} of the system is considered for the evaluation of the ITAE and FD indices. It is worth mentioning that the lower the value of these indices is, the better the system response in terms of time-domain characteristics. Numerical results of the performance and robustness for all system loading cases are shown in Fig. 9.

It can be seen that the application of the PSSs damping controller where the controllers are tuned by C-Catfish PSO, achieves better response than the ones tuned by PSO.
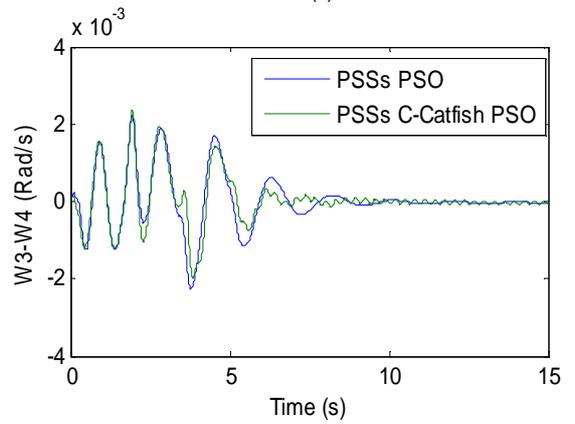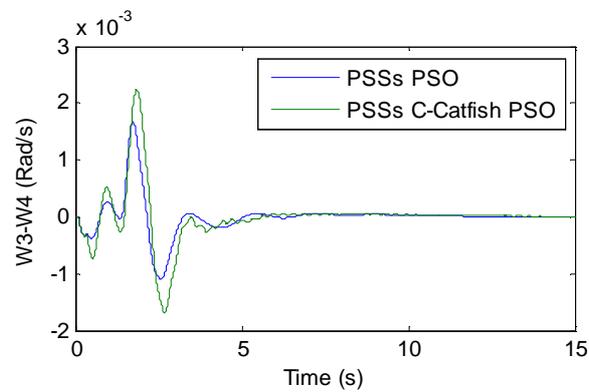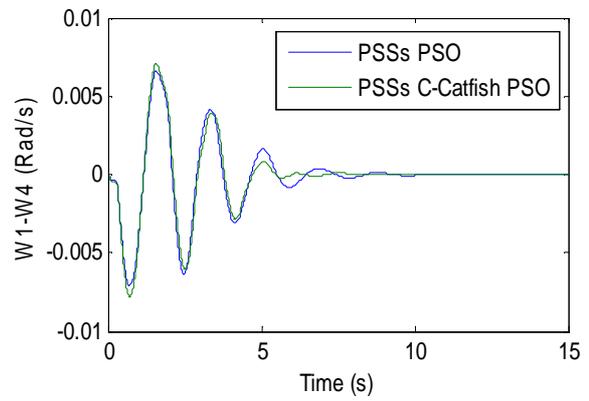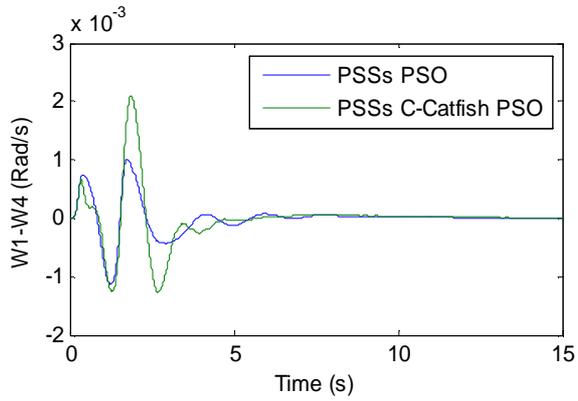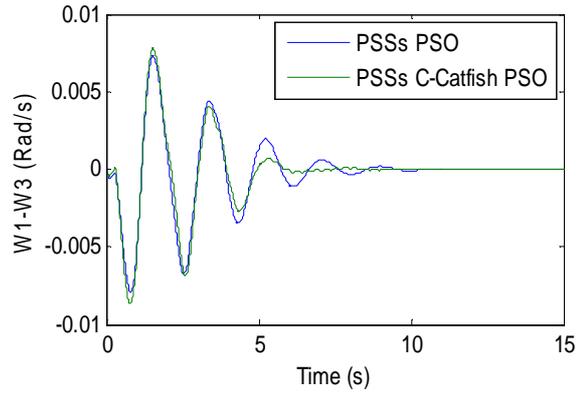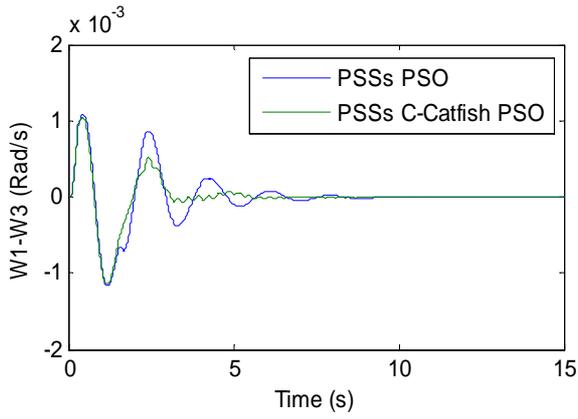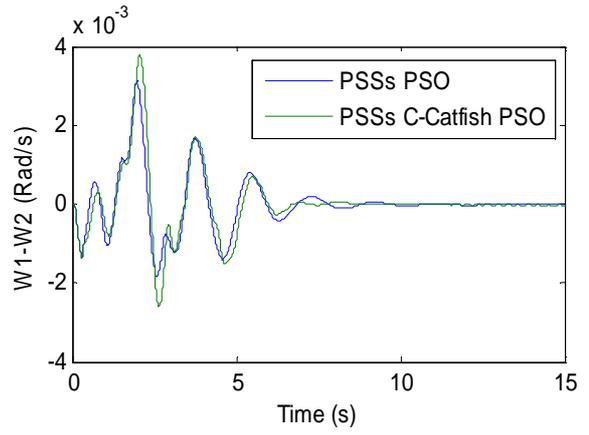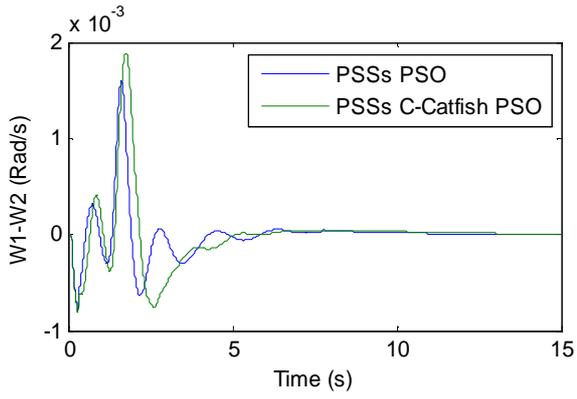
Fig. 6 Inter-area and local mode of oscillations for OP_1

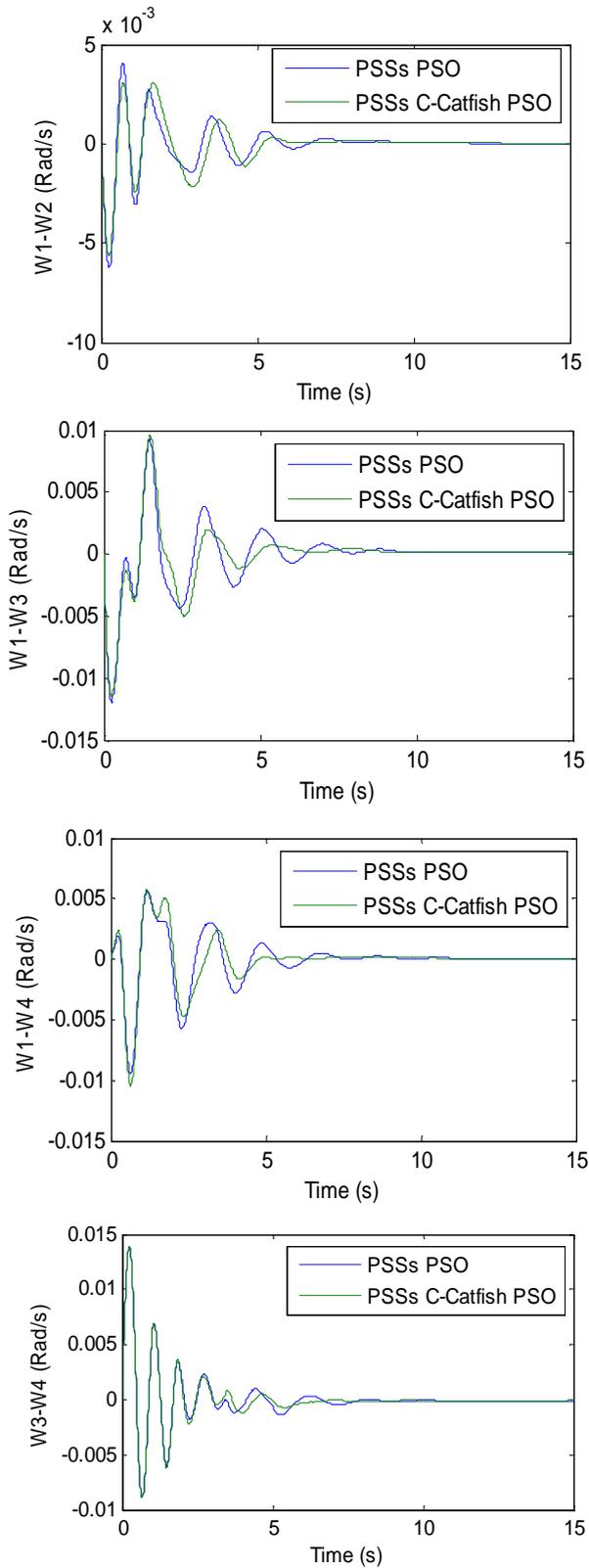Fig. 7 Inter-area and local mode of oscillations for OP_2

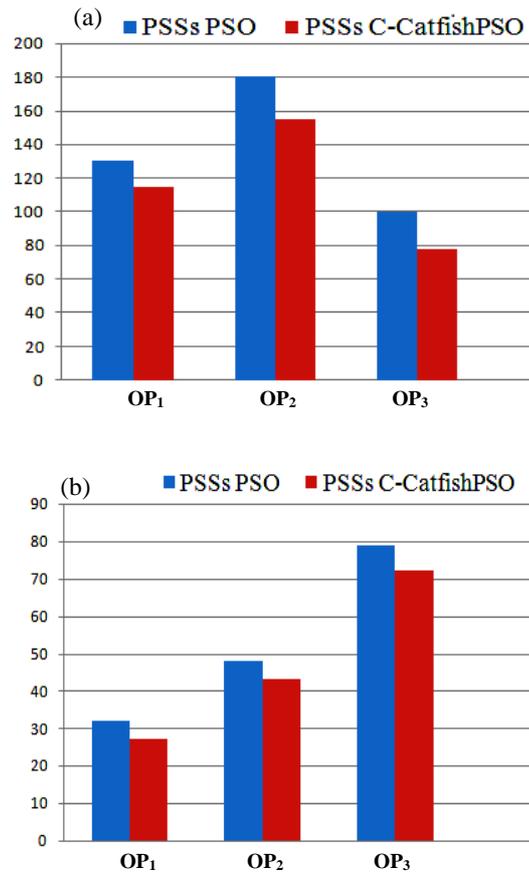Fig. 8 Inter-area and local mode of oscillations for OP_3

Fig. 9 Values of performance index; (a) FD and (b) ITAE

V. CONCLUSION

Techniques such as PSO and C-Catfisho PSO are inspired by nature, and have proved themselves to be effective solutions to optimization problems. The objective of this research is to compare the performance of these two optimization techniques for PSSs controller design. In this paper, the enhancement of power system stability is investigated via coordinated tuning of PSSs. For this reason, the PSSs parameters are tuned according to optimization of ITAE Objective function by PSO and C-Catfish PSO algorithms. The proposed C-Catfish PSO algorithm for tuning PSSs is easy to implement without additional computational complexity. Thereby experiments this algorithm gives quite promising results. The ability to jump out the local optima, the convergence precision and speed are remarkably enhanced and thus the high precision and efficiency are achieved. The effectiveness of the proposed method is tested on a 2-area 4 machines power system for three different operating conditions and applying a three-phase fault of 100 ms duration at the middle of one of the transmission lines between bus 7 and bus 10. Compared with PSO technique in terms of damping low frequency oscillations, ITAE and FD indices, the C-Catfish PSO technique demonstrates its superiority in computational complexity, success rate and solution quality. C-Catfish PSO

has a flexible and well-balanced mechanism to enhance the global and local exploration abilities. The nonlinear time simulation results confirm that the proposed C-Catfish PSO based tuned PSSs can work effectively over three different operating conditions and is superior to the PSO. The system performance characteristics in terms of 'ITAE' and 'FD' indices reveal that this control strategy is a promising control scheme for PSS design in the real world power systems.

APPENDIX A

The dynamics of each synchronous machine is given by [28] and [29]:

$$\dot{\delta}_i = \omega_b(\omega_i - 1) \tag{A1}$$

$$\dot{\omega}_i = \frac{1}{M_i}(P_{mi} - P_{ei} - D_i(\omega_i - 1)) \tag{A2}$$

$$\dot{E}'_{qi} = \frac{1}{T'_{doi}}(E_{fdi} - (x_{di} - x'_{di})i_{di} - E'_{qi}) \tag{A3}$$

$$\dot{E}_{fdi} = \frac{1}{T_{Ai}}(K_{Ai}(v_{refi} - v_i + u_i) - E_{fdi}) \tag{A4}$$

$$T_{ei} = E'_{qi}i_{qi} - (x_{qi} - x'_{di})i_{di}i_{qi} \tag{A5}$$

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