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Bio-Inspired Algorithms for the Design of Multiple Optimal Power System Stabilizers: SPPSO and BFA

Tridib Kumar Das, *Student Member, IEEE*, Ganesh Kumar Venayagamoorthy, *Senior Member, IEEE*, and Usman O. Aliyu

Abstract—Damping intra-area and interarea oscillations are critical to optimal power flow and stability in a power system. Power system stabilizers (PSSs) are effective damping devices, as they provide auxiliary control signals to the excitation systems of generators. The proper selection of PSS parameters to accommodate variations in the power system dynamics is important and is a challenging task particularly when several PSSs are involved. Two classical bio-inspired algorithms, which are small-population-based particle swarm optimization (SPPSO) and bacterial foraging algorithm (BFA), are presented in this paper for the simultaneous design of multiple optimal PSSs in two power systems. A classical PSO with a small population of particles is called SPPSO in this paper. The SPPSO uses the regeneration concept, introduced in this paper, to attain the same performance as a PSO algorithm with a large population. Both algorithms use time domain information to obtain the objective function for the determination of the optimal parameters of the PSSs. The effectiveness of the two algorithms is evaluated and compared for damping the system oscillations during small and large disturbances, and their robustness is illustrated using the transient energy analysis. In addition, the computational complexities of the two algorithms are also presented.

Index Terms—Bacterial foraging, computational complexity, multimachine power systems, Nigerian power system, particle swarm optimization (PSO), power system stabilizers (PSSs), regeneration stability, small population, transient energy (TE) analysis.

I. INTRODUCTION

IN POWER systems, reliability and transfer capability are often limited by stability constraints like transient, oscillatory, and voltage stabilities. Maintaining system stability presents new challenges, as power systems are operating today under more stressed conditions and uncertainty than in the past. If stability problems are accurately identified and properly mitigated, significant economic gains can be realized. Power system

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stabilizers (PSSs) are used as supplementary control devices to provide extra damping and improve the dynamic performance of the power system. PSSs are very effective controllers in enhancing the damping of low-frequency oscillations because they can increase the damping torque for interarea modes by introducing additional signals into the excitation controllers of the generators. These oscillations come into existence when generators fall out of step from each other. Depending on their location in the system, some generators participate in a single mode of oscillation, whereas others participate in more than one mode.

Researchers have been putting lots of efforts in the design of optimal PSSs to satisfy different system requirements. Several PSS design techniques have been reported [1]–[3]. These algorithms employ large number of particles or individuals in the optimization. The involvement of large number of particles takes a significant amount of computation time. This may pose a serious problem for systems which desire faster convergence. To avoid burden on time and resources, the need for developing small-population-based algorithms like the microgenetic algorithm (μ -GA) [4] comes into mind. μ -GA with its small population size and reinitialization process is capable of improving the exploitation characteristics of the GA without affecting its exploration characteristics. The involvement of fewer numbers of particles can be considered as the first step toward online optimization, where fast plugging of updated parameters is desired. However, studies have revealed that GA has a degraded performance if the function to be optimized is epistatic (where parameters to be optimized are highly co-related) [5]. The GA algorithm also has the demerit of premature convergence. This paper therefore explores the efficacies of two new small-population-based algorithms for the tuning of PSS parameters.

Two bio-inspired algorithms, which are small-population-based particle swarm optimization (SPPSO) and bacterial foraging algorithm (BFA), for the simultaneous design of multiple optimal PSSs are presented. SPPSO is capable of exploration and exploitation like PSO. The involvement of a number of stages in BFA greatly reduces the possibility of getting trapped in the local minima during the search process. This approach is a sincere effort by the authors toward determining the efficacies of small-population-based algorithms as a first step toward online optimization. These algorithms are selected in an effort to overcome computational overburden. The objective function formulated for the optimization takes into consideration the time domain information from the PSCAD/EMTDC models [6], making it suitable for future online optimization.

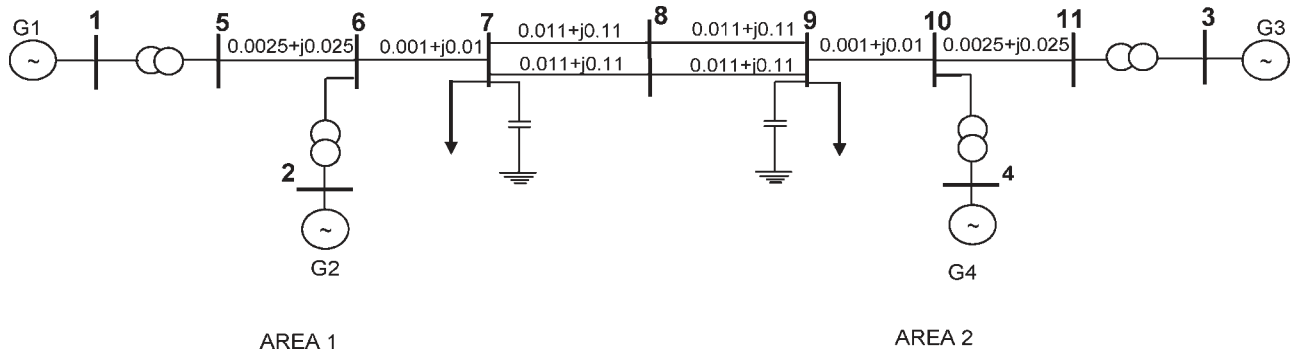


Fig. 1. Two-area multimachine power system.

The effectiveness of SPPSO and BFA as optimization algorithms for simultaneous multiple optimal PSSs design is evaluated on a two-area benchmark system [7] and the Nigerian power system [8]. The robustness of the optimally tuned PSSs is further compared using the transient energy (TE) analysis.

The rest of this paper is organized as follows. Section II presents the power systems considered in this paper. Section III describes the bio-inspired algorithms used. Section IV explains the design of an optimal PSS. Section V presents some simulation results. Section VI presents some analysis and discussions on SPPSO and BFA. Finally, the conclusions and future work are given in Section VII.

II. TWO MULTIMACHINE POWER SYSTEMS

In this paper, two different power systems are considered. The first one is a four-machine 11-bus system, and the second one is a seven-machine 25-bus system.

A. Two-Area Multimachine Power System

The two-area power system used in this paper is simulated in the PSCAD/EMTDC environment which allows the detailed representation of the power system dynamics. The small two-area power system, shown in Fig. 1, consists of two fully symmetrical areas linked together by two transmission lines. Each area is equipped with two identical synchronous generators rated 20 kV/900 MVA. All generators are equipped with identical speed governors and turbines, exciters and automatic voltage regulators (AVRs), and PSSs. The loads in the two areas are such that Area 1 is exporting about 413 MW to Area 2. This power network is specifically designed to study low-frequency electromechanical oscillations in two interconnected power systems [7].

The PSSs provide additional input signal (V_{pss}) to the voltage regulators/excitation systems to damp out the power oscillations. Some commonly used input signals are rotor speed deviation ($\Delta\omega_r$), accelerating power, and frequency. A typical PSS block diagram is shown in Fig. 2. It consists of an amplifier block of gain constant K , a block having a washout time constant T_w , and two lead-lag compensators with time constants T_1 to T_4 . The gain and four lead-lag compensator time constants are to be selected for optimal performance over a wide range of operating conditions.

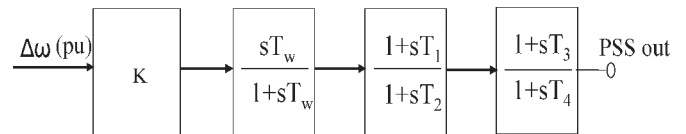


Fig. 2. Block diagram of a PSS.

B. Nigerian Power System

The Nigerian 330-kV 25-bus grid power system is shown in Fig. 3. It consists of seven generating units in two distinct areas (four thermal and three hydro units), seven generator step-up transformers equipped with tap changers, and compensation reactors of different discrete values located at eight different nodes. This system has two interarea modes (hydro and thermal) and several intra-area modes (hydro and thermal) [8]. There is a damping of 3.8% for a 1.223-Hz oscillatory mode experienced by the hydro generating units and a damping of 3.4% for a 1.225-Hz oscillatory mode experienced by the thermal generating units. This makes the system potentially unstable when experiencing large disturbances, thus the need for the design of optimal PSSs for the hydro and thermal areas. Hence, two PSSs of the form in Fig. 2 are added to the excitations of generators at Shiroro and Egbin power stations (Fig. 3).

III. BIO-INSPIRED ALGORITHMS WITH SMALL POPULATION

The beauty of PSO lies in its ability to explore and exploit the search space by varying its parameters (inertia weight and acceleration constants). BFA due to its unique operators (elimination–dispersal events) can find favorable regions during search. These unique features of the algorithms overcome the premature convergence problem and enhance the search capability. Hence, they are suitable algorithms for simultaneous design of multiple optimal PSSs. Improvements over the classical PSO and BFA algorithms have been reported in the literature [9]–[12]. The improvements to the classical PSO are reported by modifying the PSO parameters, using adaptive critics [9], or by introducing a mutation operator [10]. Similarly, the improvements to the classical BFA are reported by varying the run step length, using fuzzy [11] or adaptive [12] techniques. The authors in this paper, however, compare the classical BFA [13] and PSO [14] with algorithms employing a small population.

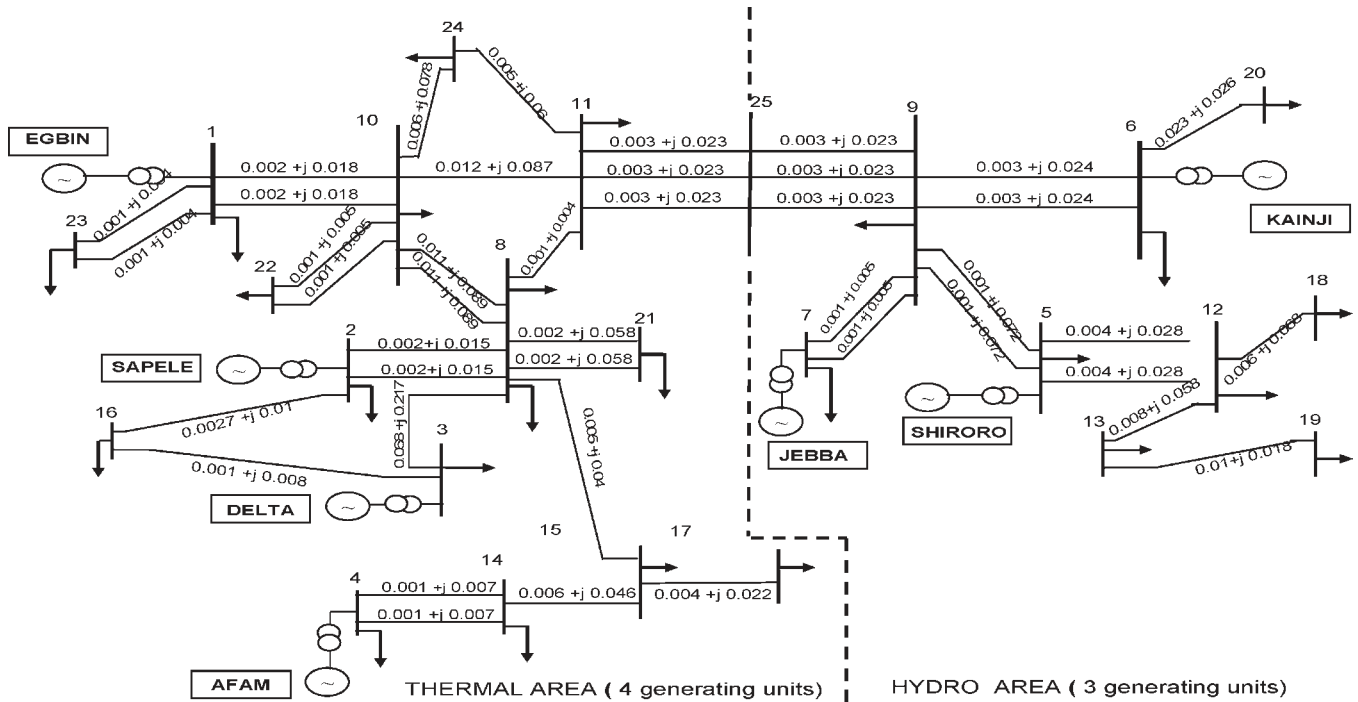


Fig. 3. Nigerian 330-kV 25-bus grid power system.

The comparison is made in terms of their computational complexities and speed for the design of multiple optimal PSSs. The two classical bio-inspired algorithms used in this paper are described hereafter.

A. SPPSO Algorithm

The SPPSO algorithm is derived from the PSO algorithm. PSO is a form of evolutionary computation technique (a search method based on natural systems) developed by Kennedy and Eberhart [9], [10]. The PSO, like GA, is a population (swarm)-based optimization tool. However, unlike in GA, individuals are not eliminated from the population from one generation to the next. One major difference between particle swarm and traditional evolutionary computation methods is that the velocities of the particles are adjusted, whereas the positions of evolutionary individuals are acted upon; it is as if the “fate” is altered rather than the “state” of the particle swarm individuals [11].

Each potential solution, called *particle*, is given a random velocity and is flown through the problem space. The particles have memory, and each particle keeps track of previous best position and corresponding fitness. The previous best value is called the p_{best} of the particle and represented as p_{id} . Thus, p_{id} is related only to a particular particle i . The best value of all the particles’ p_{best} in the swarm is called the g_{best} and is represented as p_{gd} . The basic concept of PSO technique lies in accelerating each particle toward its p_{id} and the p_{gd} locations at each time step. The amount of acceleration with respect to both p_{id} and p_{gd} locations is given random weighting.

Fig. 4 shows briefly the concept of PSO, where x_i is the current position, x_{i+1} is the modified position, v_{ini} is the initial velocity, v_{mod} is modified velocity, v_{pid} is the velocity

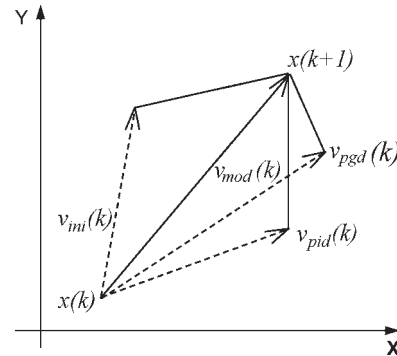


Fig. 4. Movement of a PSO particle in two dimensions from one instant k to another instant $k + 1$.

considering p_{id} , and v_{pgd} is the velocity considering p_{gd} . The following steps explain the procedure in the classical PSO algorithm.

- 1) Initialize a population of particles with random positions and velocities in d dimensions of the problem space.
- 2) For each particle, evaluate the desired optimization fitness function.
- 3) Compare every particle’s fitness evaluation with its p_{best} value p_{id} . If the current value is better than p_{id} , then set p_{id} value to be equal to the current value and the p_{id} location to be equal to the current location in d -dimensional space.
- 4) Compare the updated p_{best} values with the population’s previous g_{best} value. If any of the p_{best} values are better than p_{gd} , then update p_{gd} and its parameters.
- 5) Compute the new velocities and positions of the particles according to (1). v_{id} and x_{id} represent the velocity and position of i th particle in the d th dimension, respectively,

and rand_1 and rand_2 are two uniform random functions in a unit interval

$$x_{\text{id}}(k+1) = x_{\text{id}}(k) + w \times v_{\text{id}}(k) + c_1 \times \text{rand}_1(p_{\text{id}}(k) - x_{\text{id}}(k)) + c_2 \times \text{rand}_2 \times (p_{\text{gd}}(k) - x_{\text{id}}(k)). \quad (1)$$

- 6) Repeat from step 2) until a specified termination condition is met, usually a sufficiently good fitness or a maximum number of iterations.

The PSO parameter w in (1) is called the inertia weight, which controls the exploration and exploitation of the search space. Local minima are avoided by small local neighborhood, but faster convergence is obtained by larger global neighborhood, and in general, global neighborhood is preferred.

The velocity is restricted to a certain dynamic range. v_{max} is the maximum allowable velocity for the particles, i.e., in case the velocity of the particle exceeds v_{max} , then it is reduced to v_{max} . Thus, the resolution and fitness of search depend on v_{max} . If v_{max} is too high, then the particles will move beyond good solution, and if v_{max} is too low, then the particles will be trapped in local minima. c_1 and c_2 , termed as cognition and social components, respectively, are the acceleration constants which change the velocity of a particle toward p_{id} and p_{gd} (generally, somewhere between p_{id} and p_{gd}).

The SPPSO is a classical PSO algorithm but with a small population. The concept of regeneration is introduced by the authors to give particles the ability to keep carrying out the search despite a small population. The particles are regenerated after every N iterations, retaining their previous g_{best} (p_{gd}) and p_{best} (p_{id}) fitness values and positions. The selection of the value N is crucial in realizing an efficient SPPSO algorithm. If the value of N is low, the new particles may be regenerated too quickly and, in turn, disturb the search process. Thus, the particles will move erratically in the search space. On the other hand, if the particles are regenerated at a higher value of N , the search process will be delayed. Randomizing the positions and velocities of the particles every N iterations aids the particles in avoiding local minima and finding the global minimum. The regeneration concept drastically reduces the number of evaluations required to find the best solution, and each evaluation is less computationally intensive compared to the classical PSO algorithm.

B. BFA

Animals with poor foraging strategies (methods for locating, handling, and ingesting food) are eliminated by the process of natural selection. This process, in turn, favors the propagation of genes of those animals that have been successful in their foraging strategies. Species who have better food searching ability are capable of enjoying reproductive success, and the ones with poor search ability are either eliminated or reshaped. The BFA mimics the foraging behavior of the *E. coli* bacterium present in our intestines. This algorithm has been successfully demonstrated as an optimization tool in power system harmonic estimation [11], [12]. The foraging process consists of four stages: chemotaxis, swarming, reproduction, and elimination [13],

and these are briefly explained hereafter. More information on the BFA is given in [13].

1) *Chemotaxis*: This stage mimics the bacteria's ability to climb to regions of nutrient concentration, avoiding noxious substances and searching for a way out of neutral media. The bacterium usually takes a tumble, followed by a tumble or a swim to carry out this search. For N_c number of chemotactic steps, the direction of movement after a tumble is given by

$$\theta^i(j+1, k, l) = \theta(j, k, l) + C(i) \times \phi(j) \quad (2)$$

where $C(i)$ is the step size taken in the direction of the tumble by the i th bacterium, j is the index for the chemotactic step taken, k is the index for the number of reproduction step, l is the index for the number of elimination–dispersal event, and $\phi(j)$ is the unit length random direction taken at each step. In other published applications [11], [12], the number of bacteria is reported to be eight or more in the BFA. In this paper, the authors experimented with the step size for a small population of bacteria (five or less) and found that using a linearly decreasing step size resulted in faster convergence for the BFA. Thus, the populations of the BFA and SPPSO are comparable.

If the cost at $\theta^i(j+1, k, l)$ is better than the cost at $\theta^i(j, k, l)$, then the bacterium takes another step of size $C(i)$ in that direction (swimming). This process is continued until the number of steps taken is not greater than N_s (counter for the number of swim steps). This is done to prevent the bacteria to be trapped in the local minima. There should be a tradeoff between the values of N_s to be chosen. It could be half of the value of N_c .

2) *Swarming*: The bacteria in times of stresses release attractants to signal other bacteria to swarm together. It however also releases a repellent to signal others to be at a minimum distance from it. Thus, all of them have a cell to cell attraction via the attractant and cell to cell repulsion via the repellent. The following equation represents the swarming behavior in the bacteria foraging:

$$\begin{aligned} J_{\text{cc}}(\theta, P(j, k, l)) &= \sum_{i=1}^S J_{\text{cc}}^i(\theta, \theta^i(j, k, l)) \\ &= \sum_{i=1}^S \left[-d_{\text{attract}} \exp \left(-w_{\text{attract}} \sum_{m=1}^p (\theta_m - \theta_m^i)^2 \right) \right] \\ &\quad + \sum_{i=1}^S \left[h_{\text{repellent}} \exp \left(-w_{\text{repellent}} \sum_{m=1}^p (\theta_m - \theta_m^i)^2 \right) \right] \end{aligned} \quad (3)$$

where

d_{attract}	depth of the attractant effect;
w_{attract}	measure of the width of the attractant;
$h_{\text{repellent}} = d_{\text{attract}}$	height of the repellent effect;
$w_{\text{repellent}}$	measure of the width of the repellent;
p	number of parameters to be optimized;
s	number of bacteria.

The total cost function to be optimized by the BFA can be represented by

$$J(i, j, k, l) + J_{cc}(\theta, P) \quad (4)$$

where $J(i, j, k, l)$ is the cost function for the optimal PSS design described in Section IV and given in (5). The values of d_{attract} and $h_{\text{repellant}}$ should be same so that, after certain number of iterations after the bacteria converge, there should not be any contribution from the swarming part ($J_{cc} = 0$). The values of w_{attract} and $w_{\text{repellant}}$ should be such that, when the bacteria move farther from each other, the penalty added to the cost function by J_{cc} should be large.

3) *Reproduction*: After all the N_c chemotactic steps have been covered, a reproduction step takes place. S_r ($S_r = S/2$) bacteria having a lower survival value (less healthy) die, and the remaining S_r 's are allowed to split into two, thus keeping the maintaining a constant population size.

4) *Elimination–Dispersal*: Environment changes for the bacteria all the time. Bacteria are either destroyed or moved to different parts of the intestine, resulting in positive and negative influences on their lives. This process is incorporated in the BFA. For each elimination–dispersal event, each bacterium is eliminated with a probability of p_{ed} . A low value of N_{ed} (number of elimination–dispersal events) dictates that the algorithm will not rely on random elimination–dispersal events to try to find favorable regions. A high value increases computational complexity but allows the bacteria to find favorable regions. The p_{ed} should not be large either, or else, it should lead to an exhaustive search. The number of reproduction and elimination–dispersal events is problem specific. The values used in this paper are decided by trial and error.

IV. OPTIMAL PSS DESIGN

This section describes how the bio-inspired algorithms are used to determine the optimal parameters of the PSSs for the power systems in Figs. 1 and 3. For each PSS, the optimal parameters are determined by the SPPSO and BFA, i.e., 20 parameters (four PSSs) in total for the small two-area multimachine power system and ten parameters (two PSSs) for Nigerian power system. Just like any other optimization problem, a cost or an objective function needs to be formulated for the optimal PSS design. The objective in the optimal PSS design is to maximize damping; in other words, minimize the overshoots and settling time in system oscillations.

The integrated transient response area of the speed deviation of the generators is used as the cost function to be minimized by the bio-inspired algorithms. This, in turn, means improved system damping. Because, in an interconnected power system, there are several generators that experience the impact of a transient, a single objective function is formulated, which accounts for the impact seen by all generators, and is given by

$$J^t = \sum_{n=1}^N \sum_{G_n}^m J_{G_n} \quad (5)$$

TABLE I
PARAMETER LIMITS USED IN THE OPTIMIZATION

Two Area Power System	Nigerian Power System
$5 \leq K \leq 30$	$0.05 \leq K \leq 30$
$0.005 \leq T_1 \leq 2$	$0.005 \leq T_1 \leq 2$
$0.001 \leq T_2 \leq 1$	$0.001 \leq T_2 \leq 1$
$0.01 \leq T_3 \leq 10$	$0.01 \leq T_3 \leq 10$
$0.005 \leq T_4 \leq 15$	$0.005 \leq T_4 \leq 15$

where

$$J_{G_n} = \sum_{j=1}^{\text{NP}} \sum_{t=t_0}^{t_2/\Delta t} (\Delta\omega_{G_n}(t)) \times (A \times (t - t_0) \times \Delta t) \quad (6)$$

where NP is the number of operating points for which optimization is carried out, N is the number of faults for which the optimization is carried out, A is a weighing factor, m is the number of generators in the system, $\Delta\omega_{G_n}$ is the speed deviation of the generator G_n , t_0 is the time that the fault is cleared, t_0 and t_2 are the start and end times of the simulation, respectively, considered for the transient area calculation, Δt is the speed signal sampling period, and t is the simulation time in seconds. Limits are placed on the PSS parameters to keep the system within the stability margin during the online optimization. The PSS parameter limits used for the two-area multimachine power system (Fig. 1) and the Nigerian power system (Fig. 3) are given in Table I.

The optimization is carried out by subjecting the power systems to small and large disturbances. In this paper, first, a temporary 200-ms-duration transmission line outage is placed (on one of the tie lines), and when the system returns to steady state, a three-phase short circuit of 200-ms duration is applied at the middle of the tie lines. The value of J^t is computed using (5) for a given set of parameters for the PSSs, and the bio-inspired algorithms are applied to compute the new set of parameters.

V. SIMULATION RESULTS

The entire simulation is carried out with the power systems simulated in the PSCAD/EMTDC environment and the bio-inspired algorithms implemented in FORTRAN. The challenging task of using the bio-inspired algorithms to tune multiple PSSs in PSCAD from the time domain information is reported for the first time to the knowledge of the authors. The number of particles used in SPPSO is five, and the number of bacteria in BFA is four. The values of parameters used in this study are as follows: $N_c = 4$, $N_{\text{re}} = 15$, $N_{\text{ed}} = 10$, $N_s = 4$, $d_{\text{att}} = 0.01$, $h_{\text{rep}} = 0.01$, $w_{\text{att}} = 0.4$, $w_{\text{rep}} = 0.42$, $w = 0.8$, $c_1 = 2.0$, and $c_2 = 2.0$. The fitness evaluations of the particles and the bacteria are carried out online. The performances of the PSSs optimized by the PSO, SPPSO, and BFA algorithms are evaluated on Kundur's two-area and Nigerian power systems for small and large disturbances.

TABLE II
TWO-AREA POWER SYSTEM OPTIMIZED PSS PARAMETERS

Generator	PSO optimized parameters	SPPSO optimized parameters	BFA optimized parameters
G1	$K = 30.00$ $T_1 = 1.17$ s $T_2 = 0.39$ s $T_3 = 5.77$ s $T_4 = 15.00$ s	$K = 23.71$ $T_1 = 1.28$ s $T_2 = 0.50$ s $T_3 = 3.77$ s $T_4 = 7.03$ s	$K = 23.84$ $T_1 = 2.00$ s $T_2 = 1.00$ s $T_3 = 6.16$ s $T_4 = 8.25$ s
G2	$K = 30.00$ $T_1 = 1.21$ s $T_2 = 0.34$ s $T_3 = 4.36$ s $T_4 = 14.66$ s	$K = 22.76$ $T_1 = 1.54$ s $T_2 = 0.49$ s $T_3 = 3.61$ s $T_4 = 8.45$ s	$K = 21.48$ $T_1 = 2.00$ s $T_2 = 1.00$ s $T_3 = 4.93$ s $T_4 = 8.19$ s
G3	$K = 17.71$ $T_1 = 0.83$ s $T_2 = 0.36$ s $T_3 = 10.00$ s $T_4 = 15.00$ s	$K = 23.88$ $T_1 = 1.25$ s $T_2 = 0.75$ s $T_3 = 5.35$ s $T_4 = 8.57$ s	$K = 18.22$ $T_1 = 2.00$ s $T_2 = 1.00$ s $T_3 = 4.87$ s $T_4 = 7.24$ s
G4	$K = 29.77$ $T_1 = 0.90$ s $T_2 = 0.55$ s $T_3 = 4.10$ s $T_4 = 15.00$ s	$K = 27.31$ $T_1 = 1.17$ s $T_2 = 1.00$ s $T_3 = 2.96$ s $T_4 = 8.18$ s	$K = 20.71$ $T_1 = 2.00$ s $T_2 = 1.00$ s $T_3 = 4.74$ s $T_4 = 8.92$ s

A. Two-Area Multimachine Power System

Three tests are carried out, and the responses are studied for the five cases mentioned hereafter. The respective optimized PSS parameters for these cases are given in Table II.

- 1) *No PSS*: In this case, the power system is without any PSSs.
- 2) *Conventional PSS (CPSS)*: The PSS parameters in this case are those obtained from [17]. These parameters are the same for all four generators and are as follows: $K = 20.00$, $T_1 = 0.05$ s, $T_2 = 0.02$ s, $T_3 = 3.00$ s, and $T_4 = 5.40$ s, respectively.
- 3) *PSO optimized PSS*: The PSS parameters in this case are the optimized parameters obtained using the PSO algorithm.
- 4) *SPPSO optimized PSS*: The PSS parameters in this case are the optimized parameters obtained using the SPPSO algorithm.
- 5) *BFA optimized PSS*: The PSS parameters in this case are the optimized parameters obtained using the BFA algorithm.

1) *Single Fault—Temporary Transmission Line Outage*: A 200-ms transmission line outage is applied between buses 8 and 9 in Fig. 1. This is a small type of disturbance for a power system where a transmission line between buses 8 and 9 is removed for 200 ms. The speed responses of generators G2 and G3 for the aforementioned cases are shown in Figs. 5 and 6, respectively. Similar responses are observed for generators G1 and G4 and are not shown to limit the length of this paper. The addition of PSSs improved the damping in the system oscillations. The response of G2 clearly shows that the responses of PSO and SPPSO are comparable. PSO and SPPSO optimized PSSs exhibit better damping than BFA optimized PSSs, which, in turn, exhibit better damping than CPSS. For generator G3, the performances of SPPSO and PSO optimized PSSs are comparable and better than those with BFA optimized PSSs and CPSS.

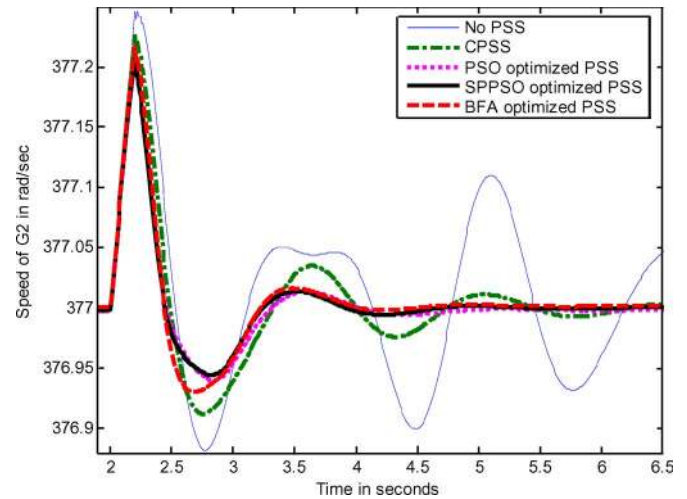


Fig. 5. Speed response of generator G2 for a 200-ms line outage between buses 8 and 9.

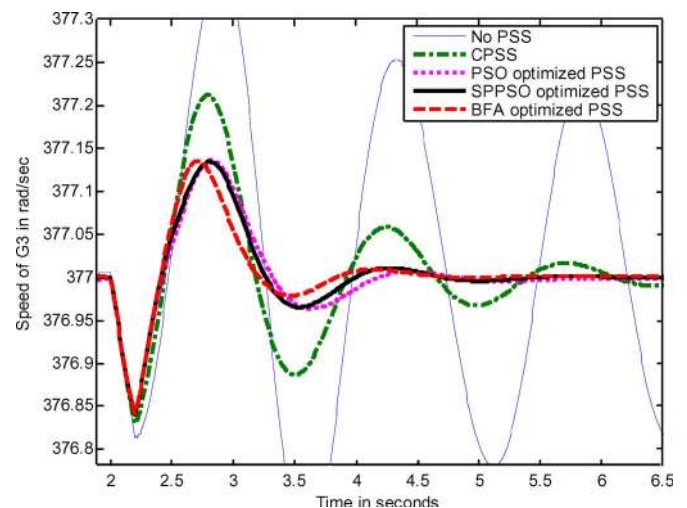


Fig. 6. Speed response of generator G3 for a 200-ms line outage between buses 8 and 9.

2) *Single Fault—Three-Phase Short Circuit*: A three-phase short circuit of 200-ms duration is applied at bus 8 in Fig. 1. This is a severe fault compared to the transmission line outage of 200 ms. The speed responses of generators G1 and G4 for the aforementioned cases are shown in Figs. 7 and 8, respectively. Similar responses are observed for generators G2 and G3. It is clear from these figures, once again, that the PSSs improve the damping in the system; a system having CPSS/BFA optimized PSSs/SPPSO/PSO optimized PSSs shows better damping than the system without PSSs. Damping is best with systems having PSO and SPPSO optimized PSS followed by BFA optimized PSSs and CPSSs. The speed responses for PSO and SPPSO optimized PSS have a settling time of about a second faster than the BFA optimized PSSs.

3) *Combined Fault—Short Circuit Followed by a Transmission Line Outage*: A double cascaded fault is now applied to test the robustness of the different optimized PSS parameters. A 100-ms three-phase short circuit at bus 8 is applied, followed immediately by a 100-ms line outage between buses 8 and 9 immediately in Fig. 1. The speed responses of generators G1 and

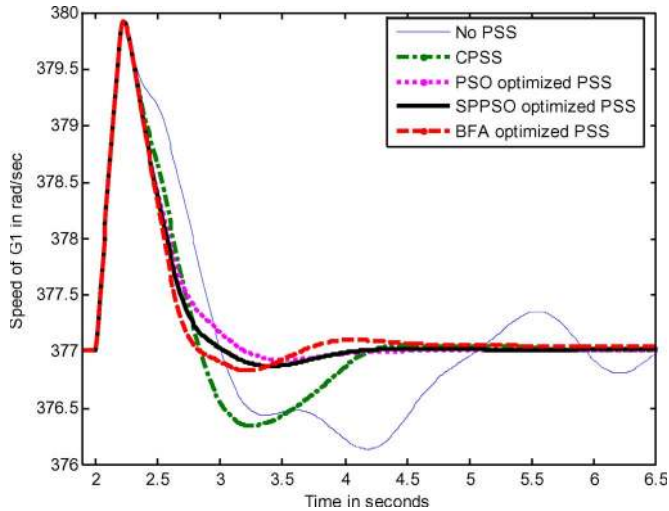


Fig. 7. Speed response of generator G1 for a three-phase 200-ms short circuit applied at bus 8.

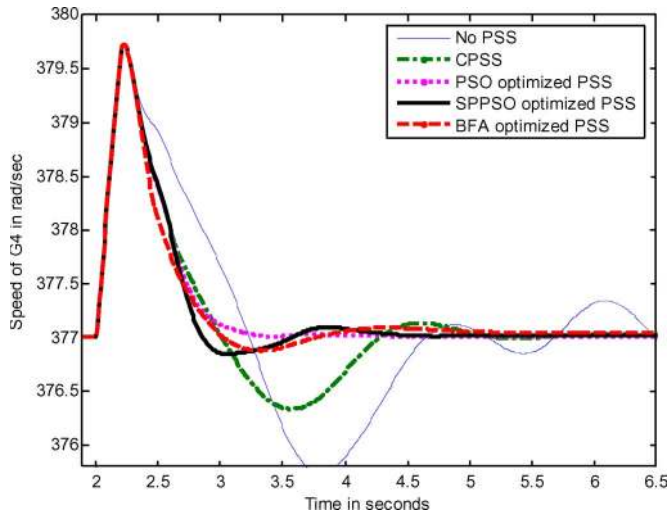


Fig. 8. Speed response of generator G4 for a three-phase 200-ms short circuit applied at bus 8.

G3 for the aforementioned cases are shown in Figs. 9 and 10, respectively. Similar responses are observed for generators G2 and G4. The damping of the system improves from a system having no PSS to SPPSO optimized PSSs. The system without any PSS has minimum or no damping; hence, the oscillations are sustained. The system with SPPSO and PSO optimized PSSs is the best. The performance of the system with the SPPSO optimized PSSs is much better than the system having BFA optimized PSSs to provide damping during multiple faults.

B. Nigerian Power System

The following three tests are carried out; the responses are studied for the three cases mentioned hereafter, and the respective optimized PSS parameters for these cases are given in Table III.

1) *No PSS*: In this case, the power system is without any PSSs.

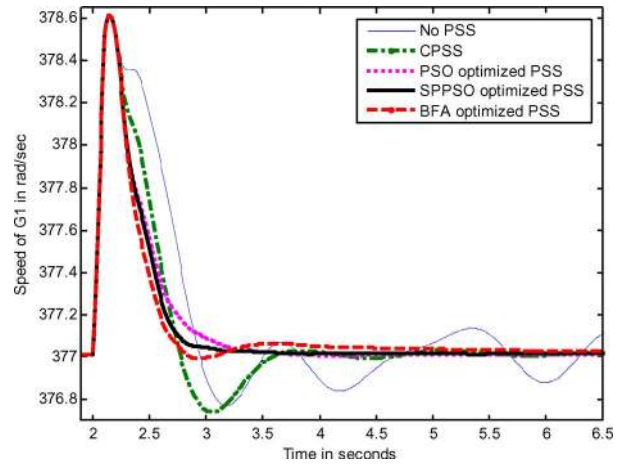


Fig. 9. Speed response of G1 for a three-phase 100-ms short circuit applied at bus 8, followed by immediate 100-ms line outage between buses 8 and 9.

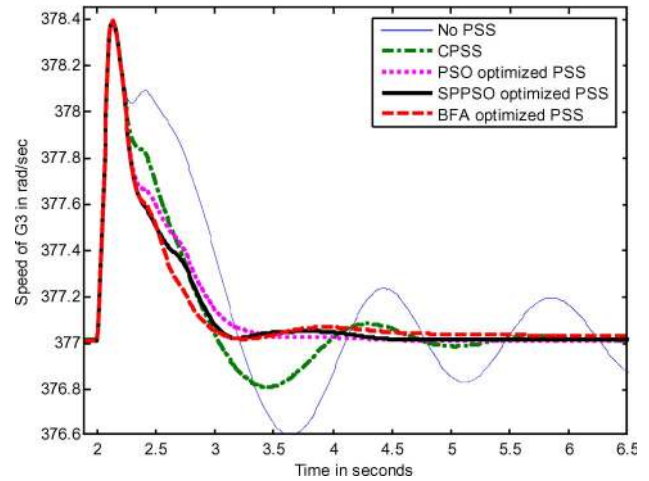


Fig. 10. Speed response of G3 for a three-phase 100-ms short circuit applied at bus 8, followed by immediate 100-ms line outage between buses 8 and 9.

TABLE III
NIGERIAN POWER SYSTEM OPTIMIZED PSS PARAMETERS

Generator	PSO optimized parameters	SPPSO optimized parameters	BFA optimized parameters
Egbin	K = 30.00 T ₁ = 0.210 s T ₂ = 0.001 s T ₃ = 10.00 s T ₄ = 10.70 s	K = 25.830 T ₁ = 0.380 s T ₂ = 0.990 s T ₃ = 0.350 s T ₄ = 0.005 s	K = 1.250 T ₁ = 0.290 s T ₂ = 0.030 s T ₃ = 0.220 s T ₄ = 0.005 s
Shiroro	K = 6.44 T ₁ = 0.670 s T ₂ = 0.001 s T ₃ = 0.010 s T ₄ = 0.050 s	K = 28.210 T ₁ = 0.690 s T ₂ = 0.770 s T ₃ = 0.230 s T ₄ = 0.005 s	K = 1.950 T ₁ = 0.250 s T ₂ = 0.050 s T ₃ = 0.280 s T ₄ = 0.030 s

- 2) *PSO optimized PSS*: The PSS parameters in this case are the optimized parameters obtained using the PSO algorithm.
- 3) *SPPSO optimized PSS*: The PSS parameters in this case are the optimized parameters obtained using the SPPSO algorithm.
- 4) *BFA optimized PSS*: The PSS parameters in this case are the optimized parameters obtained using the BFA algorithm.

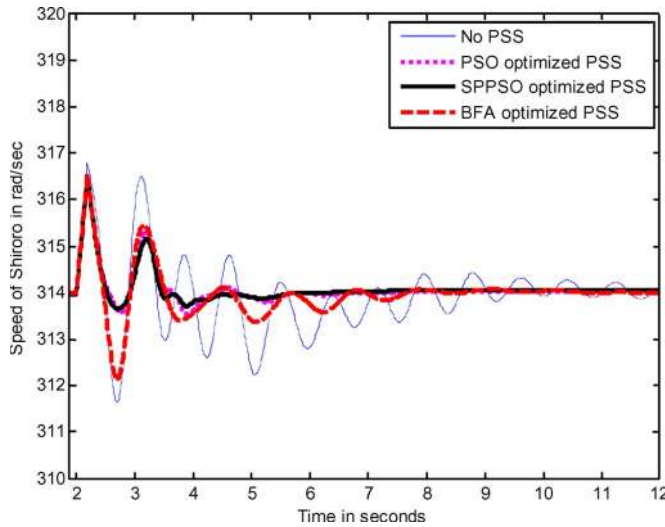


Fig. 11. Speed response of (hydro area) Shiroro generator for a 200-ms line outage between buses 9 and 11.

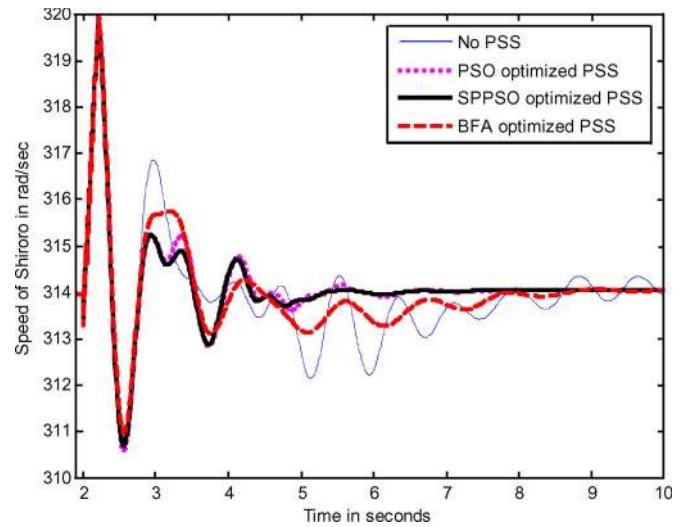


Fig. 13. Speed response of (hydro area) Shiroro for a three-phase 200-ms short circuit applied at the tie line between the thermal and hydro power stations.

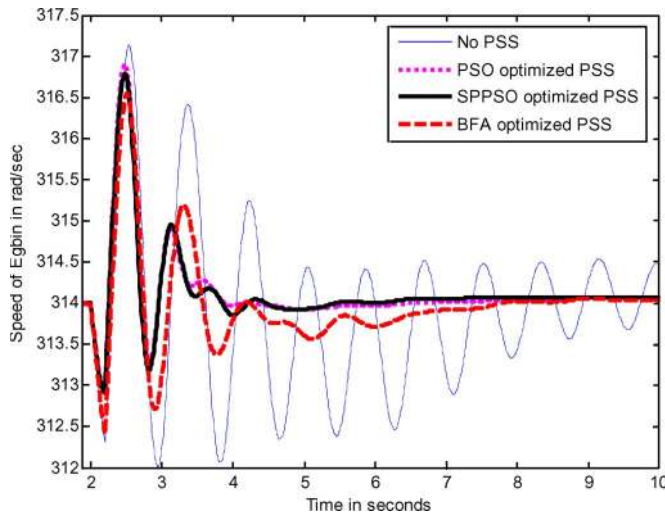


Fig. 12. Speed response of (thermal area) Egbin generator for a 200-ms line outage between buses 9 and 11.

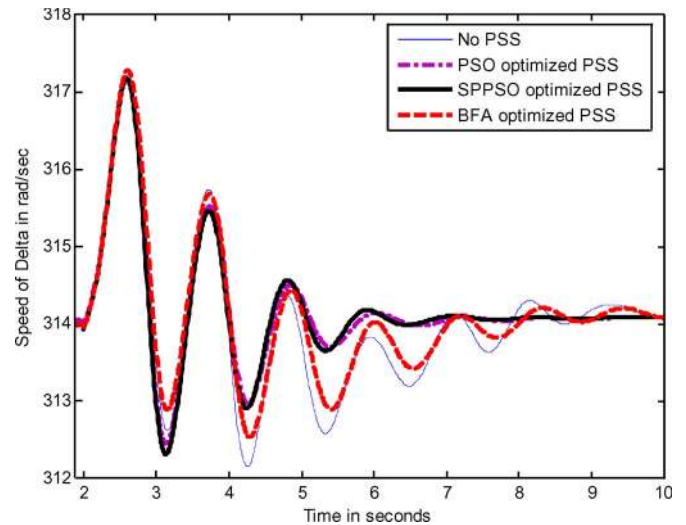


Fig. 14. Speed response of (thermal area) Delta for a three-phase 200-ms short circuit applied at the tie line between the thermal and hydro power stations.

1) *Single Fault—Temporary Transmission Line Outage:* A temporary 200-ms-duration transmission line outage is placed on the tie lines connecting the hydro and thermal areas between buses 9 and 11. The speed responses of the generators in both hydro and thermal areas for the aforementioned cases are shown in Figs. 11 and 12, respectively. The Nigerian power system without PSS for a short-duration transmission line outage exhibits minimum damping and maximum overshoot with many oscillatory modes. The overshoot and the settling time are minimized with the SPPSO optimized PSSs. Here, it is clear that, even for disturbances not as severe as a three-phase short circuit, the SPPSO outperforms the BFA. This is because the PSO and SPPSO optimized PSS gains are greater than the BFA optimized PSS gains.

2) *Single Fault—Three-Phase Short Circuit:* A three-phase short circuit of 200-ms duration is applied at the middle of the tie line (bus 25) connecting the thermal area to the hydro area in Fig. 3. The speed responses of two generators, one in the thermal area (Delta) and the other in the hydro area (Shiroro),

are shown in Figs. 13 and 14, respectively. The PSSs with SPPSO optimized parameters exhibit the best performance, followed by PSO optimized parameters and further followed by BFA optimized parameters. The settling time is minimized, and the system gets damped quickly within 3 to 4 s of the disturbance for the PSO and SPPSO optimized PSS parameters.

3) *Combined Fault—Short Circuit and Transmission Line Outage:* A double cascaded fault is now applied to test the robustness of the different optimized PSS parameters. A 100-ms short circuit is applied at the middle of the tie lines connecting the thermal area to the hydro area (bus 25), immediately followed by a 100-ms line outage of the tie lines between buses 9 and 11. The speed responses of the generators in hydro and thermal areas for the aforementioned cases are shown in Figs. 15 and 16, respectively. The performance of the system with PSO and SPPSO optimized parameters is the best. The oscillations in the system settle down faster and overshoot minimized for PSS parameters obtained using PSO and SPPSO.

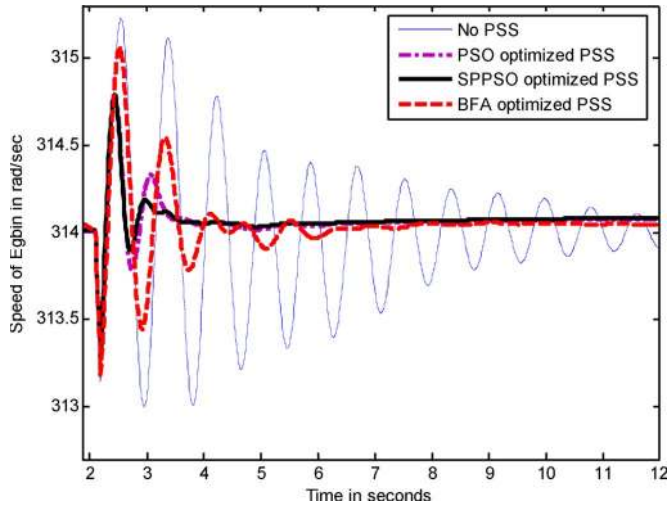


Fig. 15. Speed response of (hydro area) Shiroro for a three-phase 100-ms short circuit applied at bus 25, followed by immediate 100-ms line outage of the tie lines between buses 9 and 11 (Fig. 3).

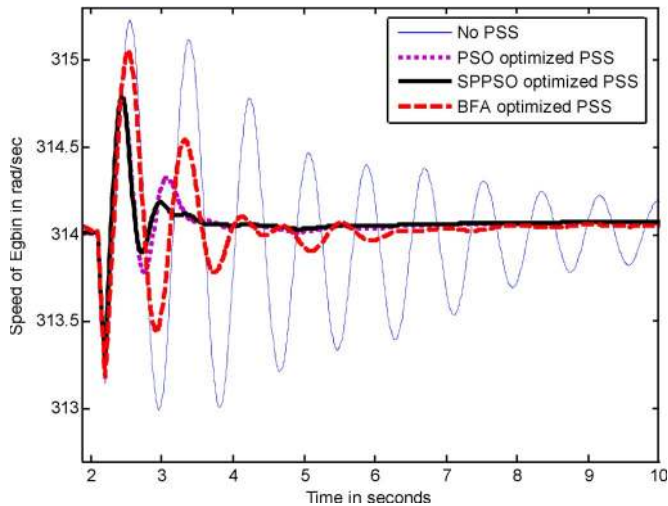


Fig. 16. Speed response of (thermal area) Egbin for a three-phase 100-ms short circuit applied at bus 25, followed by immediate 100-ms line outage of the tie lines between buses 9 and 11 (Fig. 3).

VI. DISCUSSIONS OF SPPSO AND BFA PSS DESIGNS

This section compares the two bio-inspired algorithms for the design of multiple optimal PSS in terms of their computational complexities and performances of the optimized PSSs using the TE analysis.

A. Computational Complexities

The number of fitness evaluations involved in BFA is more than those involved in SPPSO for a single iteration. In BFA, for each bacterium, the fitness is evaluated a number of times. The number of stages involved makes the algorithm computationally intensive. In addition, the number of factors involved in BFA is twice as much as in PSO/SPPSO, as shown in Table IV, and this makes BFA more complex. These factors need to be properly chosen for the algorithm to perform optimally. The dependence of the algorithm on so many parameters

TABLE IV
FACTORS AFFECTING THE PERFORMANCE OF SPPSO AND BFA ALGORITHMS

No. of factors	PSO/SPPSO	BFA
1	w	$d_{attract}$
2	c_1	$w_{attract}$
3	c_2	$h_{repellant}$
4	v_{max}	$w_{repellant}$
5	v_{min}	N_C
6	$-N$	N_{re}
7	-	N_{ed}
8	-	N_s
9	-	$C(i)$
10	-	P_{ed}

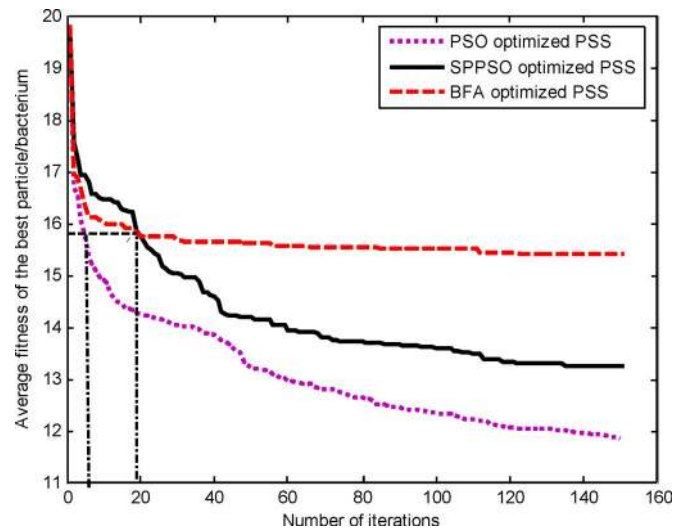


Fig. 17. Average fitness of the best particle in SPPSO and the best bacterium in BFA for the study on the two-area multimachine power system.

makes it handicapped in finding out the global optimum. The performance of the BFA can be improved by choosing the parameters effectively [12]. Similarly, PSO performance can also be improved [9]. However, this paper mainly focuses in comparing the classical BFA with the classical PSO. In BFA, for every reproduction and elimination–dispersal stage, a fitness evaluation is carried out after all the chemotactic steps are covered; hence, $S \times N_c$ evaluations are performed. This is equivalent to one PSO iteration. In the case of SPPSO/PSO, m/n fitness evaluations are carried out for m/n particles, respectively.

The average fitness over ten trials of the best bacterium (BFA) and best particle (PSO and SPPSO) versus the number of iterations during the optimization process is shown in Figs. 17 and 18 for the two multimachine power systems, respectively.

It can be seen in Figs. 17 and 18 that the fitness of the best particle in SPPSO and PSO converges faster as compared to the fitness of the best bacterium in BFA for the same number of iterations (150) in both power systems under study. PSO and SPPSO are faster in finding lower fitness values than BFA. For the two-area power system, PSO converges to a lower average fitness than SPPSO. The fitness, however, is close to the fitness

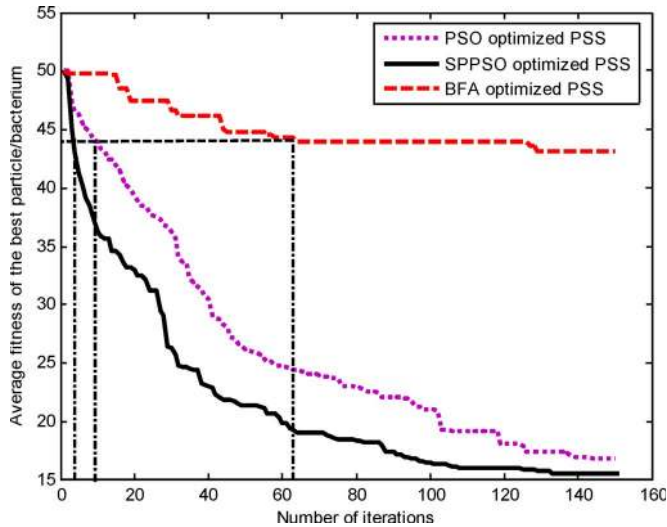


Fig. 18. Average fitness of the best particle in SPPSO and the best bacterium in BFA for the study on the Nigerian power system.

TABLE V
COMPARISON OF THE GENERAL COMPUTATIONAL COMPLEXITY OF PSO, SPPSO, AND BFA

Algorithms	Number of stages involved	Number of Fitness Evaluations	Number of Additions	Number of Multiplications
PSO – n particles	1	$n \times iterations$	$5 \times n \times d \times iterations$	$5 \times n \times d \times iterations$
SPPSO – m particles	1	$m \times iterations$	$5 \times m \times d \times iterations$	$5 \times m \times d \times iterations$
BFA – S bacteria (Chemotaxis, Swarming, Reproduction, and Elimination and Dispersal)	4	$S \times N_c \times N_{re} \times N_{ed}$ (1 PSO iteration = $S \times N_c$)	$(4p-1) \times S \times N_c \times N_{re} \times N_{ed}$	$(4+2p) \times S \times N_c \times N_{re} \times N_{ed}$

at which SPPSO converges. The x -coordinate is the number of iterations, which, if interpreted in terms of fitness evaluations, would be high for PSO. If fitness closer to what PSO achieves in 150 iterations can be achieved in fewer computations and less time, then the algorithm could be considered as a potential online optimization tool. Computational burden is reduced drastically in SPPSO as explained hereafter.

Table V gives a general comparative analysis on the computational complexities of the PSO, SPPSO, and BFA algorithms. Table VI shows specifically the computational complexities of the algorithms in the optimal PSS design for the two-area multimachine power system in Fig. 1. The number of fitness evaluations in PSO is higher than the number of fitness evaluations in BFA and SPPSO; the number of additions and multiplications in SPPSO is lower in comparison to that of the PSO and BFA. For example, from Fig. 17 for the two-area multimachine power system, to attain a fitness of 15.57, PSO takes five iterations; both SPPSO and BFA take 19 iterations. This translates to PSO carrying out 100 fitness evaluations,

TABLE VI
COMPARISON OF THE COMPUTATIONAL COMPLEXITY OF PSO, SPPSO, AND BFA FOR PSS DESIGN FOR THE TWO-AREA POWER SYSTEM ($N_c = 4, N_{re} = 15, \text{ AND } N_{ed} = 10$)

Algorithms	Number of stages involved	Number of Fitness Evaluations	Number of Additions	Number of Multiplications
PSO – 20 particles	1	3000	300000	300000
SPPSO – 5 particles	1	750	75000	75000
BFA – 4 bacteria	4	2400	189600	105600

TABLE VII
COMPUTATION TIME FOR PSO, SPPSO, AND BFA FOR THE TWO-AREA POWER SYSTEM

Platform	Time (seconds)		
	PSO	SPPSO	BFA
PSCAD	227557.00	12544.15	48638.93
PST	202.28	102.25	407.04

10 000 additions, and 10 000 multiplications; SPPSO carrying out 95 fitness evaluations, 9500 additions, and 9500 multiplications; and BFA carrying out 304 fitness evaluations, 24 016 additions, and 13 376 multiplications, respectively. Likewise, from Fig. 18 for the Nigerian power system, it can be seen that, to attain a fitness value of 43.97, PSO, SPPSO, and BFA take 9, 4, and 63 iterations, respectively. This translates to the PSO carrying out 180 fitness evaluations, 18 000 additions, and 18 000 multiplications; SPPSO carrying out 20 fitness evaluations, 2000 additions, and 2000 multiplications; and BFA carrying out 1008 fitness evaluations, 39 312 additions, and 24 192 multiplications. This clearly shows that the SPPSO is much less computational intensive, at least twice as fast on a small power system (Fig. 1), and at least an order faster in the Nigerian power system (Fig. 3) as compared to BFA.

The SPPSO, along with PSO and BFA, is allowed to run on an Intel (R) 4 2.79-GHz processor, and the time required to finish 150 iterations in PSCAD platform are tabulated in Table VII. Table VII also includes the computation time involved in optimizing the PSS parameters on Power System Toolbox (PST) platform [18]. It can be clearly seen that the SPPSO takes least amount of time in its row to finish 150 iterations in PSCAD and to reach zero fitness in PST. For the Nigerian power system, the times required to finish 150 iterations on the PSCAD platform are 766 325, 37 908.35, and 481 539.23 s for PSO, SPPSO, and BFA, respectively. Thus, systems employing SPPSO can save considerable amount of time and therefore are feasible for online optimization with high speed processors.

B. TE Analysis of the Damping Performance

A brief comparison of the two algorithms based on the TE calculations is shown in Tables VIII and IX. The TE of each

TABLE VIII
NORMALIZED PI FOR THE TWO-AREA MULTIMACHINE POWER SYSTEM

Disturbance	Area	No PSS	CPSS	PSO	SPPSO	BFA
Short Circuit	1	1	1.56	1.88	1.96	1.96
	2	1	1.94	2.40	2.66	2.60
Line Outage	1	1	1.40	1.50	1.63	1.63
	2	1	3.02	3.64	3.68	4.06
Short circuit and Line Outage	1	1	1.49	1.84	1.92	1.89
	2	1	2.05	2.39	2.66	2.68
Overall Performance	1	1	1.48	1.74	1.84	1.82
	2	1	2.33	2.81	3.00	3.11

TABLE IX
NORMALIZED PI FOR THE NIGERIAN POWER SYSTEM

Disturbance	Areas	No PSS	PSO	SPPSO	BFA
Short Circuit	Hydro	1.0	1.53	1.54	1.32
	Thermal	1.0	4.20	4.07	1.57
Line Outage	Hydro	1.0	2.55	2.75	1.66
	Thermal	1.0	2.38	2.55	2.06
Short circuit and Line Outage	Hydro	1.0	1.62	1.68	1.47
	Thermal	1.0	3.88	3.75	1.98
Overall Performance	Hydro	1.0	1.90	1.99	1.48
	Thermal	1.0	3.48	3.45	1.87

generator for the first 5 s of the fault has been calculated using (7), and the total TE of all the generators in a given area is given by (8)

$$TE_{Gen_i} = \frac{1}{2} H_{Gen_i} \int_{t_{ft}}^{t_{ft}+5} \Delta\omega_i^2 dt \quad (7)$$

where i is the generator number, t_{ft} is the time at which the fault is triggered, and H_{Gen_i} is the moment of inertia of the generator i

$$TE = \sum_{i=1}^N TE_{Gen_i} \quad (8)$$

where N is the number of generators present in a given area of a system. The performance index (PI), given in (9), is a measure of how the system has performed under the given conditions with the different sets of PSS parameters. The higher the PI, the better the controller damping performance

$$\text{Performance Index (PI)} = 1/TE. \quad (9)$$

TABLE X
EIGENVALUES, FREQUENCIES, AND DAMPING RATIOS OF THE GENERATING UNITS IN AREA 1 IN THE TWO-AREA POWER SYSTEM

Type of PSSs	Eigenvalues	Frequency (Hz)	Damping Ratio (%)
No PSS	-0.14 ± j4.20	0.67	3.35
	-0.4 ± j6.39	1.02	6.25
	-0.92 ± j7.48	1.20	12.21
CPSS	-0.86 ± j4.24	0.69	19.07
	-1.08 ± j6.31	1.02	17.31
	-2.29 ± j7.31	1.22	30.01
BFA optimized	-1.76 ± j4.02	0.72	40.21
	-1.82 ± j5.55	0.93	31.22
	-1.82 ± j7.25	1.19	24.35
SPPSO optimized	-1.50 ± j4.13	0.7	34.11
	-1.60 ± j5.55	0.92	27.79
	-2.74 ± j7.55	1.28	34.13

Table VIII presents the normalized PIs of Areas 1 and 2 for the different disturbances for the two-area multimachine power system. The normalized PI is obtained by dividing the PIs by the PI obtained with no PSS in the system. The results show that the PIs are best when the PSSs use the SPPSO optimized parameters. The overall performance row indicates that the bio-inspired optimization techniques improve the damping and minimize the overshoot in the oscillations for small and large disturbances. There are 19.17%, 24.65%, and 16.43% overall improvements in damping in Area 1 with the PSO, SPPSO, and BFA optimized PSS parameters, respectively, compared to the PSS parameters in [17]. Similarly, the overall improvements in the damping provided in Area 2 are 20.6%, 28.75%, and 33.47% with the PSO, SPPSO, and BFA optimized PSS parameters compared to the PSS parameters in [17].

Table IX shows the PIs of the hydro and thermal areas under different operating conditions for the Nigerian power system. PI is best with SPPSO optimized parameters, followed by PSO, and then the BFA optimized parameters. This corroborates the superiority of the SPPSO algorithm over the BFA for the same operating conditions. There are overall improvements of 48%, 90%, and 99% in damping in hydro area with the BFA, PSO, and SPPSO optimized PSS parameters, respectively, compared to the case without any PSS in the system. Similarly, overall improvements in the damping provided in thermal area are 87%, 248%, and 245% with the BFA, PSO, and SPPSO optimized PSS parameters, respectively, compared to the case without any PSS in the system.

The PSO in each of the TE calculations is comparable with SPPSO. However, the PSO after certain number of iterations can be trapped in local optima, as the velocity of the particle becomes zero when the same particle is both the p_{best} and the g_{best} . When the velocity of the particle is zero, the position of the particle cannot be updated, and thus, the search will be trapped in a local optimum. SPPSO, owing to its regeneration, can generate new particles after every N iteration, thus eliminating the drawback of zero velocity.

C. Eigenvalue Analysis

Prony analysis [19], [20] is used to determine the eigenvalues of the systems under study. Tables X–XIII list the complex

TABLE XI
EIGENVALUES, FREQUENCIES, AND DAMPING RATIOS OF THE
GENERATING UNITS IN AREA 2 IN THE TWO-AREA POWER SYSTEM

Type of PSSs	Eigenvalues	Frequency (Hz)	Damping Ratio (%)
No PSS	$-0.14 \pm j4.20$	0.67	3.41
	$-0.41 \pm j6.52$	1.04	6.64
	$-0.63 \pm j8.52$	1.36	7.44
CPSS	$-0.82 \pm j4.25$	0.69	19.10
	$-0.95 \pm j6.14$	0.99	15.37
	$-2.16 \pm j7.22$	1.20	28.77
BFA optimized	$-1.76 \pm j3.59$	0.67	42.01
	$-1.11 \pm j6.05$	0.98	18.08
	$-2.45 \pm j7.78$	1.30	30.08
SPPSO optimized	$-1.70 \pm j4.05$	0.70	38.86
	$-1.43 \pm j5.53$	0.91	25.07
	$-2.29 \pm j7.51$	1.25	29.23

TABLE XII
EIGENVALUES, FREQUENCIES, AND DAMPING RATIOS OF THE HYDRO
GENERATING UNITS IN THE NIGERIAN POWER SYSTEM

Type of PSSs	Eigenvalues	Frequency (Hz)	Damping Ratio (%)
No PSS	$-0.55 \pm j5.51$	0.88	10.07
	$-0.34 \pm j7.63$	1.21	4.44
	$-0.60 \pm j9.12$	1.45	6.57
BFA optimized	$-0.62 \pm j5.46$	0.87	11.28
	$-0.94 \pm j6.52$	1.04	14.36
	$-1.38 \pm j8.79$	1.41	15.56
SPPSO optimized	$-1.13 \pm j5.04$	0.82	21.99
	$-1.67 \pm j7.69$	1.25	21.32
	$-2.10 \pm j10.52$	1.70	19.66

TABLE XIII
EIGENVALUES, FREQUENCIES, AND DAMPING RATIOS OF THE THERMAL
GENERATING UNITS IN THE NIGERIAN POWER SYSTEM

Algorithms	Eigenvalues	Frequency (Hz)	Damping Ratio (%)
No PSS	$-0.47 \pm j5.67$	0.90	08.40
	$-0.25 \pm j7.62$	1.21	03.30
	$-0.91 \pm j9.51$	1.52	09.54
BFA optimized	$-0.60 \pm j5.42$	0.86	11.00
	$-1.62 \pm j6.56$	1.07	24.02
	$-0.87 \pm j8.34$	1.33	10.42
SPPSO optimized	$-1.15 \pm j5.75$	0.93	19.60
	$-0.83 \pm j6.66$	1.06	12.48
	$-1.58 \pm j9.76$	1.57	16.04

eigenvalues of all the generators in the two areas and the Nigerian power system. The best eigenvalue of each of the generator for each mode is highlighted in all the tables. In summary, the eigenvalues generated by a system having bio-inspired optimized PSSs have the highest negative real part in that row and thus improve system stability. SPPSO and BFA optimized PSSs exhibit best results for the interarea and local modes in different areas, for the two-area power system, as shown in Tables X and I. The SPPSO optimized PSSs exhibit the best damping for most of the modes in the different areas in the Nigerian power system, as shown in Tables XII and III.

VII. CONCLUSION

The successful implementation of the two bio-inspired algorithms for the simultaneous design of the multiple optimal PSSs

has been presented in this paper. The SPPSO and BFA algorithms give robust damping performance for various operating conditions and disturbances. The SPPSO with the regeneration concept is seen to have faster convergence with less number of fitness evaluations and algebraic operations. BFA, owing to its unique processes, can find good optimal solutions. The SPPSO, however, is found to be superior to the BFA and PSO in terms of computational complexity, TE analysis, convergence speed, and damping performances.

This paper has presented the SPPSO and the BFA as optimization tools in the PSCAD/EMTDC environment. This is a first step toward online optimization, and future work can involve in developing these algorithms further for real-time optimization in power systems.

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