CHAPTER – 5

BFOA-PSO HYBRID APPROACH FOR COORDINATED DESIGN OF PSS AND SSSC BASED CONTROLLER
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5.1 INTRODUCTION

When large power systems are interconnected by relatively weak tie lines, low frequency oscillations are observed. These oscillations may sustain and grow to cause system separation if no adequate damping is available [1]. Power system stabilizers (PSS) are now routinely used in the industry to damp out power system oscillations [84]. However, the use of PSSs only may not be, in some cases, effective in providing sufficient damping particularly with increasing transmission line loading over long distances, and other effective alternatives are needed in addition to PSS. Recent development of power electronics introduces the use of flexible AC transmission system (FACTS) controllers in power systems. FACTS controllers are capable of controlling the network condition in a very fast manner and this feature of FACTS can be exploited to improve the stability of a power system [2]. Static synchronous series compensator (SSSC) is one of the important members of FACTS family which can be installed in series in the transmission lines. SSSC is very effective in controlling power flow in a transmission line with the capability to change its reactance characteristic from capacitive to inductive [8, 28]. An auxiliary stabilizing signal can also be superimposed on the power flow control function of the SSSC so as to improve power system stability [31]. The application of SSSC for power oscillation damping and stability enhancement can be found in several references [29, 73, 74, 85]. The interaction among PSSs and SSSC-based controller may enhance or degrade the damping of certain modes of rotor’s oscillating modes. To improve overall system performance, many researches were made on the coordination between PSSs and FACTS power oscillation damping controllers [27, 46, 86-91]. There have been various publications proposing different techniques for designing PSSs and/or FACTS-based stabilizers for damping improvements. These methods include residue method, eigenvalue-distance minimization approach, linear matrix inequality technique and multiple-model adaptive control approach. One of the key issues that
should be addressed, in these coordinated design techniques, is verification of robustness of the controllers designed. Effective and efficient techniques are needed for obtaining robust controllers, particularly with respect to changes in power system configurations.

In recent years, one of the most promising research field has been “Heuristics from Nature”, an area utilizing analogies with nature or social systems. These techniques are finding popularity within research community as design tools and problem solvers because of their versatility and ability to optimize in complex multimodal search spaces applied to non-differentiable objective functions. New artificial intelligence-based approaches have been proposed to design a FACTS-based supplementary damping controller. These approaches include particle swarm optimization [27, 73, 89], genetic algorithm [86, 88], differential evolution [29, 91], multi-objective evolutionary algorithm [74, 90, 92] etc. Bacteria foraging optimization algorithm (BFOA), proposed by Passino [93], is a new comer to the family of nature-inspired optimization algorithms. BFOA is based on social and cooperative behaviors found in nature. Application of group foraging strategy of a swarm of *E.coli* bacteria in multi-optimal function optimization is the idea behind BFOA. Natural selection of bacterial foraging tends to eliminate animals with poor foraging strategies for locating, handling, and ingesting food, optimization models can be provided for social foraging where groups of parameters communicate to cooperatively forage in engineering. Recently, BFOA has been applied for controller design problem of power system [94, 95]. Also, there are several papers available in literature related to the stability issues and also in improving the algorithm. This chapter includes stability issues of BFOA algorithm related to chemotactic dynamics [96] and reproduction operator [97], new improved versions of BFOA with the adaptive chemotactic operators [98] and hybridization of particle swarm optimization (PSO) and BFOA where local search has been performed through the chemotactic movement operation of BFOA and global search over the entire search space is performed by a PSO operator [99]. Even though BFOA has satisfactory performance for optimization problems, it is observed that the convergence of the algorithm can be problematic, leading to large implementation times and the algorithm may be trapped to local optima. In BFOA, the chemotactic process is randomly set, imposing that the bacteria swarm together and keep a safe distance from each other. Such random
movements lead to some extent poor convergence as it allows bacteria in nutrient-poor areas to attract bacteria in nutrient-rich areas, thus slowing down the convergence speed. The repelling effect among bacteria also avoids the population from crowding together. To overcome these issues, principle of swarming is introduced in the framework of BFOA and the algorithm is known as hybrid BFOA PSO (hBFOA-PSO) algorithm. The hBFOA-PSO algorithm is based on the adjustment of each bacterium position according to the neighborhood environment. Experimental results have shown that the swarming mechanism of hBFOA-PSO allows for faster and more efficient convergence, preventing the bacteria from being trapped into local optima. The hybrid algorithm has shown superior performance compared to BFOA and PSO in proportional integral derivative controller tuning application [100]. In view of the above, hBFOA-PSO is employed in the present work to optimally and coordinately tune the parameters of the PSS and SSSC-based damping controller.

In this chapter, a comprehensive assessment of the effects of PSS and SSSC-based damping controller when applied coordinately has been carried out. The design problem of the proposed controllers to improve power system stability is transformed into an optimization problem. hBFOA-PSO based optimal tuning algorithm is used to optimally and simultaneously tune the parameters of the PSS and SSSC-based damping controller. The proposed multiple and multi-type controller design approach has applied and evaluated for both single-machine infinite-bus and a multi-machine power system. Simulation results are presented at different operating conditions and under various disturbances to show the effectiveness and robustness of the proposed controllers. Though, the example power systems studied in this chapter are simple two-area examples; by studying these simple systems the basic characteristics of the controllers can be assed and analyzed and conclusions can be drawn to give an insight for larger systems. Further, since all the essential dynamics required for the power system stability studies have been included, and the results have been obtained using local signals, general conclusions can be drawn from the results presented in the chapter so as to implement the proposed approach in a large realistic power system.

The main objectives of the research work presented in this chapter are as follows:

1. To test the effectiveness of the hybrid BFOA PSO (hBFOA-PSO) algorithm for coordinated design of PSS and SSSC based controllers.
2. To compare the performance of proposed hBFOA-PSO algorithm with Differential Evolution (DE) algorithm.

3. To plot, compare and analyze the system response profiles of the system under study subjected to various disturbances and compare the simulation results with a published modern heuristic optimization technique (Genetic Algorithm) for the same system under study.

4. To extend the study to a multi-machine power system.

5.2 THE PROPOSED APPROACH

5.2.1 SYSTEM MODELING WITH SMIB

In order to coordinately design PSS and SSSC-based damping controllers, as well as to assess their performance, a single-machine infinite-bus power system depicted in Fig. 4.1 is considered at the first instance. The system comprises a synchronous generator connected to an infinite-bus through a step-up transformer and a SSSC followed by a double circuit transmission line. The generator is equipped with hydraulic turbine and governor (HTG), excitation system and a power system stabilizer. The MATLAB/SIMULINK model of SMIB power system with SSSC is shown in Fig. 5.1.

![Fig. 5.1 MATLAB/SIMULINK model of SMIB power system with SSSC](image-url)
The HTG represents a nonlinear hydraulic turbine model, a PID governor system, and a servomotor. The excitation system consists of a voltage regulator and DC exciter, without the exciter's saturation function. In Fig. 4.1, $T$ represents the transformer, $V_T$ and $V_B$ are the generator terminal and infinite-bus voltages respectively, $V_1$ and $V_2$ are the bus voltages, $V_{DC}$ and $V_{cnv}$ are the DC voltage source and output voltage of the SSSC converter respectively, $I$ is the line current and $P_L$ and $P_{L1}$ are the total real power flow in the transmission lines and that in one line respectively. All the relevant parameters are given in Appendix-IV.

### 5.2.2 Structures of PSS and SSSC-Based Damping Controller

The structure of SSSC-based damping controller, to modulate the SSSC injected voltage $V_q$, is shown in Fig. 3.5. The input signal of the proposed controller is the speed deviation ($\Delta \omega$), and the output signal is the injected voltage $V_q$. The structure consists of a gain block with gain $K_S$, a signal washout block and two-stage phase compensation block as shown in Fig. 3.5. The signal washout block serves as a high-pass filter, with the time constant $T_W$, high enough to allow signals associated with oscillations in input signal to pass unchanged. Without it steady changes in input would modify the output. From the viewpoint of the washout function, the value of $T_W$ is not critical and may be in the range of 1 to 20 seconds [1]. The phase compensation blocks (time constants $T_{1S}$, $T_{2S}$ and $T_{3S}$, $T_{4S}$) provide the appropriate phase-lead characteristics to compensate for the phase lag between input and the output signals. In Fig. 3.5, $V_{qref}$ represents the reference injected voltage as desired by the steady state power flow control loop. The desired value of compensation is obtained according to the change in the SSSC injected voltage $\Delta V_q$ which is added to $V_{qref}$.

Fig. 4.5 shows the structure of the power system stabilizer used in the present study. It consists of a gain block with gain $K_{PS}$, a signal washout block and two-stage phase compensation block. The input signal to the PSS is the speed deviation $\Delta \omega$ of generator where the PSS is installed and the output signal is the voltage setting $V_S$ which is added to the excitation system reference voltage $V_{ref}$.

Owing to the recent advances in optical fiber communication and global positioning systems, the wide-area measurement system can realize phasor measurement synchronously and deliver it to the control center even in real time. This opens up the possibility of using remote signals to design more efficient control
schemes. However, these new control schemes present numerous challenges such as the delays involved in the transmission channels. In today’s technology, dedicated communication channels should not have more than 50-ms delay for the transmission of measured signals even in the worst scenarios [101]. Time delays of this order can degrade the system performance and therefore they should be taken into account in the control design. Generator rotor angle and speed deviation can be used as remote signals. However rotor speed seems to be a better alternative as input signal for FACTS based controller [102]. In view of the above, speed deviations are chosen as input signal for the SSSC based controller. For PSSs a sensor time constant of 15 ms is considered. For SSSC-based controller a signal transmission delay of 50 ms is considered along with the sensor time constant of 15 ms.

5.2.3 OPTIMIZATION PROBLEM

In lead-lag structured FACTS-based controllers, the washout time constant $T_W$ is usually pre specified [1]. In the present study, $T_W = T_{WP} = 10s$ is used. The controller gains and the time constants are to be determined. During steady state conditions $\Delta V_q$ is zero and $V_{qref}$ is constant. During dynamic conditions the series injected voltage $V_q$ is modulated to damp system oscillations. The steady state power flow loop acts quite slowly in practice and hence, in the present study $V_{qref}$ is assumed to be constant during disturbance transient period. Hence, the effective value of $V_q$ in dynamic conditions is given by:

$$V_q = V_{qref} + \Delta V_q$$  \hspace{1cm} (5.1)

It is worth mentioning that the PSS and SSSC-based controllers are designed to minimize the power system oscillations after a large disturbance so as to improve the power system stability. These oscillations are reflected in the deviations in power angle, rotor speed and tie-line power. Minimization of any one or all of the above deviations could be chosen as the objective. In the present study, an integral time absolute error of the speed deviations is taken as the objective function for single-machine infinite-bus power system. For the case of multi-machine power system, an integral time absolute error of the speed signals corresponding to the local and inter-area modes of oscillations is taken as the objective function. The objective functions are expressed as:
For single-machine infinite-bus power system:

\[
J = \int_{t=0}^{t_{\text{sim}}} |\Delta \omega| \cdot t \cdot dt
\]

For multi-machine power system:

\[
J = \int_{t=0}^{t_{\text{sim}}} \left( \sum |\Delta \omega_L| + \sum |\Delta \omega_I| \right) \cdot t \cdot dt
\]

Where, $\Delta \omega$ is the speed deviation in single-machine infinite-bus system; $\Delta \omega_L$ and $\Delta \omega_I$ are the speed deviations of local and inter-area modes of oscillations respectively and $t_{\text{sim}}$ is the time range of the simulation.

For objective function calculation, the time-domain simulation of the power system model is carried out for the simulation period. It is aimed to minimize this objective function in order to improve the system response in terms of the settling time and overshoots. The problem constraints are the PSS and SSSC controller parameter bounds. Therefore, the design problem can be formulated as the following optimization problem.

Minimize $J$ \hspace{1cm} (5.4)

Subject to

\[
K_i^{\text{min}} \leq K_i \leq K_i^{\text{max}}
\]

\[
T_{li}^{\text{min}} \leq T_{li} \leq T_{li}^{\text{max}}
\]

\[
T_{2i}^{\text{min}} \leq T_{2i} \leq T_{2i}^{\text{max}}
\]

\[
T_{3i}^{\text{min}} \leq T_{3i} \leq T_{3i}^{\text{max}}
\]

\[
T_{4i}^{\text{min}} \leq T_{4i} \leq T_{4i}^{\text{max}}
\]

where $K_i^{\text{min}}$ and $K_i^{\text{max}}$ are the lower and upper bounds of gains (SSSC and PSS) and $T_{ji}^{\text{min}}$ and $T_{ji}^{\text{max}}$ are the lower and upper bounds of the time constants of all controllers. Note that for a SMIB system which consists of one PSS and one SSSC-
based controller, hence the parameters to be optimized are two gains and eight time constants. In case of multi-machine power system consisting of one SSSC-based controller and multiple PSSs (equal to no. of generators) all the parameters to be optimized.

5.3 HYBRID BACTERIA FORAGING PARTICLE SWARM OPTIMIZATION ALGORITHM

5.3.1 BACTERIA FORAGING OPTIMIZATION ALGORITHM

Bacteria foraging optimization algorithm (BFOA), proposed by Passino [93], is a new comer to the family of nature-inspired optimization algorithms. BFOA is based on social and cooperative behaviors found in nature. Application of group foraging strategy of a swarm of E.coli bacteria in multi-optimal function optimization is the idea behind BFOA. The foraging behavior of E. coli bacteria present in our intestines, which includes the methods of locating, handling and ingesting food, has been successfully mimicked in BFOA. Each bacteria tries to maximize its obtained energy per each unit of time expended on the foraging process and avoiding noxious substances. Further, individual bacterium communicates with other individuals by sending signals. The optimization technique consists of determining the minimum of a function $J(\alpha)$ where the variables under consideration constitute the high-dimensional vector $\alpha \in \mathbb{R}^p$ and it is very difficult or almost impossible to determine $\delta J(\alpha)$. Here $\alpha$ determines the position of a bacterium in high dimensional space. A negative value of $J(\alpha)$ indicates that the bacterium is in nutrient-rich environment, a zero value indicates a neutral environment and a positive value indicates a noxious environment. The objective will be to try and implement a biased random walk for each bacterium where it will try to climb up the nutrient concentration and try and avoid noxious substances and will attempt to leave a neutral environment as soon as possible. This optimization procedure comprises of four basic steps: Swarming and Tumbling Chemotaxis, Reproduction and Elimination and Dispersal [38, 93, 103-104].

5.3.1.1 Swarming and Tumbling via flagella ($N_s$)

During foraging of the bacteria, locomotion is realized by a set of tensile flagella. An E. coli bacterium can move in two different ways, it can swim for a period of time or it can tumble. When they rotate the flagella in the clockwise direction, each flagellum pulls on the cell, which results in the moving of flagella
independently and finally the bacterium tumbles with lesser number of tumbling. In a harmful place it tumbles frequently to find a nutrient gradient. Moving the flagella in the counterclockwise direction helps the bacterium to swim at a very fast rate. The bacterium alternates between these two modes of operation its entire life time. The cell-to-cell signaling in *E. coli* swarm may be represented by:

\[
J_C(\alpha, P(j, k, l)) = \sum_{i=1}^{N} J_C(\alpha, \alpha'^i(j, k, l))
\]

\[
= \sum_{i=1}^{N} [-d_{at} \exp(-w_{at} \sum_{m=1}^{P} (\alpha_m - \alpha'_m)^2)] + \sum_{i=1}^{N} [h_{re} \exp(-w_{re} \sum_{m=1}^{P} (\alpha_m - \alpha'_m)^2)]
\]

(5.6)

In the above equation, \( J_C(\alpha, P(j, k, l)) \) is the objective function value which is to be added to the actual objective function to get a time varying objective function, \( N \) is the total number of bacteria, \( P \) is the number of variables to be optimized, \( \alpha = [\alpha_1, \alpha_2, \ldots, \alpha_P]^T \) is a point in the \( P \)-dimensional search domain and \( d_{at}, w_{at}, h_{re}, w_{re} \) are different attractant and repellant coefficients.

5.3.1.2 Chemotaxis (\( N_C \))

Chemotaxis process simulates the movement of an *E. coli* cell through swimming and tumbling via flagella. Suppose \( \alpha'^i(j, k, l) \) represents \( i \)-th bacterium at \( j \)-th chemotactic, \( k \)-th reproductive and \( l \)-th elimination-dispersal step. \( S(i) \) is the size of the step taken in the random direction specified by the tumble (run length unit). Then in computational chemotaxis the movement of the bacterium may be represented by:

\[
\alpha'^i(j+1,k,l) = \alpha'^i(j,k,l) + S(i) \frac{\delta(i)}{\sqrt{\delta(i)^2 + \delta(i)}}
\]

(5.7)

Where \( \delta \) indicates a vector in the random direction in the range (-1, 1).

5.3.1.3 Reproduction (\( N_{re} \))

In this process, the least healthy bacteria eventually die while each of the healthier bacteria giving better objective function values asexually split into two bacteria. These new bacteria are placed in the same location to keep the swarm size constant.
5.3.1.4 Elimination and dispersal ($N_{ed}$)

Gradual or sudden changes in the local environment where a bacterium population lives may occur due to various reasons. When local significant increase in heat kills a population of bacteria that are currently in a region with a high concentration of nutrient gradients is called the elimination process. A sudden flow of water can disperse bacteria from one place to another. Elimination and dispersal events may destroy chemotactic progress, but they also have the effect of assisting in Chemotaxis, since dispersal may place bacteria near good food sources. To simulate this phenomenon in BFOA some bacteria are liquidated at random with a very small probability while the new replacements are randomly initialized over the search space.

5.3.2 HYBRID BACTERIA FORAGING OPTIMIZATION ALGORITHM AND PARTICLE SWARM OPTIMIZATION

The hBFOA-PSO algorithm combines both algorithms BFOA and PSO thus using advantages of both techniques. The aim is to make use of PSO ability to exchange social information and BFOA ability in finding a new solution by elimination and dispersal. In BFOA, a unit length direction of tumble behavior is randomly generated which may lead to delay in reaching the global solution. In the hBFOA-PSO technique the unit length random direction of tumble behavior can be obtained by the global best position and the best position of each bacteria by PSO algorithm. During the chemotaxis loop, the update of the tumble direction is determined by equations (1.2) and (1.3) where $g_{best}$ and $p_{best}$ represents the global best position and the best position of each bacteria.

The hybrid bacteria foraging optimization algorithm and particle swarm optimization algorithm to search optimal values of parameters is described as follows [100, 105,106]:

**Step 1:** Initialize the following parameters:

\[ p, S, N_c, N_h, N_{re}, N_{ed}, P_{ed}, C(i) \] and \[ \theta' \]

where

\[ p = \text{number of parameters to be optimized} \]

\[ S = \text{number of bacteria used for searching} \]
\( N_s \) = swimming length after which tumbling of bacteria is performed in a chemotaxis loop

\( N_c \) = maximum number of iterations in a chemotaxis loop

\( N_{re} \) = the maximum number of reproduction to be performed

\( N_{ed} \) = the maximum number of elimination and dispersal events to be performed over the bacteria

\( P_{ed} \) = the probability of elimination and dispersal

\( C(i) \) = is the size of the step taken in the random direction specified by the tumble

\( d_{at}, w_{at}, h_{re}, w_{re} \) = attractant and repellant coefficients

\( \Delta (p, i) \) = direction of bacterium 

\( P (i, j) \) = position of bacterium.

\( c_1, c_2 \) = cognitive and social acceleration factors respectively for PSO algorithm

\( r_1, r_2 \) = random numbers uniformly distributed in the range \((0,1)\) for PSO algorithm

In the above notations, \( j \) is the index for the chemotactic step, \( k \) is the index for the reproduction step and \( l \) is the index of the elimination-dispersal event.

**Step 2:** Elimination and dispersal loop: \( l=l+1 \)

**Step 3:** Reproduction loop: \( k=k+1 \)

**Step 4:** Chemotaxis loop: \( j=j+1 \)

Sub step a: For \( i = 1, 2, \ldots S \) take a chemotactic step for bacterium \( i \) as follows

- Compute fitness function, \( J (i, j, k, l) \)

  Let \( J (i, j, k, l) = J (i, j, k, l) + J_{cc} (\theta (j, k, l), P(j, k, l)) \)

- Let \( J_{last} = J (i, j, k, l) \)
Sub step b: For \( i = 1, 2, \ldots, S \) take a take the tumbling/swimming decision.

- For the first iteration, generate a random vector \( \Delta (i) \in \mathbb{R}^p \) where each element \( \Delta_m (i), m = 1, 2, \ldots, p \) a random number on \([-1, 1]\). For subsequent iterations, update the direction and position of bacteria using PSO.

\[
\theta^i (j+1, k, l) = \theta^i (j, k, l) + C(i) \cdot \frac{\Delta(i)}{\sqrt{\Delta^T(i)\Delta(i)}}
\]

- Move bacteria by letting

This results in a step of size \( C(i) \) in the direction of the tumble for bacterium \( i \).

- Compute \( J (i, j+1, k, l) = J (i, j, k, l) + J_{cc} (\theta^i (j+1, k, l), \theta^i_{en}(j+1, k, l)) \)

- Swim

(i) Let \( m=0 \) (counter for swim length)

(ii) While \( m < N_s \)

Let \( m=m+1 \)

If \( J (i, j+1, k, l) < J_{\text{last}} \), let \( J_{\text{last}} = J (i, j+1, k, l) \)

and

\[
\theta^i (j+1, k, l) = \theta^i (j, k, l) + C(i) \cdot \frac{\Delta(i)}{\sqrt{\Delta^T(i)\Delta(i)}}
\]

Use this new \( \theta^i (j+1, k, l) \) to compute new \( J (i, j+1, k, l) \),

(iii) Else, let \( m=N_s \). This is the end of the while statement for swim.

Sub step c: Go to next bacterium \((i+1)\) if \( i \neq S \) (i.e., go to substep b to process the next bacterium).
5.4 RESULTS AND DISCUSSIONS

5.4.1 SINGLE-MACHINE INFINITE-BUS POWER SYSTEM

The model of the example power system shown in Fig. 4.1 is developed using SimPowerSystems Blockset as shown in Fig. 5.1. The system consists of a of 2100 MVA, 13.8 kV, 60 Hz hydraulic generating unit, connected to a 300 km long double-circuit transmission line through a 3-phase 13.8/500 kV step-up transformer and a 100 MVA SSSC. All the relevant parameters are given in appendix IV. For the purpose of optimization of Eq. (5.4), hBFOA-PSO algorithm is employed. For the implementation of BFOA, several parameters are required to be specified. For the
efficient performance of BFOA, these parameters should be selected carefully. In the present study, based on the previous experience $N=8$, $N_C=5$, $N_S=3$, $N_{re}=8$, $N_{ed}=3$, $P_b=0.25$, $d_{at}=0.01$, $w_{at}=0.004$, $h_{re}=0.01$, $w_{re}=10$ are chosen [99-101]. In case of PSO implementation, $c_1$ and $c_2$ (cognitive and social acceleration factors respectively), initial inertia weights, swarm size and stopping criteria etc are to be specified. The constants $c_1$ and $c_2$ represent the weighting of the stochastic acceleration terms that pull each particle toward $p_{best}$ and $g_{best}$ positions. Low values allow particles to roam far from the target regions before being tugged back. On the other hand, high values result in abrupt movement toward or past, target regions. Hence, the acceleration constants were often set to be 2.0 according to past experiences. Suitable selection of inertia weight $w$ provides a balance between global and local explorations, thus requiring less iteration on average to find a sufficiently optimal solution. As originally developed, $w$ often decreases linearly from about 0.9 to 0.4 during a run [27, 74]. One more important factor that affects the optimal solution more or less is the range for unknowns. For the very first execution of the program, a wider solution space can be given and after getting the solution one can shorten the solution space nearer to the values obtained in the previous iteration. Simulations were conducted on a Pentium 4, 3 GHz, 504 MB RAM computer, in the MATLAB 7.0.1 environment. The solver options used in the paper are, Variable step type, ode23s (stiff/Mod. Rosenbroc) solver, with a maximum time step of one cycle of the fundamental frequency. The flowchart of the hybrid BFOA-PSO algorithm is shown in Fig 5.2. The optimization processes is run 20 times and the best values of PSS and SSSC-based controller parameters obtained by the proposed algorithm among the 20 runs corresponding to minimum fitness value along with the minimum, maximum and average fitness values are given in Table 5.1. To show the superiority of proposed hBFOA-PSO technique, results are compared with DE technique as given in Table 5.1. It is clear from Table 5.1 that, minimum objective function value is obtained with proposed hBFOA-PSO technique ($ITAE=6.1541x10^{-4}$) compared to same with DE technique ($ITAE=7.1377x10^{-4}$). It is also clear from Table 5.1 that better results are obtained with proposed hBFOA-PSO technique compared to DE technique in terms of maximum and average value of objective function. Hence it can be concluded that proposed hBFOA-PSO technique outperforms DE technique.
Fig. 5.2 Flow chat for hBFOA-PSO optimization technique

5.4.2 COMPARISON OF HYBRID BFOA-PSO TECHNIQUE WITH DE

To validate the superiority of the proposed hBFOA-PSO technique in coordinated tuning of PSS and SSSC based controllers, simulation results are compared with those with DE technique. A 3-cycles, 3-phase fault is applied at the middle of one transmission line connecting bus 2 and bus 3, at $t = 1$ s. The original system is restored after fault clearance. The system response under this severe disturbance is shown in Figs. 5.3 – 5.5. It can also be seen from Figs. 5.3 – 5.5 that the performance of proposed hBFOA-PSO is superior to DE as hBFOA-PSO optimized controllers stabilizes the system quickly.
Table 5.1: Comparison of hBFOA-PSO and DE techniques

<table>
<thead>
<tr>
<th>Technique/Parameters</th>
<th>DE</th>
<th>hBFOA-PSO</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>SSSC</td>
<td>PSS</td>
</tr>
<tr>
<td>$K$</td>
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<td>0.8070</td>
</tr>
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<td>$T_4$</td>
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<tr>
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<td>6.1541x10^{-4}</td>
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<tr>
<td>Average fitness</td>
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<td>6.5204x10^{-4}</td>
</tr>
</tbody>
</table>

Fig. 5.3 Speed deviation with nominal loading condition

Fig. 5.4 Power angle response with nominal loading
Next, the generator loading is changed to light loading condition ($P_e=0.5$ pu, $\delta_0=29.47^\circ$) and a 3-cycle, 3-phase fault in the transmission line near bus 3 at $t=1$ s is considered. The fault is cleared by opening the faulty line and the line is reclosed after 3-cycles. The system response under this contingency is shown in Figs. 5.6-5.7 from which it is clear that better responses are obtained with proposed hBFOA-PSO technique compared to DE technique.

**Fig. 5.5** Tie line power with nominal loading condition

**Fig. 5.6** Speed deviation with light loading condition
The load at bus 1 is disconnected for 100 ms at \( t = 1 \text{ s} \) at heavy loading condition \((P_e = 1.0 \text{ pu}, \delta_0 = 60.73^{\circ})\) to simulate a small disturbance. It is clear from system responses shown in Figs. 5.8-5.9 that proposed hBFOA-PSO technique outperforms DE technique.
5.4.3 COMPARISON OF HYBRID BFOA-PSO TECHNIQUE WITH BFOA, PSO AND GA

The results of proposed hBFOA-PSO are also compared with the individual results obtained with BFOA and PSO techniques. Table 5.2 shows the corresponding values when BFOA and PSO techniques are individually applied to the same system along with the values obtained with proposed hBFOA-PSO technique. It is clear from Table 5.2 that proposed hBFOA-PSO technique outperform individual PSO and BFOA techniques in terms of minimum, maximum and average fitness values. Fig. 5.10 shows the typical convergence characteristics of PSO, BFOA and hBFOA-PSO algorithm. From Fig. 5.10 and Table 5.2 it is quite clear that among the three techniques considered, the convergence of hBFOA-PSO is the fastest and the final value of objective function is minimum.

Table 5.2: hBFOA-PSO optimized controller parameters for SMIB

<table>
<thead>
<tr>
<th>Technique/Parameters</th>
<th>PSO</th>
<th>BFOA</th>
<th>hBFOA-PSO</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>SSSC</td>
<td>PSS</td>
<td>SSSC</td>
</tr>
<tr>
<td>$K$</td>
<td>77.4308</td>
<td>7.2394</td>
<td>102.9637</td>
</tr>
<tr>
<td>$T_1$</td>
<td>0.4564</td>
<td>0.2031</td>
<td>0.3108</td>
</tr>
<tr>
<td>$T_2$</td>
<td>0.4837</td>
<td>0.4363</td>
<td>0.2836</td>
</tr>
<tr>
<td>$T_3$</td>
<td>0.3189</td>
<td>0.2017</td>
<td>0.2434</td>
</tr>
<tr>
<td>$T_4$</td>
<td>0.1554</td>
<td>0.4257</td>
<td>0.2337</td>
</tr>
<tr>
<td>Minimum fitness</td>
<td>7.1105x10^{-4}</td>
<td>7.1207x10^{-4}</td>
<td>6.1541x10^{-4}</td>
</tr>
<tr>
<td>Maximum fitness</td>
<td>8.0176x10^{-4}</td>
<td>7.8421x10^{-4}</td>
<td>6.9013x10^{-4}</td>
</tr>
<tr>
<td>Average fitness</td>
<td>7.5266x10^{-4}</td>
<td>7.4749x10^{-4}</td>
<td>6.5204x10^{-4}</td>
</tr>
</tbody>
</table>

![Fig. 5.10](image-url) Convergence characteristics of PSO, BFOA and hBFOA-PSO algorithm
The controllers are designed at nominal operating conditions for the system subjected to one particular severe disturbance (3-phase fault). To show the robustness of the proposed design approach, different operating conditions and contingencies are considered for the system with and without controller. In all cases, the optimized parameters obtained for the nominal operating condition given in Table 5.2, are used as the controller parameters. Also, the simulation results are compared with a conventional power system stabilizer [1]. Three different operating conditions (nominal, light and heavy) are considered and simulation studies are carried out under different fault disturbances and fault clearing sequences. The response without controller is shown with dotted lines with legend ‘No Control’; the response with conventional power system stabilizer is shown with dashed line with legend ‘CPSS’ (please refer appendix for CPSS parameters) and the response with proposed coordinated PSS and SSSC-based damping controller is shown with solid lines with legend ‘CC: hBFOA-PSO’. For comparison, the responses are compared with a recently published result where Genetic Algorithm (GA) has been applied [107] to coordinately design PSS and SSSC-based controller parameters (shown with dash-dot line with legend ‘CC: GA’.

Case 1: Nominal loading condition, 3-phase self clearing fault

The behavior of the proposed controllers is verified at nominal loading condition ($P_e = 0.8 \text{ pu}, \delta_0 = 48.4^\circ$) under a severe disturbance. A 3-cycles, 3-phase fault is applied at the middle of one transmission line connecting bus 2 and bus 3, at $t = 1 \text{ s}$. The original system is restored after fault clearance. The system response under this severe disturbance is shown in Figs. 5.11-5.14. The plots in Figs. 5.11-5.14 are speed deviation $\Delta \omega$ in pu, power angle $\delta$ in degrees, real power flow in the transmission line $P_L$ in MW and SSSC injected voltage $V_q$ in pu respectively. It is clear from these Figs. 5.11-5.14 that, the system is oscillatory without control under this severe disturbance. It is also clear from the Figs. that, stability of the system is improved with the application of CPSS. However, the proposed controllers provide much better damping characteristics to low frequency oscillations and quickly stabilize the system by modulating the SSSC injected voltage and stabilizing signal of PSS. It can also be seen from Figs that the performance of proposed hBFOA-PSO is superior to GA as hBFOA-PSO optimized controllers stabilizes the system quickly without any overshoot.
**Fig. 5.11** Speed deviation response for 3-cycle 3-phase fault at middle of transmission line with normal loading condition

**Fig. 5.12** Power angle response for 3-cycle 3-phase fault at middle of transmission line with normal loading condition

**Fig. 5.13** Tie-line power response for 3-cycle 3-phase fault at middle of transmission line with normal loading condition
The effectiveness of the proposed coordinated design approach with variation in the signal transport delays is also verified by simulating the system with different values of transport delays. Fig. 5.15 shows the system speed deviation response for a self clearing 3-phase fault disturbance at the middle of the transmission line. It can be seen from Fig. 5.15 that the performance of the proposed controllers slightly deteriorates with the increase in the transport delays and improves further with decrease in transport delay.
Case 2: Light loading condition, 3-phase fault cleared by line tripping

In order to test the robustness of the controllers, the generator loading is changed to light loading condition ($P_e = 0.5$ pu, $\delta_0 = 29.47^0$) and a 3-cycle, 3-phase fault in the transmission line near bus 3 at $t = 1$ s is considered. The fault is cleared by opening the faulty line and the line is reclosed after 3-cycles. The system speed deviation under this contingency is shown in Fig. 5.16, which clearly depicts the robustness of proposed controllers for changes in operating condition and fault location and its superiority over GA.

![Fig. 5.16 System speed deviation response for 3-cycle 3-phase fault near Bus 3 cleared by line tripping with light loading condition](image)

Case 3: Heavy Loading condition, small disturbance

The effectiveness of the proposed controllers is also examined at heavy loading condition by disconnecting load at bus 1 at $t = 1$ s for 100 ms at heavy loading condition ($P_e = 1.0$ pu, $\delta_0 = 60.73^0$). Fig. 5.17 show the system speed deviation response under the above contingency from which it is clear that the proposed controllers which are designed at nominal loading condition for a 3-phase fault disturbance, damps the power system oscillations effectively and stabilizes the system quickly when operating condition and contingency changes.
5.4.4 EXTENSION TO THREE-MACHINE SIX-BUS POWER SYSTEM

The proposed approach of coordinated design of PSS and SSSC based damping controller is extended to a three-machine Six-bus power system shown in Fig. 3.31. It is similar to the power systems used in references [74, 73, 29, 91]. The system consists of three generators divided into two subsystems and are connected via an intertie. Following a disturbance, the two subsystems swing against each other resulting in instability. To improve the stability the line is sectionalized and a SSSC is assumed on the mid-point of the tie line. Also, PSSs are installed with each machine. The MATLAB/SIMULINK model of three-machine Six-bus power system with SSSC is shown in Fig. 5.18. The relevant data for the system is given in appendix V. The same approach as explained in section 5.4.1, for single-machine case is followed to optimize the PSSs and SSSC-based damping controller parameters for three-machine case. Speed deviations of generators G1 and G3 are selected as the input signal of the SSSC-based controller.

Fig. 5.17 System speed deviation response for small disturbance with heavy loading condition
Simulations studies are carried out and presented under different contingencies. The uncontrolled response is shown with dotted lines and the response of the system when the proposed MFOA-PSO optimized PSSs and SSSC-based damping controller are present, is shown with solid lines with legend ‘Coordinated’.

Fig. 5.18 MATLAB/SIMULINK model of three-machine six-bus power system with SSSC

Speed deviations of the individual generators are chosen as the input signals for all three PSSs. The optimized values of the controller are shown in Table 5.3. Simulation studies are carried out and presented under different contingencies. The uncontrolled response is shown with dotted lines and the response of the system when the proposed MFOA-PSO optimized PSSs and SSSC-based damping controller are present, is shown with solid lines with legend ‘Coordinated’.
Table 5.3: hBFOA-PSO optimized controller parameters for multi-machine power system

<table>
<thead>
<tr>
<th>Controller /Parameters</th>
<th>$K$</th>
<th>$T_1$</th>
<th>$T_2$</th>
<th>$T_3$</th>
<th>$T_4$</th>
</tr>
</thead>
<tbody>
<tr>
<td>SSSC</td>
<td>96.2385</td>
<td>0.37</td>
<td>0.2053</td>
<td>0.2571</td>
<td>0.1482</td>
</tr>
<tr>
<td>PSS-1</td>
<td>5.294</td>
<td>0.2104</td>
<td>0.3271</td>
<td>0.182</td>
<td>0.3022</td>
</tr>
<tr>
<td>PSS-2</td>
<td>8.7205</td>
<td>0.3349</td>
<td>0.1285</td>
<td>0.3328</td>
<td>0.2643</td>
</tr>
<tr>
<td>PSS-2</td>
<td>4.9672</td>
<td>0.207</td>
<td>0.1715</td>
<td>0.2477</td>
<td>0.3589</td>
</tr>
</tbody>
</table>

The following cases are considered:

**Case 1: Three-phase fault disturbance**

A 3-cycle, 3-phase self clearing fault is applied at one of the line sections between bus 1 and bus 6 near bus 6 at $t = 1$ s. The original system is restored after the fault clearance. The system response is shown in Figs. 5.19 -5.22. From these Figs. it can be seen that, both inter-area and local mode of oscillations are highly oscillatory without controllers. The proposed controllers significantly improve the power system stability by suppressing these oscillations by modulating the SSSC injected voltage and stabilizing signals of PSSs.

In order to verify the effectiveness of the proposed coordinated design approach with the variation in the signal transport delays, different values of transport delays are simulated for the above disturbance. Figs. 5.23 and 5.24 show the system response from which it is clear that the variation in transport delay has almost negligible effect on the performance of the proposed controller.

**Fig. 5.19** Inter-area mode of oscillations for 3-phase 3-cycle fault disturbance
Fig. 5.20 Local mode of oscillations for 3-phase 3-cycle fault disturbance

Fig. 5.21 Tie-line power flow response for 3-phase 3-cycle fault disturbance

Fig. 5.22 SSSC injected voltage response for 3-phase 3-cycle fault disturbance
Fig. 5.23 Inter-area mode of oscillations with variation in signal transmission delays

Fig. 5.24 Local mode of oscillations with variation in signal transmission delays

**Case 2: Line outage disturbance**

In order to test the robustness of the controllers to type of disturbance, one of the parallel transmission lines between bus 1 to bus 6 is tripped off at $t = 1$ s. the line is reclosed after 3-cycles and the original system is restored after the line reclosure. Figs. 5.25 and 5.26 show the system response for the above contingency.
Case 3: Small disturbance

For completeness, the performance of the proposed controllers is also investigated under small disturbance. The load at bus 4 is disconnected at $t = 1.0$ s for 100 ms (This simulates a small disturbance). Figs. 5.27 and 5.28 show the system response for the above contingency. It is clear from the Figs. that the proposed controller is robust and provides efficient damping even under small disturbance conditions.
Chapter 5: BFOA-PSO Hybrid Approach for Coordinated Design of PSS and SSSC Based Controller

Fig. 5.27 Inter-area mode of oscillations for 100 ms small disturbance

Fig. 5.28 Local mode of oscillations for 100 ms small disturbance
5.5 CONCLUSIONS

In this study, power system stability enhancement by the coordinated application of multiple and multi-type damping controllers is thoroughly investigated. For the proposed controllers design problem, a time-domain simulation-based objective function to minimize the power system oscillations is used. Then, a hybrid bacteria foraging optimization algorithm and particle swarm optimization (hBFOA-PSO) technique is employed to optimally and coordinately tune the controller parameters. Simulation results are presented for various loading conditions and disturbances to show the effectiveness of the proposed coordinated design approach. The superiority of the proposed hBFOA-PSO has been demonstrated by comparing the results with DE, BFOA, PSO and GA. The proposed controllers are found to be robust to fault location and change in operating conditions and generate appropriate stabilizing output control signals to improve stability. Finally, the proposed coordinated design approach is extended to a multi-machine power system and simulation results are presented to show the effectiveness of the proposed controllers to damp modal oscillations in a multi-machine power system. The proposed control scheme is adaptive, simple to implement, yet is valid over a wide range of operating conditions.