Power System Stabilizer Optimization Using BBO Algorithm for a Better Damping of Rotor Oscillations Owing to Small Disturbances

In a practical power system, the synchronous generators should cope with changes in both real and reactive power demand. In general, stabilization of real power variations is possible by rescheduling the operation of generators. To control the demand of the reactive power load, electric limits of the excitation loop is adjusted to initiate the reactive power of the network. In order to accelerate the reactive power delivery, a power system stabilizer (PSS) is connected to the generator through an exciter. We introduce here a latest biogeography-based optimization (BBO) algorithm to adjust PSS parameters for different operating conditions in order to improve the stability margin and the system damping. This is possible when the integral square error (ISE), which is the objective function, of the speed deviation in asynchronous machine intended to a range of turbulence is reduced. A relative comparative study is conducted between the algorithms such as BBO, particle swarm optimization (PSO) and the adaptation law based PSS on SMIB. The simulation results indicate that when compared to other available methods, the BBO algorithm damps out low-frequency oscillations in the synchronous machine rotor in an effective manner. Algorithms are simulated with the help of MATLAB® and Simulink®. Results obtained from simulations indicate that the recommended algorithm yields rapid convergence rate and improved dynamic performance; system stability, efficiency, dynamism and reliability are also improved.

Keywords: Power System Stabilizer, Single machine infinite bus system, PSO algorithm, AL-based PSS, BBO algorithm

1. INTRODUCTION

An important phenomenon in power system operation is low-frequency oscillation (LFO) stabilization. Basically, the automatic voltage regulator and field coil in generator produce torque (damping) in order to suppress these oscillations automatically. If LFOs are not controlled properly, there will be system damage. To overcome this, a power system stabilizer (PSS) is commonly used to damp out LFOs of machines in a power system. PSS acts as a feedback controller and is connected to the excitation system of a rotating machine through an AVR.

The design of a usual CPSS is modelled which is on a set of parameters associated with linear control theory and which is by the function of certain working conditions. And also has disadvantages such as time consumption for tuning and non-robust damping parameters when subjected to other operating conditions as power systems are virtually nonlinear [1]. However, the usual PSS do not guarantee’s to optimal damping in the operating process. Later, techniques involving AI were used to design conventional PSSs; this aided in damping out LFO under various disturbances [2-7]. Fuzzy logic and neural networks do not need a precise mathematical model, similar to other classical control methods, because they depend on speed and robustness. However, these techniques are unable to execute a decent optimization, and reproduce surges and overshoots. Several Artificial techniques are used such as genetic algorithm (GA) [8-10], evolutionary programming [11], and differential evolution [12-14], to enhance conventional PSS tuning techniques. Although EA is known for its proven competence, it still possess a few drawbacks when applied to real-time systems including poor premature convergence rate, computational difficulty and no assertion of deciding global optimum solution. Because of their capability to create accurate results within a short time frame and their variation to different operating conditions though fine-tuning the PSS, further the research can be incensed on swarm intelligence (SI) techniques. Many researchers implemented SI techniques in their research work for parameters tuning of PSS: artificial bee colony (ABC) algorithm [15-16], ant colony optimization (ACO) [17-19] and particle swarm optimization (PSO) [20-22].

The proposed method is based on biogeography based optimization algorithm to optimize parameters of PSS towards PSS optimizing to damp out LFOs in a
power system. A relative study of the proposed BBO, (PSO and adaptation law is conducted to find better damping oscillation simulations. BBO is a new technique, which is based on population, of the EA [23]. Bio-geography is a division of biology and describes the new species evolution, species migration between islands and species extinction [24]. Further studies about species migration from less habitable island to better habitable island in order to information share related to migration (probability-based). In BBO algorithm, species movement depends on suitability index variables (SIVs) such as water resource, vegetation diversity, temperature and landmass. Vector of real numbers are used to represent these. In BBO, the quality of solution set is represented by habitat suitability index (HSI). When quality or performance of a particular solution set in an optimization problem increases, HSI also increases. The BBO algorithm has seen successful application in several real-world problems, including sensor selection for aircraft engines, optimal power reactive flow problem and robot controller tuning. Many researchers applied the BBO algorithm for their applications because of minimum complexity and robustness with respect to optimization of controller parameters. In 2010 [25], the BBO algorithm was applied to solve optimal power flow crisis in power systems. Later [26], the BBO algorithm was introduced for real and reactive power compensation of distributed system. The results were matched with the PSO algorithm. Furthermore, the design of BBO algorithm was carried out to obtain the optimal valve of PID controller to improve the rotating machine rotor angle stability subjected to different operating ranges [27]. BBO algorithm can be applied to tune PID controller parameters for vibration control application of an active suspension system [28]. Later, to optimize the gains of a PID controller, the BBO algorithm was used and compared with other conventional techniques to analyse the performance of the synchronous machine [29].

From the detailed survey, the proposed BBO algorithm reveals the better-quality solution and computation efficiency over the other optimization methods. Therefore, this article made an attempt by proposing the BBO algorithm to optimize PSS parameters to enhance power system stability subjected to a variety of operating conditions. The simulation results are validated with other optimization techniques such as PSO and adaptation law in Simulink environment. The recommended method has proved efficiency and robustness by analysing the performance characteristics of synchronous machine like rotor angle deviation, speed deviation and load angle compared to exciting methods. The paper is laid out as follows: Section 1 describes the reason why PSS is necessary and provides a detailed literature survey. Section 2 briefly explained about PSS. In Section 3, Problem formulation and objective function is discussed. Methodologies for tuning PSS are discussed in Section 4. In section 5, system description is explained in detail. Section 6 explains simulation results and different case studies. The final section concludes the paper.

2. POWER SYSTEM STABILIZER

The PSSs function generates complementary feedback stabilizing signals to excitation system to subdue LFOs. The feedback stabilizing signal of PSS is directly proportional to actual speed deviation from synchronous speed of the synchronous machine. As soon as the rotor oscillates, the stabilizing signal acts as a damping torque that counters LFOs of the power system. PSS structure is presented in Fig.1 that consist of Power System stabilizer gain (K_PSS), washout time constant (Tw) and lead-lag compensator time (T1 & T2). In PSS, for certain operating conditions, parameters are optimized and fixed; this provides a superior damping over wide ranges. Speed deviation signal (Δw) as input and the stabilizing signal (ΔV_{PSS}) as output of PSS. The value of the gain (K_PSS) must be selected in the range of 20 – 200 to reduce damping in gain block. Damping over-response during severe events can be reduced by washout block which acts as a high-pass filter. This block allows the PSS to respond when speed deviation occurs, and Tw must be selected within 0.5 and 20 seconds. In synchronous machine the phase lag between electrical torque and excitation voltage can be compensated by lead-lag block. The output of the PSS is controlled by limiter.

\[
Δw \rightarrow K_{PSS} \rightarrow \frac{sT_e}{1+sT_w} \rightarrow \left[\frac{(1+sT_1)}{(1+sT_2)}\right] \rightarrow V_{PSS}
\]

Figure 1.Power System Stabilizer

From Fig. 1, V_PSS can be formulated as follows:

\[
V_{PSS} = K_{PSS} \frac{sT_e}{1+sT_w} \left[\frac{(1+sT_1)}{(1+sT_2)}\right] Δω
\]

where,

PSS gain,

\[
K_{PSS} = \frac{2τω_s M}{T(s)|G_s|}
\]

(2)

\[
ω_s = \sqrt{k_2ω_1 M
\]

(3)

\[
G_s = \frac{1+sT_1}{1+sT_2}
\]

(4)

τ = Damping ratio (0.6)

With the value of the damping factor (0.6), the proposed controller significantly suppresses the oscillations for different loading condition compared to other values.

3. PROBLEM FORMULATION

In modelling a power system, the PSS design is established using a set of non-linear differential algebraic equations. This can be formulated as

\[
\dot{x} = f(x, r, z, λ) \quad (5)
\]

\[
y = g(x, r, z, λ) \quad (6)
\]

where, x is the vector of system input variables, r is a vector of algebraic variables denoting the transmission network, z is the current vector of system output into the network from the device and λ is the vector denoting
load levels and other quantities outlining system operating conditions. In a PSS design, the non-linear differential equation should be linearized to achieve analysis of small signals. As a result, the above equations are represented as follows:

\[ \dot{\theta}(t) = Ax(t) + Br(t) \quad (7) \]
\[ y(t) = Cx(t) + Dr(t) \quad (8) \]

These equations represent a deviation from the steady-state value with respect to (5) and (6). In the proposed model, there is absence of direct coupling between system input and controlled output; therefore, the term \( r(t) \) can be eliminated in (8).

### 3.1 Objective Function

The chief objective is to improve system stability to minimization of performance index \( J \). In other words, the optimal PSS design is to minimize overshoots and settling time in system oscillations. Here speed deviation by integral square error (ISE) is considered as the objective function to be minimized. The advantage of ISE performance index over ITAE (integral time absolute error) or IAE (integral of the absolute error) is that the former produces smaller overshoots and oscillations compared to the latter. Using the performance index (ISE), PSS parameters are tuned.

The fitness function is as follows:

\[ ISE : J = \int_0^\infty \Delta \omega^2(t) dt, \omega = \omega_{sim} \quad (9) \]

where, \( t_{sim} \) refers to time taken for simulation and \( \Delta \omega \) is synchronous machine speed deviation. \( \Delta \omega \) is selected for performance evaluation of the design system. As random sets of \( K_{PSS}, T_1 \) and \( T_2 \) are created at initial state of problem space, to feed each into the PSS and achieved speed variation act by evaluating the performance index, \( J \). The \( K_{PSS}, T_1 \) and \( T_2 \) produce the smallest \( J \) which fulfills the minimum error state for optimum PSS values. The system and generator loading levels are given in Table 1.

<table>
<thead>
<tr>
<th>Table 1. Loading Conditions for the system</th>
</tr>
</thead>
<tbody>
<tr>
<td>Loading conditions</td>
</tr>
<tr>
<td>Base load</td>
</tr>
<tr>
<td>Heavy load</td>
</tr>
</tbody>
</table>

### 4. METHODOLOGY

#### 4.1 PSO ALGORITHM

This algorithm provides an optimal solution for desired parameters. This technique is motivated by the intelligence of birds flocking and fish schooling. This concept consists of moving a pre-defined number of particles throughout the searching space to find both local best and global best solutions. Particle movement is defined by the social interaction between the entities in the population. PSO aids in convergence speed improvement; it also results in a good fitness function.

The proposed PSO algorithm is described as follows [30]:

**Step 1:** Selection of PSO parameters: \( N \) Generation, \( w \) Inertia coefficient and \( C_1, C_2 \) weighting coefficients.

**Step 2:** Initialization of velocity \( V \) and particles with random positions in the problem space.

**Step 3:** Optimization fitness function \( J \) for each particle of \( X \) are evaluated.

**Step 4:** Particle’s fitness evaluation \( X_{pbest} \) is compared. If the current value is better than \( X_{pbest} \), then set \( X_{pbest} \) equal to the current value and \( X_i \) equal to the current location \( P_i \).

**Step 5:** Fitness evaluation is compared with overall previous best of the population. If the present value is better than \( X_{gbest} \), then

**Step 6:** Updating the particle velocity \( V \) and positions according to (10) and (11). In this case, the inertia weight method was utilized to change the particle velocity.

\[ V_i = w \times V_{i-1} + C_1 \times \left( X_{pbest} - X_i \right) + C_2 \times \left( X_{gbest} - X_i \right) \]

**Step 7:** Repetition of step (3) till optimization is attained.

**Step 8:** Acquiring optimal values of PSS parameters.

PSO parameters and the values are as follows: Iteration \( k_{max} = 50 \); Generation \( N = 20 \); \( w_{min} = 0.4 \); \( w_{max} = 0.9 \); \( C_1 \) and \( C_2 = 2 \). The PSO algorithm is utilized to resolve the optimization problem and examine the optimal set of PSS parameters. The range of PSS parameters using PSO algorithm is \( 0 \leq K_{PSS} \leq 110.0 \leq T_1 \leq 3.0 \leq T_2 \leq 0.2 \).

### 4.2 ADAPTATION LAW BASED PSS

Adaptation law (AL) helps in the identification of system parameters and optimization of the gain of PID stabilizer to bring the system to a stable state [31]. The tuning of PID gains is based on the eigenvalue placement method.

Assuming the system model is described by its linearity:

\[ P_y(k) = Qx(k-1)\sqrt{2} \quad (12) \]

Where \( x(k-1) \) refers to a discrete delay input signal and \( y(k) \) refers to discrete output signal.

\[ y(k) + p_1 y(k-1) + p_2 y(k-2) = q_1 u(k-1) + q_2 u(k-2) \quad (13) \]

Here, \( y \) is the yield sample and \( u \) is the key sample and the coefficients can be assessed by the RLS identifier process. Here, the sampled values of speed variation \( \Delta \omega \) are used as the input and the sampled values of excitation system in field voltage are used as the output.
In the vector form, (13) can be rewritten as
\[
y(k) = \psi^T(k)\hat{\theta}(k-1)
\]  
where \(\psi\) is the data vector and \(\hat{\theta}(k)\) is a parameter vector and is given by
\[
\psi(k) = [y(k-1), y(-2), u(k-1), u(k-2)]^T
\]  
\[
\hat{\theta}(k-1) = [p_1, p_2, q_1, q_2]^T
\]

The recursive formula is given by
\[
\hat{\theta}(k) = \hat{\theta}(k-1) + H(k-1)[y(k) - \psi^T(k)\hat{\theta}(k-1)]
\]
Where, \(H(k-1)\) is the correction vector.

To initiate the recursive formula, assume \(\hat{\theta}(0) = 0\)

(13) can be written as
\[
P(z^{-1})y(z^{-1}) = z^{-1}Q(z^{-1})u(z^{-1})
\]  
where, \(z^{-1}\) is the backward shift operator.

The control signal, \(u(z^{-1})\) can be described as
\[
u(z^{-1}) = \frac{T(z^{-1})y_r(z^{-1}) - S(z^{-1})y(z^{-1})}{R(z^{-1})}
\]  

Transfer function for the closed-loop system can be calculated by combining (18) and (19):
\[
G(z^{-1}) = \frac{y_r(z^{-1})}{y_r(z^{-1})} = \frac{z^{-1}T(z^{-1})Q(z^{-1})}{P(z^{-1})R(z^{-1}) + z^{-1}Q(z^{-1})S(z^{-1})}
\]

On comparing (20) with the preferred closed-loop transfer function, we obtain
\[
P(z^{-1})R_2(z^{-1}) + z^{-1}Q_2(z^{-1})S(z^{-1}) = A(z^{-1})
\]

To find the optimized PID gains, let us assume
\[
R(z^{-1}) = (1 + r_2z^{-1})(1 - z^{-1})
\]
\[
S(z^{-1}) = s_0 + s_1z^{-1} + s_2z^{-2}
\]
\[
T(z^{-1}) = s_0 + s_1 + s_2
\]
\[
A(z^{-1})Q_2(z^{-1}) = (1 + b_2z^{-2})(1 + (q_2 / q_1)z^{-1})
\]
where,
\[
b_1 = -2e^{-\alpha T} \cos(\alpha T) \sqrt{(1 - \xi^2)} , b_2 = e^{-2\alpha T} ;
\]
with \(a_1, a_2, b_1\) and \(b_2\) estimated using the RLS identifier method, the four parameters \(r_1, s_0, s_1, \text{ and } s_2\) can be obtained by solving these equations:
\[
\eta + q_1s_0 = 1 - p_1 + \frac{q_2}{q_1} + b_1
\]
\[
\eta(p_1 - 1) + q_2s_0 + q_1s_1 = -p_2 + \frac{q_3}{q_1} + b_2 + p_1
\]
\[
\eta(p_2 - p_1) + q_2s_1 + q_1s_2 = p_2 + \frac{b_3q_2}{q_1}
\]
\[
-p_2\eta + q_2s_2 = 0
\]

The values of \(p_1, p_2, q_1\), and \(q_2\) will differ for various operational conditions and sampling periods. The damping factor \(\zeta\) value is expected to be between 0 and 1 for the finest PID gain settings [32].

Substitute the values of \(r_1, s_0, s_1 \text{ and } s_2\) in the below equations.
\[
K_p = (s_1 + 2s_2) / (1 + \eta)
\]
\[
K_p = (s_1 + 2s_2) / (1 + \eta)
\]
\[
K_p = (s_1 + 2s_2) / (1 + \eta)
\]

The gains \(K_p, K_i\) and \(K_d\) are calculated at each sampling instance using the current estimated values of the four coefficients \(p_1, p_2, q_1\), and \(q_2\) describing the dynamic behavior of the generator at that instance.

The values of these parameters are depicted in Table 2 when the damping factor \(\alpha = 0.72\) and sampling time \(T_s = 0.01\) seconds.

### Table 2. The RLS Identifier Method parameter

<table>
<thead>
<tr>
<th>Load</th>
<th>(P_r)</th>
<th>(P_r)</th>
<th>(Q_r)</th>
<th>(Q_r)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Base Load</td>
<td>0.1947</td>
<td>0.7551</td>
<td>34.47</td>
<td>-34.48</td>
</tr>
<tr>
<td>Fault Condition</td>
<td>0.3094</td>
<td>0.6351</td>
<td>34.33</td>
<td>-34.34</td>
</tr>
<tr>
<td>Increasing in Load</td>
<td>0.2860</td>
<td>0.4810</td>
<td>23.66</td>
<td>-22.68</td>
</tr>
</tbody>
</table>

At each sampling instance gain settings of PID controllers are computed using the existing values of estimated coefficients. The optimized PID controller combined with PSS of synchronous generator for the excitation control. The values of PSS parameters are \(K_{PSS} = 125; T_a = 2; T_1 = 5000\) and \(T_2 = 2000\). This AL-based PSS yields good damping characteristic and improves the transient stability, but it has computation complexity.

### 4.3 BBO ALGORITHM

Dan Simon first introduced BBO in 2008 (Dan Simon, 2008). It is a technique based on population (EA). The BBO algorithm model describes formation of new species, migration of species and extinctions. As already indicated earlier, Habitat Suitability Index (HSI) defines a suitable species for survival place. A place with high HSI is usually considered as fine act on optimization problem and vice versa. The important feature available in each habitat or island is called suitability index variable (SIV). In this works, HSI is a dependent variable and SIVs are considered independent variables. A model of immigration and emigration rates between species in island with a good HSI as shown in Fig. 2.

### Figure 2. The model depicting emigration rates and immigration

Where, \(S_0\) is the number of species at equilibrium, \(S_{max}\) is the maximum number of species, \(\lambda\) is the immigration rate and \(\mu\) is the emigration rate.
The graph is Fig. 2 helps us to obtain emigration and immigration rates.

\[
\lambda = I \left(1 - \frac{S}{S_{\text{max}}} \right) \tag{33}
\]

\[
\mu = \frac{E \cdot S}{S_{\text{max}}} \tag{34}
\]

BBO algorithm comprises two significant sub-algorithms: Models of migration and mutation algorithms used to achieve the best PSS parameters. Fig. 2 represents basic model of biota in an island, which gives good overall interaction between immigration and emigration. To develop BBO idea in aspect, assume \(P_s\) as a habitat containing perfectly \(S\) species and it modifies from time \(t\) to \((t+\Delta t)\) as indicated:

\[
P_s(t+\Delta t) = P_s(t)(1 - \lambda_s \Delta t - \mu_s \Delta t + P_s^{-1} \lambda_s^{-1} \Delta t) + P_s + \mu_s \Delta t) \tag{35}
\]

Where, \(\lambda_s\) and \(\mu_s\) are immigration and emigration rates while there are \(S\) species in habitat.

4.4 Migration

In SIV each value of \(K_{\text{PSS}}, T_1\) and \(T_2\) are solution vector. To understand how superior or awful the habitat is, calculation is carried out on the HSI. For optimizing PSS constraint values, HSI is considered as the objective function. In this work, the objective function or performance index is integral square error (ISE) of the speed deviation (\(\Delta \omega\)). Initially, random values of \(K_{\text{PSS}}, T_1\) and \(T_2\) are initialized in space problem based on experience and each set of those values is fed to PSS and the performance of speed variation is obtained by evaluation of the objective function, \(J\). The values of \(K_{\text{PSS}}, T_1\) and \(T_2\) that generate the minimum \(J\) which convince the least error condition.

Consequently, the challenge in PSS parameters tuning is choosing the best habitat to reduce the performance index, \(J\). In BBO, it is understood that a high HSI habitat has enough species and vice versa. Ultimately the number of species will aid the selection of immigration and emigration rates of each habitat.

4.5 Mutation

Mutation in BBO is deliberated as an SIV mutation, which is \(K_{\text{PSS}}, T_1\) and \(T_2\) values in a habitat. The mutation rates are determined by probability of species count. When compared to a medium HSI habitat, very low HSI and very high HSI have less chance to mutate. This is because medium HSI habitats are unlikely to mutate because they already might have a solution. Elitism can be employed to save a habitat’s features that have the best \(K_{\text{PSS}}, T_1\) and \(T_2\) values in the BBO process; therefore, even if the mutation remains its HSI, we can regress based on the save attribute.

\[
m = m_{\text{max}} \left(1 - \frac{P_s}{P_{\text{max}}} \right) \tag{36}
\]

where, \(P_s\) is the \(S\) species probability of each island; \(P_{\text{max}}\) is the maximum of \(P_s\), \(m_{\text{max}}\) is the maximum mutation rate defined by the user; \(m\) is the mutation rate.

The range of PSS parameters using BBO algorithm are \(1 \leq K_{\text{PSS}} \leq 60, 0.2 \leq T_1 \leq 2\) and \(0.2 \leq T_2 \leq 2\).

Figure 3 depicts the flow chart of the BBO algorithm.

The BBO algorithm is shown below,

1: The BBO parameters are initialized
2: Random set of habitats are generated
3: The fitness (HSI) are calculated for each habitat
4: The map \(\mu\) and \(\lambda\) are calculated
5: Attaining \(J_{\text{best}}\) will leads to optimal solution
6: while not (termination criterion) do
7: continue with Migration process
8: continue with Mutation process
9: Calculation of Fitness \(\mu\) and \(\lambda\) and mapping
10: Attaining \(J_{\text{best}}\) will leads to optimal solution
11: end while
12: return
5. SYSTEM DESCRIPTION

The PSS model is developed to analyse the system in MATLAB Simulink environment. Fig. 4 shows the Simulink model of SMIB system subjected to fault and different loading conditions. The model consists of a synchronous machine associated with infinite bus system with transmission line. The mechanical power ($P_m$) is given as input to the synchronous machine from hydraulic turbine and governor (HTG) block. The output power of machine is fed to transmission voltage through infinite bus. The PSS is linked with synchronous machine through the excitation system to enhance the performance (transient) after vulnerable conditions. The speed variation rotor of $\Delta \omega$ is provided to the input PSS and stabilizing voltage ($\Delta V_{\text{PSS}}$) as output. Voltage is provided to the excitation system consisting of a voltage regulator and the exciter in order to provide additional stabilization of power system oscillations. The output field voltage ($V_f$) is provided to the synchronous machine from the excitation system.

6. RESULT AND DISCUSSION

By Simulink environment (MATLAB), BBO, PSO and AL performance based PSS are analysed with various operating situation. The recommended BBO algorithm is systematically inspect for its effectiveness with the help of various case studies. BBO, PSO and AL Results of PSS parameter are given in Table 3.

Table 3. Different optimization algorithms Parameter for PSS damping controller

<table>
<thead>
<tr>
<th>Parameter</th>
<th>BBO</th>
<th>PSO</th>
<th>Adaptation Law</th>
</tr>
</thead>
<tbody>
<tr>
<td>$K_{\text{PSS}}$</td>
<td>31.7</td>
<td>0.80</td>
<td>0.38</td>
</tr>
<tr>
<td>$T_1$</td>
<td>74.65</td>
<td>1.87</td>
<td>0.074</td>
</tr>
<tr>
<td>$T_2$</td>
<td>125</td>
<td>5000</td>
<td>2000</td>
</tr>
</tbody>
</table>

The PSO and BBO methods convergence characteristics are shown in Fig. 5.

![Figure 5. Comparison of fitness function](image)

From the figure, we can see that the convergence plot of the BBO algorithm is comparatively better. Moreover, with the help of standard deviation ($\sigma$) and statistical indices mean ($M$). The convergence characteristics and dynamic behaviors of both are analyzed:

$$M = \frac{1}{n} \sum_{i=1}^{n} f(K_i)$$  \hspace{1cm} (37)

$$\sigma = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (f(K_i) - M)^2}$$  \hspace{1cm} (38)

where, $f(K_i)$ individual $K_i$ fitness value and $n$ is the population size.

BBO algorithm results shows better fitness value as shown in Table 4.

In evaluation, the optimal parameters of the BBO-based PSS controller are quicker and efficient. Performances of BBO, PSO and AL based PSS were simulated and analysed in the MATLAB for a wide range of operating conditions.
Table 4. Comparison of Efficiency

<table>
<thead>
<tr>
<th>Method</th>
<th>Max.</th>
<th>Min.</th>
<th>Range</th>
<th>Mean (M)</th>
<th>Standard. deviation (σ)</th>
</tr>
</thead>
<tbody>
<tr>
<td>PSO</td>
<td>45</td>
<td>23.41</td>
<td>21.59</td>
<td>26.59</td>
<td>5.4904</td>
</tr>
<tr>
<td>BBO</td>
<td>45</td>
<td>16.4</td>
<td>28.6</td>
<td>23.9</td>
<td>8.38</td>
</tr>
</tbody>
</table>

6.1 Unvarying load condition

The synchronous machine is exposed to ground fault condition in the transmission line of 200MVA load. By BBO, PSO and AL, PSS values were tuned. Figure 6 shows that BBO-based PSS provides better dampness comparatively.

The overshoot minimized to 0.012 from 0.032. Consequently, the system settle down to 3.8 sec. From Figure 7, we can understand that BBO-PSS perk up the maximum level of rotor angle by the settling time in 3 sec. Conversely, the rotor angle is in the negative side and the proposed method recovers the performance when compared to other methods. The load angle reaches the constant state at around $10^0$ (Fig. 8). In general, for the smart system, the load angle should be preserved at around $5^0$–$50^0$.

6.2 Fault condition

In this scenario, a three phase fault in transmission line had been presented. In three phase fault condition, the fault is switched to phase A, and phases B and C were triggered. The breaker which is opened initially. Here, the transition time is applied at $t = 0.6/60$ sec and closed at $t = 6/60$ sec in the transmission line, akin to the ground fault. Figures 9 to 11 depict the performance analysis of the system through the fault condition. In Fig. 10, the PSO-PSS have more settling time and less overshoot. The AL-based PSS produces more overshoot and settles around 7 sec comparatively. The recommended method promotes a reduction of overshoot up to 50% (0.04 to 0.02) and the settling time improves to 4 sec. From Fig. 11, we can infer that there is an increase in rate of flow of velocity of the rotor with respect to fault duration. Nevertheless, the BBO-PSS preserve normal level of rotor angle. PSO-PSS cannot damp the load angle swiftly during the fault duration. However, the BBO-PSS offers the load angle around $10^0$. 
6.3 Load Incremental State

Here, the synchronous machine is projected to increase in load (3 times the normal load) of 600MVA with ground fault state in the transmission line. Figures 12 to 14 provide the simulation results, confirming the robustness of BBO-PSS compared to other optimization methods. Simulation results show that the recommended algorithm yields better dynamic behavior and quicker convergence rate. It also retains system stability, effectiveness, dynamism, system stability and consistency.

During severe fault and loading conditions but with negative damping, it is cleared that proposed damping controller maintains a synchronous machine at the synchronous speed. The comparison results with respect to settling time for different algorithms as shown in Fig. 15.
Table 5 explains the performance characteristic analysis such as overshoot and settling time of proposed BBO based PSS controller with other controllers. From the analysis we conclude that the BBO based PSS controller reduces the overshoot to the maximum of 0.02p.u with the settling time 3.8 sec compared to other conventional methods.

Table 5. Performance analysis of BBO with other methods

<table>
<thead>
<tr>
<th>Case Studies</th>
<th>Overshoot (p.u)</th>
<th>Setting time (secs)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Base Load (100 MVA)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fault Condition (3φ Fault)</td>
<td>0.015</td>
<td>0.03</td>
</tr>
<tr>
<td>Heavy load (600MVA)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.014</td>
<td>0.035</td>
</tr>
</tbody>
</table>

7. CONCLUSION

This paper illustrates to optimize the parameter of PSS for speed control of the synchronous machine using BBO algorithm. For optimization problem, PSS parameter tuning is considered and optimal controller parameters are searched by BBO. A speed deviation for different operating conditions based objective function is optimized. The effect of BBO-PSS under small disturbances due to change in load and fault conditions was compared and analysed with PSO-PSS and AL-based PSS using MATLAB. From the Simulation results for different range and analysed with PSO-PSS and AL-based PSS using PSO-PSS and AL-based PSS using.

REFERENCES

APPENDIX

Generator parameters (per unit)
Nominal power, $P_n = 200 \times 10^3$ VA

Frequency, $f_n = 50$ Hz
$X_d = 1.305$; $X_q = 0.474$
Time constants, $T_d = 1.01$ sec; $T_q = 0.053$ sec; $T_{f0} = 0.1$ sec
Stator resistance, $R_s = 2.8544 \times 10^3$
Inertia coefficient, $H = 3.2$ seconds

Exciter parameters (per unit)
Low-pass filter time constant, $T_f = 20 \times 10^3$ seconds
Regulator gain and time constants, $K_A = 300$; $T_A = 0.001$ sec
Exciter, $K_E = 1$; $T_E = 0$ seconds
Damping filter gain and time constant, $K_D = 0.001$; $T_D = 0.1$ sec
Regulator output limits and gain,
$E_{min} = -11.5$; $E_{max} = 11.5$; $K_p = 0$
Initial values of terminal voltage and field voltage,
$V_{f0} = 1.0$; $V_{f0} = 1.0$

Distributed line parameters
Number of phases, $N = 3$
Frequency used for RLC specification = 50 Hz
Resistance per unit length: $6.365 \times 10^3$ ohms/km
Inductance per unit length: $13 \times 10^{-3}$ F/km
Capacitance per unit length: $10 \times 10^{-9}$ H/km
Line length = 100 km

OПТИМИЗАЦИЈА СТАБИЛИЗАТОРА ЕЛЕКТРОЕНЕРГЕТСКОГ СИСТЕМА ПРИМЕНОМ ББО АЛГОРИТМА У ЦИЉУ БОЉЕ ПРИГУШЉЕЊА ОСЦИЛАЦИЈА РОТОРА ИЗЗАВАНИХ МАЛИМ ПОРЕМЕЂАЛИМА

Г. Касилингам, Ј. Пасупулети, Ц. Бхаратираја, Ј. Аделајо

У електроенергетском систему синхрони мотори наилазе на промене у потребама за реалном и реакцијном снагом. Стабилизација реалних варијација снаге је могућа промено плана функционисања генератора. У циљу контролисања потребе за оптималном реакцијном снагом електрично ограничење експлозивне петље се прилагођава да би се покренула реактивна снага мреже. У сврху испорукe реактивне снаге стабилизатор електроенергетског система се повезује са генератором преко побуђивача. У раду се уводи ББО алгоритам (алгоритам базиран на оптимизацији биогеографије) да би се параметри стабилизатора прилагодили различитим радним условима чиме би се побољшао мрежа сигурности и пригушење система. Ово је могуће када се смањи интеграл квадрата грешке, који је функција циља, а при девијацији брзине асинхроне машина може да издржи велики обим турбулентија. Извршено је поређење следећих алгоритама: ББО, оптимизација појем честича и закон адаптације базиран на стабилизатору система. Резултати симулације показују да ББО алгоритам у једној од друге доступне методе ефикасно пригушује осцилације мањих фреквенција код
ротора синхроне машине. Симулација алгоритама је изведена помоћу софтвера MATLAB и Simulink. Резултати симулације показују да се препорученим алгоритмом постиже већа брзина конвергенције и боље динамичке перформансе: стабилност система, степен искоришћености, динамизам и поузданост.