Power System Stabilizer Optimiza– tion Using BBO Algorithm for a Better Damping of Rotor Oscilla– tions Owing to Small Disturbances

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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 gene–rator 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 con–ditions. And also has disadvantages such as time con–sumption 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, beca–use they depend on speed and robustness. However, these techniques are unable to execute a decent optimi–zation, and reproduce surges and overshoots. Several Artificial techniques are used such as genetic algorithm (GA) [8-10], evolutionary programming [11], and dif–ferential 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 pre–mature convergence rate, computational difficulty and no assertion of deciding global optimum solution. Beca–use 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 techni–ques 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

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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]. Biogeography 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 (T_w) and lead-lag compensator time (T_1 & T_2). In PSS, for certain operating conditions, parameters are optimized and fixed; this provides a superior damping over wide ranges. Speed deviation signal ($\Delta\omega$) 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 T_w 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.

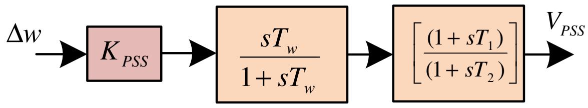

Figure 1.Power System Stabilizer

From Fig. 1, V_{PSS} can be formulated as follows:

$$V_{PSS} = K_{PSS}\frac{sT_W}{1+sT_W}\left[\frac{(1+sT_1)}{(1+sT_2)}\right]\Delta\omega \tag{1}$$

where,

PSS gain, $$K_{PSS} = \frac{2\tau\omega_n M}{T(s)|G_e|} \tag{2}$$

$$\omega_n = \sqrt{k_1\omega_b / M} \tag{3}$$

$$G_e = \frac{1+sT_1}{1+sT_2} \tag{4}$$

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

$$\dot{x} = f(x, r, z, \lambda) \tag{5}$$

$$y = g(x, r, z, \lambda) \tag{6}$$

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:

$$\dot{x}(t) = Ax(t) + Br(t) \quad (7)$$

$$y(t) = Cx(t) + Dr(t) \quad (8)$$

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:

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

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 1. Loading Conditions for the system

Loading conditions	P(MW)	Q(MVar)
Base load	150	132.28
Heavy load	400	396.6

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.
Step4: 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}, the global best fitness value then resets X_{Gbest},to the current particle's array index and value.
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.

$$V_i = w \times V_i(k-1) + C_1 r_1 (X_{iPbest}(k-1) - X_i(k-1)) + \\ + C_2 r_2 (X_{iGbest}(k-1) - X_i(k-1)) \quad (10)$$

$$X_i(t) = X_i(t-1) + V_i(t) \quad (11)$$

where, *k* refers iterations number, *i* refers number of particles – which ranges from 1 to *n*, $r_{1,2}$ are random values in the range (0,1), $C_{1,2}$ are acceleration constants and *w* is the inertia weight. To bonus up the performance in all applications, *w* is frequently decreased linearly from about 0.9 to 0.4 during the search process.
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 $0 \le K_{PSS} \le 110.0 \le T_i \le 3.0 \le T_2 \le 0.2$

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,

$$Py(k) = Qx(k-1)\sqrt{2} \quad (12)$$

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

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

2here, *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

$$y(k) = \psi^T(k)\hat{\theta}(k-1) \tag{14}$$

where ψ(kis the data vector and $\hat{\theta}(k)$ is a parameter vector and is given by

$$\psi(k) = [y(k-1), y(-2), u(k-1), u(k-2)]^T \tag{15}$$

$$\hat{\theta}(k-1) = [p_1 \quad p_2 \quad q_1 \quad q_2]^T \tag{16}$$

The recursive formula is given by

$$\hat{\theta}(k) = \hat{\theta}(k-1) + H(k-1)[y(k) - \psi^T(k)\hat{\theta}(k-1)] \tag{17}$$

Where, *H(k-1)* is the correction vector.

To initiate the recursive formula, assume $\hat{\theta}(0) = 0$ (13) can be written as

$$P(z^{-1})y(z^{-1}) = z^{-1}Q(z^{-1})u(z^{-1}) \tag{18}$$

where, $z^{-1}$is the backward shift operator.

The control signal, $u(z^{-1})$ can be described as

$$u(z^{-1}) = \frac{T(z^{-1})}{R(z^{-1})} y_r(z^{-1}) - \frac{S(z^{-1})}{R(z^{-1})} y(z^{-1}) \tag{19}$$

Transfer function for the closed-loop system can be calculated by combining (18) and (19):

$$G(z^{-1}) = \frac{y(z^{-1})}{y_r(z^{-1})} = \frac{z^{-1}T(z^{-1})Q(z^{-1})}{P(z^{-1})R(z^{-1}) + z^{-1}Q(z^{-1})S(z^{-1})} \tag{20}$$

On comparing (20) with the preferred closed-loop transfer function, we obtain

$$P(z^{-1})R_1(z^{-1}) + z^{-1}Q_1(z^{-1})S(z^{-1}) = A_1(z^{-1}) \tag{21}$$

To find the optimized PID gains, let us assume

$$R(z^{-1}) = (1 + r_1 z^{-1})(1 - z^{-1}) \tag{22}$$

$$S(z^{-1}) = s_0 + s_1 z^{-1} + s_2 z^{-2} \tag{23}$$

$$T(z^{-1}) = s_0 + s_1 + s_2 \tag{24}$$

$$A_1(z^{-1})Q_2(z^{-1}) = (1 + b_1 z^{-1} + b_2 z^{-2})(1 + (q_2/q_1)z^{-1}) \tag{25}$$

where,

$$b_1 = -2e^{-\zeta\omega T_s}\cos(\omega T_s\sqrt{(1-\zeta^2)}), b_2 = e^{-2\zeta\omega T_s};$$

with a_1, a_2, b_1 and b2 estimated using the RLS identifier method, the four parameters r_1, S_0, S_1, and S_2 can be obtained by solving these equations:

$$r_1 + q_1 s_0 = 1 - p_1 + \frac{q_2}{q_1} + b_1 \tag{26}$$

$$r_1(p_1 - 1) + q_2 s_0 + q_1 s_1 = -p_2 + \frac{b_1 q_2}{q_1} + b_2 + p_1 \tag{27}$$

$$r_1(p_2 - p_1) + q_2 s_1 + q_1 s_2 = p_2 + \frac{b_2 q_2}{q_1} \tag{28}$$

$$-p_2 r_1 + q_2 s_2 = 0 \tag{29}$$

The values of p_1,p_2,q_1 and q_2 will differ for various operational conditions and sampling periods. The damping factor (ζ) 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 and s_2 in the below equations.

$$K_P = (s_1 + 2s_2)/(1 + r_1) \tag{30}$$

$$K_P = (s_1 + 2s_2)/(1 + r_1) \tag{31}$$

$$K_P = (s_1 + 2s_2)/(1 + r_1) \tag{32}$$

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 α = 0.72 and sampling time T_s = 0.01 seconds.

Table 2. The RLS Identifier Method parameter

Load	P_1	P_2	Q_1	Q_2
Base Load	0.1947	0.7551	34.47	-34.48
Fault Condition	0.3094	0.6351	34.33	-34.34
Increasing in Load	0.2860	0.4810	23.66	-22.68

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_w = 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 (HIS) 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 HIS as shown in Fig. 2.

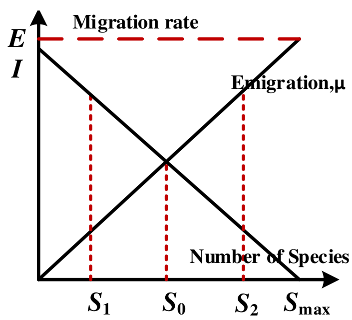

Figure 2. The model depicting emigration rates and immigration

Where, S_0 is the number of species at equilibrium, S_{max} is the maximum number of species, λ is the immigration rate and μ is the emigration rate.

The graph is Fig. 2 helps us to obtain emigration and immigration rates.

$$\lambda = I.\left(1-\frac{S}{S_{\max}}\right) \quad (33)$$

$$\mu = \frac{E.S}{S_{\max}} \quad (34)$$

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

$$P_S(t+\Delta t) = P_S(t)(1-\lambda_S\Delta t-\mu_S\Delta t+P_{S-1}\lambda_{S-1}\Delta t+P_{S+1}\mu_{S+1}\Delta t) \quad (35)$$

Where, λ_S are immigration and μ_S are emigration rates while there are S species are in habitat.

4.4 Migration

In SIV each value of K_{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 (Δω). Initially, random values of K_{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_{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_{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_{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.

$$m = m_{\max}\left(1-\frac{P_s}{P_{\max}}\right) \quad (36)$$

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

Figure 3 depicts the flow chart of the BBO algo–rithm.

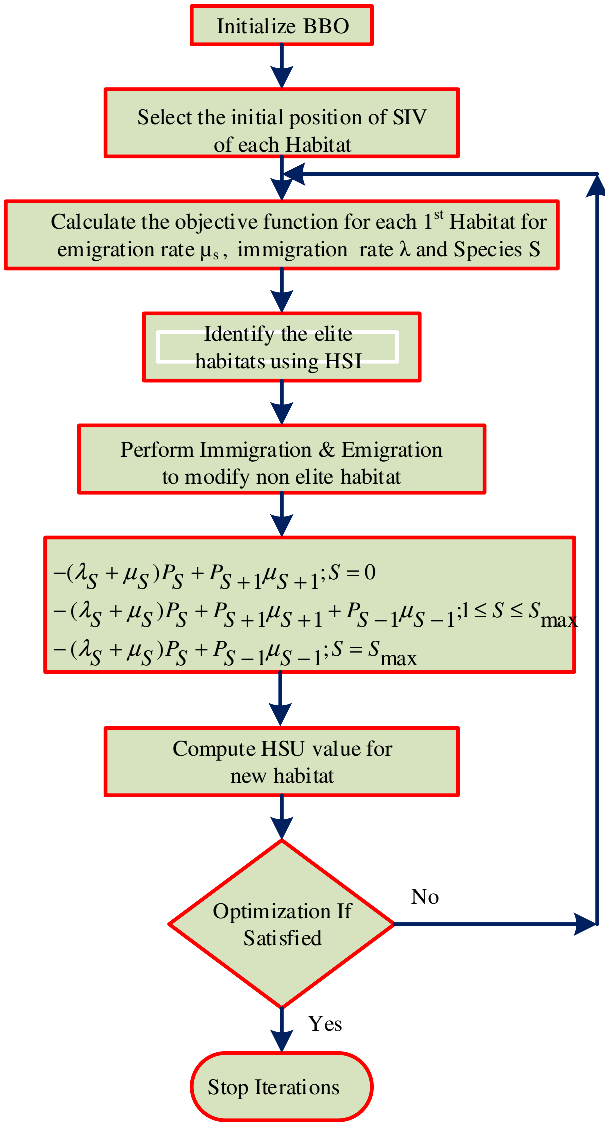

Figure 3. BBO algorithm flow chart

The BBO algorithm is shown below,

1: The BBO parameters are initialized
2: Random set of habitats are generated

(I_i and $i \in [1, N)$

3: The fitness (HSI) are calculated for each habitat
4: The map μ and λ are calculated
5: Attaining J_{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 μ and λ and mapping
10: Attaining J_{Best} will leads to optimal solution
11: end while
12: return

BBO parameters and values are habitat modification probability = 1; population number = 50, mutation rate = 0.5, iteration count = 50, number of elite habitat = 3, maximum emigration and immigration rates = 1. The range of PSS parameters using BBO algorithm are 1 $\le K_{PSS} \le$ 60, 0.2$\le T_1 \le$ 2 and 0.2 $\le T_2 \le$ 2.

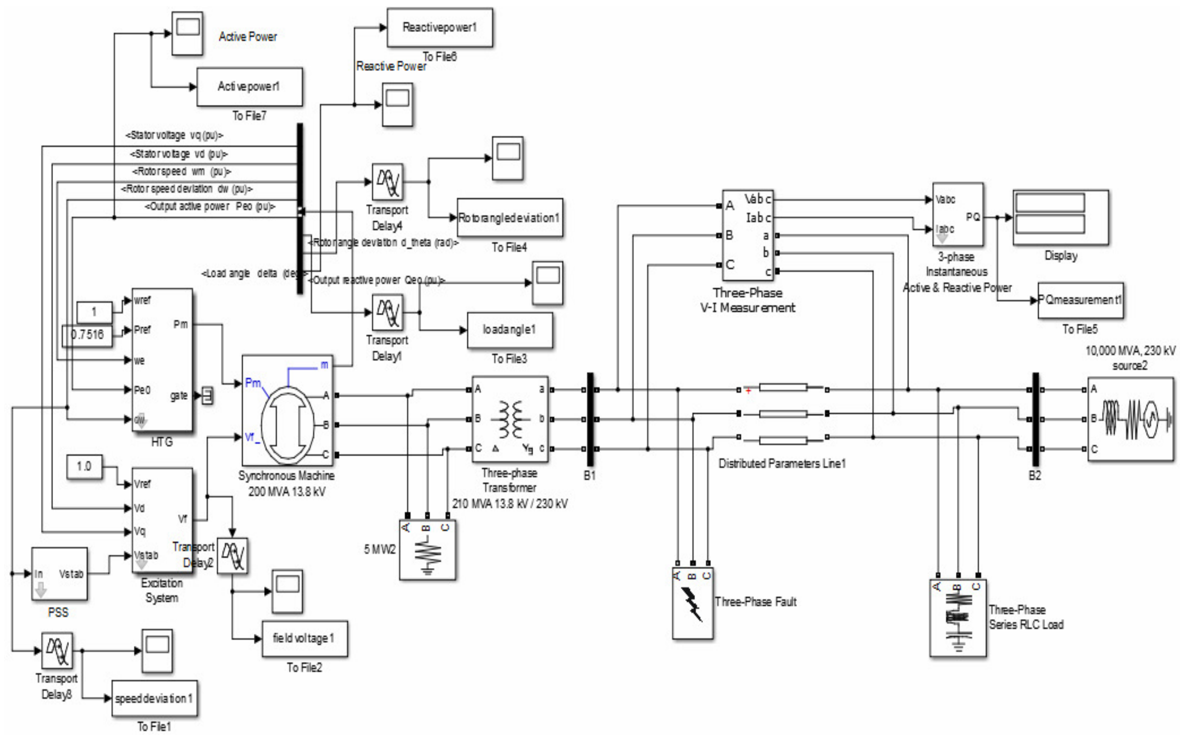

Figure 4. Simulink model of SMIB system

5. SYSTEM DESCRIPTION

The PSS model is developed to analysis 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 (ΔV_{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

	BBO	PSO	Adaptation Law
K_{PSS}	31.7	0.80	0.38
T_1	74.65	1.87	0.074
T_2	125	5000	2000

The PSO and BBO methods convergence charac–teristics are shown in Fig. 5.

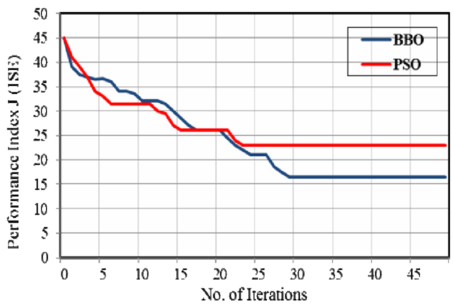

Figure 5. Comparison of fitness function

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

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

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

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. Perfor–mances 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

Method	Max.	Min.	Range	Mean (M)	Standard. deviation (σ)
PSO	45	23.41	21.59	26.592	5.4904
BBO	45	16.4	28.6	23.9	8.38

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.

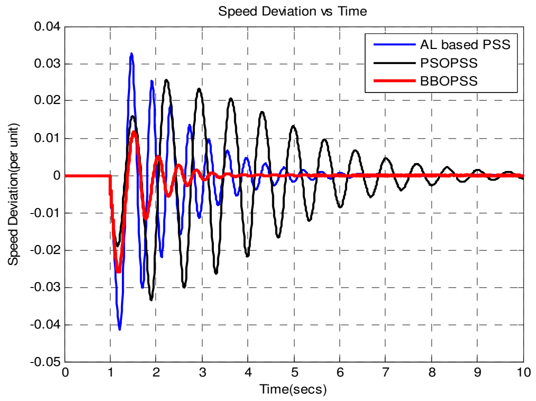

Figure 6. Unvarying load condition simulation results: The speed deviation response

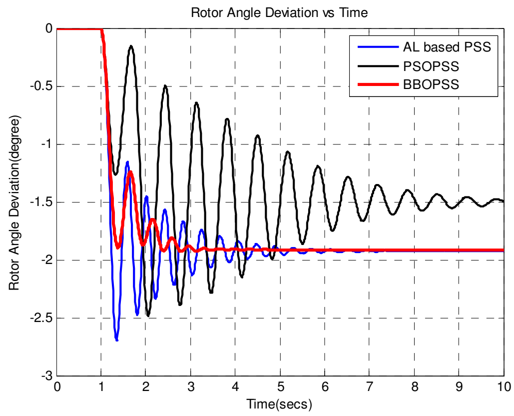

Figure 7. Unvarying load condition simulation results: The rotor angle deviation response

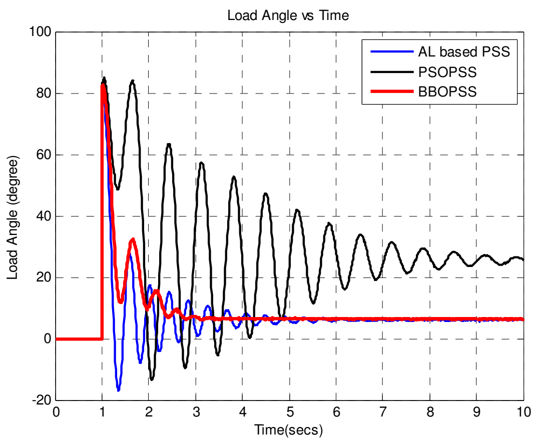

Figure 8. Unvarying load condition simulation results: The load angle response

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 recom–mended 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.

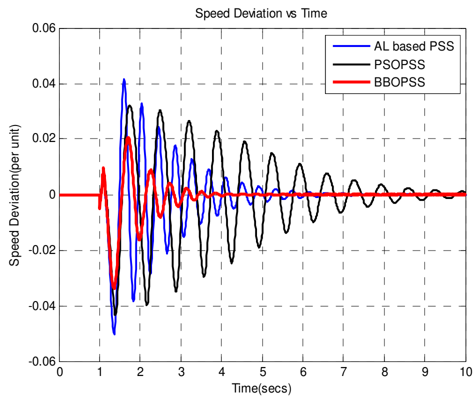

Figure 9. Fault condition simulation results: The speed deviation response

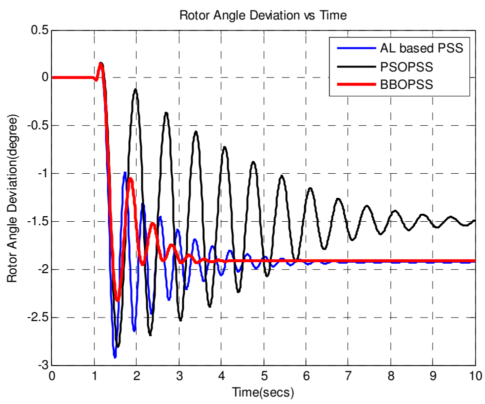

Figure 10. Fault condition results: The rotor angle deviation response

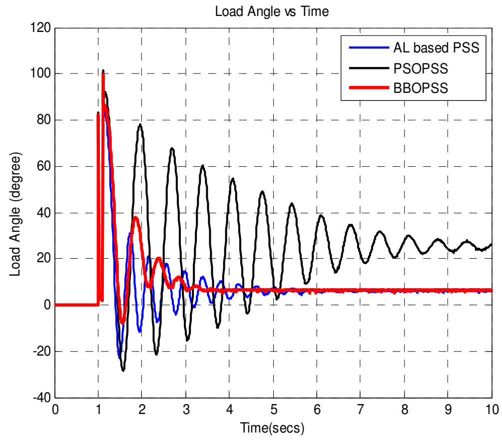

Figure 11. Fault condition simulation results: The load angle response

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.

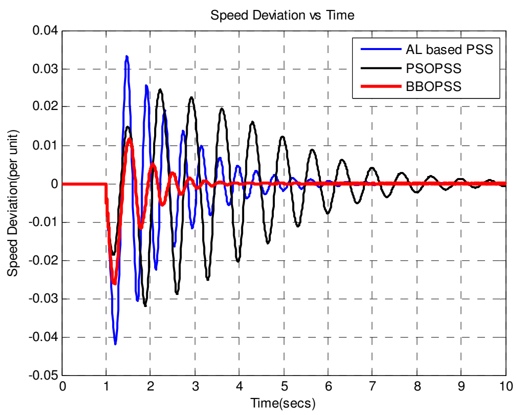

Figure 12. Load incremental state simulation results: The speed deviation response

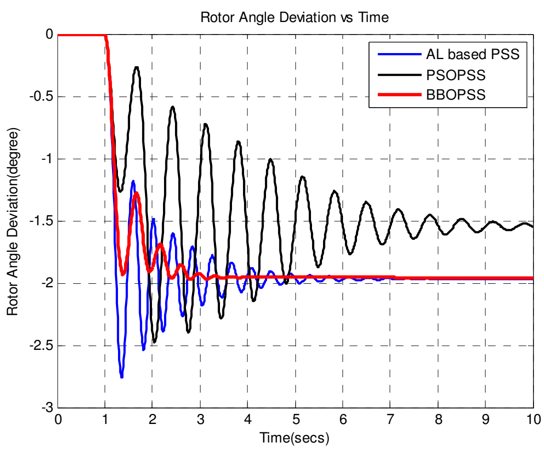

Figure13. Load incremental state condition results: The rotor angle deviation response

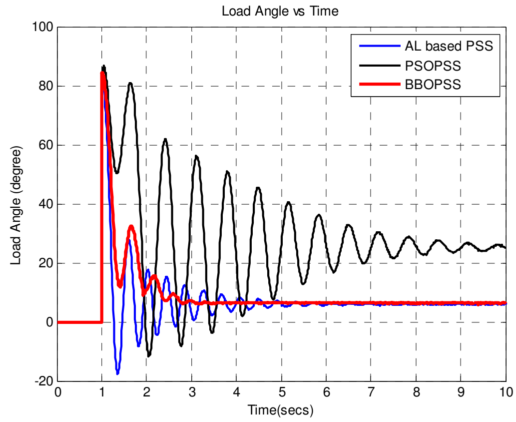

Figure 14. Load incremental state simulation results: The load angle response

During severe fault and loading conditions but with negative damping, it is cleared that proposed damping controller maintains a synchronous machine at the syn–chronous speed. The comparison result with respect to settling time for different algorithm as shown in Fig. 15.

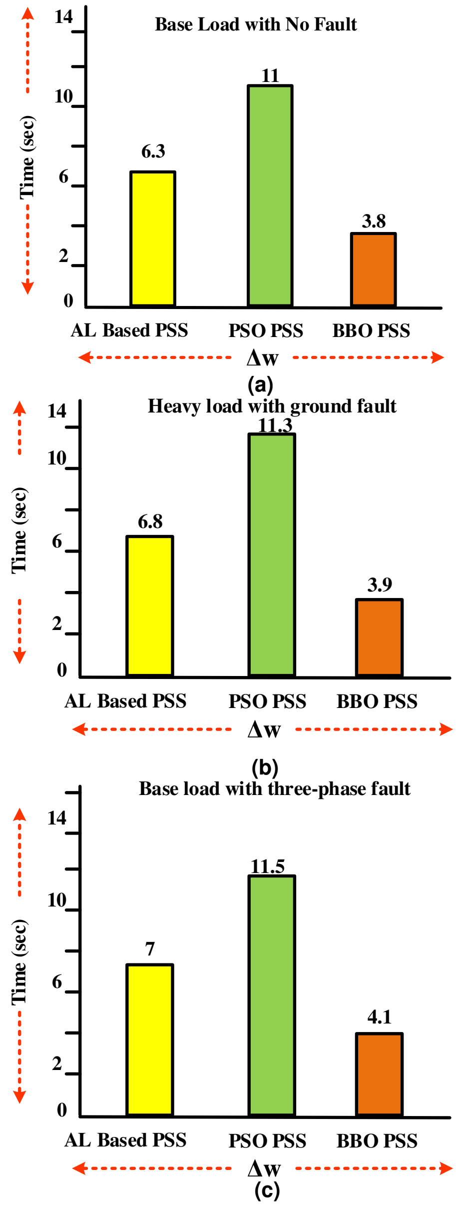

Figure 15. Speed deviation with settling time comparison for different case studies

Table 5 explains the performance characteristic analysis such as overshoot and setting 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

Case Studies	Overshoot (p.u)			Settling time (secs)		
	PSO	AL	BBO	PSO	AL	BBO
Base Load (100 MVA)	0.015	0.03	0.01	11	6.3	3.8
Fault Condition (3ϕ Fault)	0.03	0.04	0.02	11.5	7	4.1
Heavy load (600MVA)	0.014	0.035	0.01	11.3	6.8	3.9

7. CONSLUSION

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 opti–mized. 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 of operating conditions proposed controller providing good damping characteristics to system oscillations. Also the validated results, the efficiency of proposed method in suppressing LFOs of the rotor speed and en–hance the power system stability over wide range of operating conditions compared with PSO and AL met–hod.

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APPENDIX

Generator parameters (per unit)
Nominal power, $P_n = 200 \times 10^6$ VA
Frequency, $f_n = 50$ Hz
$X_d = 1.305$; $X_q = 0.474$
Time constants, $T_d = 1.01$ sec; $T_d = 0.053$ sec; $T_{q0} = 0.1$ 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, $T_r = 20 \times 10^{-3}$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,
$K_F = 0.001$; $T_F = 0.1$ sec
Regulator output limits and gain,
$E_{fmin} = -11.5$; $E_{fmax} = 11.5$; $K_p = 0$
Initial values of terminal voltage and field voltage,
$V_{t0} = 1.0$; $V_{f0} = 1.0$

Distributed line parameters
Number of phases, N = 3
Frequency used for RLC specification = 50 Hz
Resistance per unit length: 6.365×10^{-3} to 0.1932 ohms/km
Inductance per unit length: 13×10^{-4} to 3×10^{-3} H/km
Capacitance per unit length: 10×10^{-9} to 4×10^{-9} F/km
Line length = 100 km

ОПТИМИЗАЦИЈА СТАБИЛИЗАТОРА ЕЛЕКТРОЕНЕРГЕТСКОГ СИСТЕМА ПРИМЕНОМ ББО АЛГОРИТМА У ЦИЉУ БОЉЕГ ПРИГУШЕЊА ОСЦИЛАЦИЈА РОТОРА ИЗАЗВАНИХ МАЛИМ ПОРЕМЕЋАЈИМА

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

У електроенергетском систему синхрони мотори наилазе на промене у потребама за реалном и реак–тивном снагом. Стабилизација реалних варијација снаге је могућа променом плана функционисања генератора. У циљу контролисања потребе за опте–рећењем реактивном снагом електрично ограничење ексцитативне петље се прилагођава да би се покренула реактивна снага мреже. У сврху испоруке 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 побољшава маргина сигурности и пригушење система. Ово је могуће када се смањи интеграл квадрата грешке, који је функција циља, а при девијацији брзине асинхрона машина може да издржи велики обим турбуленција. Извршено је поређење следећих алгоритама: ББО, оптимизација ројем честица и закон адаптације базиран на стабилизатору система. Резултати симулације показују да ББО алгоритам у односу на друге доступне методе ефикасно пригушује осцилације малих 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.