BBO algorithm-based tuning of PID controller for speed control of synchronous machine

Gowrishankar KASILINGAM*, **Jagadeesh PASUPULETI**
Department of Electrical Power, College of Engineering, Universiti Tenaga Nasional, Selangor, Malaysia

Abstract: A biogeography-based optimization (BBO) algorithm was used for tuning the parameters of a proportional integral derivative (PID) controller-based power system stabilizer (PSS). The proposed method minimizes the low frequency electromechanical oscillations (0.1–2.5 Hz) and enhances the stability of the power system by optimally tuning the PID parameters. This was achieved by minimizing the objective function of the integral square error for various disturbances. The performance of the BBO algorithm was tested on a single machine infinite bus system for a different range of operating conditions and the results were compared with particle swam optimization, adaptation law, and conventional PSS. The result analysis concluded that the BBO algorithm damps out the low frequency oscillations in the rotor of the synchronous machine effectively when compared to other methods. The algorithms were simulated with MATLAB/Simulink. The results from the simulation showed that the proposed controller yields a fast convergence rate and better dynamic performance.

Key words: Power system stabilizer, PID controller, particle swarm optimization, adaptation law, biogeography-based optimization algorithm

1. Introduction

The ability of a system to regain its steady state when subjected to any disturbances is referred to as power system stability. In general, power systems are nonlinear and complex. Due to insufficient damping torque, these systems exhibit low frequency electromechanical oscillations caused by disturbances such as faults, load changes, and voltage collapse [1]. Power system stability includes 2 distinct types of system oscillations: interarea mode oscillations (0.1 to 0.8 Hz) and local mode oscillations (1 to 2 Hz). In interarea mode, generators are in the same area and, because of the strong electric link, the oscillation between these generators tend to be of higher frequency. In local mode, one generator swings in a generating station against the rest of the system.

Power system stabilizers (PSSs) are used to generate supplementary feedback stabilizing signals to the excitation system to suppress these oscillations. Conventional power system stabilizers (CPSSs) are designed based on stabilizer gain (K_{stab}), washout time (T_w), and lead–lag compensators (T_1 & T_2). In a CPSS, the parameters are fine-tuned and fixed for certain operating conditions to provide better damping over a defined operating range. When the operating condition changes, the low frequency oscillations may not be damped satisfactorily and they exhibit a lack of robustness [2].

The proportional integral derivative (PID) controller is one of the earliest and most efficient control

---

*Correspondence: gowri200@yahoo.com

devices and is used widely in industrial control systems. Their performance is robust, and implementation is easy [3]. In view of these advantages, the PID controller is used as an additional controller for the power system stabilizer to damp low frequency electromechanical oscillations in the single machine infinite bus (SMIB) system under a wide range of operating conditions.

We have designed a coordinated controller, where the parameters of the PID controller were tuned using a trial and error method for certain operating conditions. The effectiveness of the coordinated controller was tested for different case studies and proved to provide a better stability enhancement in the power system [4]. However, sometimes these methods do not provide good optimization and tend to produce surges and overshoots. Several intelligent approaches have been suggested, such as the genetic algorithm (GA) [5–7], particle swarm optimization (PSO) [8–10], and ant colony optimization (ACO) [11], to enhance the traditional PID gains tuning techniques.

The PSO algorithm proposed by Eberhart and Kennedy [12] is a stochastic optimization technique based on the social behavior of fish schooling and bird flocking. There are many similarities between PSO and evolution computation techniques such as the GA. A random solution of the population is initialized and will search for optimum values by updating the generations. However, PSO differs from the GA in that it has no evolution operator such as mutation or crossover, but it shares some drawbacks like the premature convergence phenomenon.

Adaptation law (AL), a method suggested by Hsu and Wu [13], is a real-time self-tuning PID controller based on the continuous measurement of inputs and outputs of the system. AL maintains a good damping characteristic whenever there is a severe change in the system operating conditions. Here the recursive least square identifier method was used to minimize the search space. Although the AL method has advantages, it requires more sample data of inputs and outputs for its optimization process.

The biogeography-based optimization (BBO) algorithm was first introduced by Simon [14]. It is a new population-based type of evolutionary algorithm (EA). Biogeography is a branch of biology, and it is a synthetic discipline that relies heavily on the theory and data collected from earth sciences, population biology, systematics, and ecology [15]. It studies the migration of species between islands from less to more habitable places and how they share information with others by probability-based migration. In biogeography, the species movement from one island to another depends on suitability index variables, which include water resources, the diversity of vegetation, temperature, and land area and are represented as vectors of real numbers. Many researchers have applied the BBO to optimize the PID gains for several applications. In [16], the BBO algorithm was applied to optimize the PID controller for nonlinear systems and was tested over an inverted pendulum and mass–spring damper system. In [17], the BBO algorithm was introduced for self-tuning PID parameters by improving the efficiency of migration and overcoming the premature convergence. Furthermore, the optimal PID controller was designed using the BBO to improve the rotor angle stability of the synchronous machine and results were tested on the SMIB system for a wide operating range [18]. The simulation results confirm the robustness of the BBO-PID over the BBO-PSS and CPSS.

Earlier, the BBO algorithm was used to tune the parameters of a PID controller alone and the stability of the power system was improved, using either the BBO-PID or BBO-PSS. An attempt is made in this paper, by combining the effectiveness of the BBO-PID and PSS, to further enhance the stability of the power system when subjected to different operating conditions.

In this paper, a method of applying the BBO algorithm is used that has better search speed and optimization compared to a PSO algorithm and AL. The proposed method has been proved to be the best

by comparing the performance of a synchronous machine (i.e. speed deviation and rotor angle deviation) with other methods. In this scheme, the BBO algorithm is used to optimize PID gains and this objective is achieved by minimizing the integral square error (ISE). This approach improves system stability, efficiency, dynamism, and reliability of the designed controller.

2. Background

2.1. Power system stabilizer (PSS)

A block diagram of the CPSS is shown in Figure 1. A generic PSS consists of the stabilizer gain, wash-out block, phase compensation system, and output limiter. The input signal given to the PSS is the speed deviation signal ($\Delta\omega$) and the output is the stabilizing signal (ΔV_{PSS}). In a CPSS, the gain block determines the extent of damping that the stabilizer imposes, and the value of the gain K_{PSS} must be chosen in the range between 20 and 200. The wash-out block acts as a high pass filter used to reduce the overresponse of the damping during severe events. This block allows the PSS to respond when speed deviation occurs, and T_w must be selected within 10–200. The lead-lag block is used to provide phase lead to compensate the phase lag between the electrical torque and excitation voltage of the synchronous machine. The limiter is used to limit the output of the PSS.
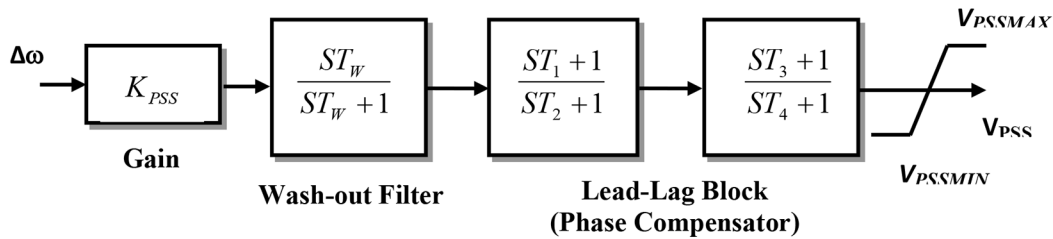

Figure 1. Conventional power system stabilizer.

2.2. PID tuning

The tuning of the PID controller is a process of determining the controller parameters, which produce the desired output, improve robust stabilization, and minimize error. The controller tuning involves the selection of optimized values of proportional gain (K_P), integral gain (K_I), and derivative gain (K_D). The mathematical expression of the PID controller consists of control signal u(t) and control error e(t). The expression is given by:

$$u(t) = K_P e(t) + \frac{1}{T_i} \int_0^t e(\tau)d\tau + T_d \frac{de(t)}{dt} \tag{1}$$

where T_i = integral time, T_d = derivative time.

The gain K_I and K_D can be described as $K_D = K_P T_d$ and $K_I = K_P/T_i$, respectively. Increasing the value of K_P makes the controller action slower, which in turn slows down the system response and increases the error. Increasing values of K_I removes or reduces the steady state error and may lead to the oscillatory response increasing or decreasing the amplitude, which is undesirable, and the system may become unstable. Increasing values of K_D decreases the overshoot, but the system becomes unstable due to the amplification of error signals. The stability of any system depends on rise time, decay ratio, overshoot, and settling time. The structure of the PID controller is shown in Figure 2.
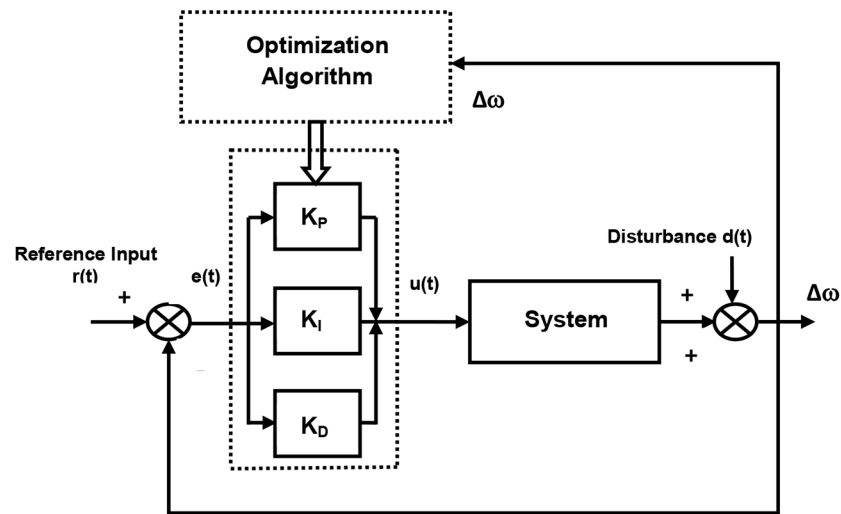
Figure 2. PID structure.

3. Tuning of PID gains using optimization methods

3.1. Adaptation law

In [13], AL was used to tune the PID controller connected with a PSS to enhance the stability of a power system over a wide range of operating condition. To maintain good damping characteristics in real time, the PID gains are optimized using the system inputs and outputs. In this method, the inputs and outputs were the sampled data of field voltage and speed deviation. In [19], AL-based PID tuning was clearly explained and implemented on a SMIB system.

The gains, K_P, K_I, and K_D, are calculated at each sampling instant using the estimated values of the 4 coefficients a_1, a_2, b_l, and b_2, characterizing the dynamic behavior of the generator at that instant. The values of these parameters when the damping factor $\alpha = 0.72$ and sampling time Ts $= 0.01$ s are shown in the Table 1.

Table 1. Parameters obtained using recursive least square algorithm.

Load	Faults	a_1	a_2	b_1	b_2
Normal load 200 MV	Ground	−0.3603	−0.3238	−0.0135	0.0143
	3-Phase	−0.348	−0.5004	−0.0359	0.0381
Heavy load 600 MV	Ground	−0.3741	−0.334	−0.0146	0.0182
	3-Phase	−0.357	−0.514	−0.038	0.040

3.2. Particle swarm optimization algorithm

PSO was developed and proposed by Kennedy and Eberhart in 1995 [12]. The PSO algorithm was designed to simulate the behavior of birds seeking food, which is defined as a cornfield vector. Birds cooperate with others to find food. This approach was expanded to multidimensional searches. In [20] the optimization of PID gains using the PSO algorithm was explained extensively.

PSO parameters and values are: iteration $k_{max} = 50$; generation $n = 20$; $w_{min} = 0.4$; $w_{max} = 0.9$; C_1 & $C_2 = 2$. The PSO algorithm is used to solve the optimization problem and search for the optimal set of PID

parameters. The range of PID parameters using the PSO algorithm are: $0 \leq K_P \leq 9$, $0 \leq K_I \leq 1.2$, and $0 \leq K_D \leq 1.9$.

3.3. Biogeography-based optimization

A new computation algorithm based on population-based evolutionary theory was introduced based on biogeography by Simon in 2008 [14]. The BBO model algorithm explains the migration of species from one island to another, forming new species and making some species extinct. The habitat suitability index (HSI) defines a suitable place for the species to reside, which features diversity of vegetation, rainfall, temperature, and land area. An island or habitat with high HSI is considered as a good performance in an optimization problem and a low HSI means bad performance. The number of features in each habitat is called the suitability index variable (SIV). The number of SIVs in each of the habitats corresponds to the problem's dimensions. SIVs are the independent variables and HSI is considered as the dependent variable. An island with a good HSI has a high emigration rate and a low immigration rate, and vice versa for an island having low HSI, as shown in Figure 3.
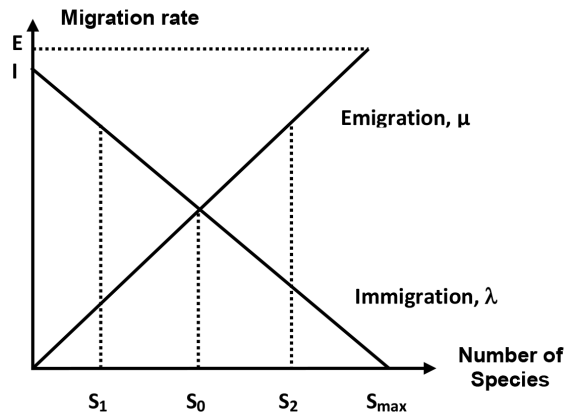

Figure 3. Model of immigration rate and emigration rate.

Here, S_o = number of species at equilibrium; S_{max} = maximum number of species; λ = immigration rate; mu = emigration rate.

The emigration rate and immigration rate can be obtained from the graph.

$$\lambda = I.\left(1 - \frac{S}{S_{\max}}\right) \tag{2}$$

$$\mu = \frac{E.S}{S_{\max}} \tag{3}$$

The BBO algorithm consists of 2 important subalgorithms, which are migration and mutation. A model of the migration and mutation algorithm was developed to obtain the best K_P, K_I, and K_D parameters of the PID controller.

Figure 3 is a simplified model of biota of an island; this simplified model still provides good general relationships of immigration and emigration. In order to model the concepts of BBO in detail, consider P_S as the habitat containing exactly S species. P_S changes from time t to $(t + \Delta t)$ as below:

$$P_S(t + \Delta t) = P_S(t)(1 - \lambda_S \Delta t - \mu_S \Delta t + P_{S-1}\lambda_{S-1}\Delta t + P_{S+1}\mu_{S+1}\Delta t) \tag{4}$$

where λ_S and μ_S are the immigration and emigration rates when there are S species in the habitat.

3.3.1. Migration

Each value of K_P, K_I, and K_D in the solution vector is considered as a SIV. In order to know how good or bad the habitat (solution) is, a computation is made on the HSI. In order to optimize the PID values, the HSI would be considered as the objective functions, which are ITAE, IAE, ITSE, and ISE. In this paper, the integral square error (ISE) of the speed deviation ($\Delta\omega$) is considered as the objective function. The ISE performance index has the advantages of producing smaller overshoots and oscillations than the IAE (integral of the absolute error) or the ITAE (integral time absolute error) performance indices. The parameters of the PID controller are tuned using a performance index (ISE).

The fitness function is as follows:

$$ISE : J = \int_{0}^{\infty} \Delta\omega^2(t)dt, \infty = t_{\sim} \tag{5}$$

where tsim = simulation time.

The speed deviation ($\Delta\omega$) is the parameter that was chosen to evaluate the performance of the design system. As the random set of K_P, K_I, and K_D values is generated in initialization of the problem space, each set of K_P, K_I, and K_D is fed into the PID controller and the speed deviation performance is obtained by evaluating the performance index, J. The K_P, K_I, and K_D values that generate the smallest J to satisfy the least error condition are the best values.

Thus, the problem in tuning the PID is in choosing the best habitat (solution) to minimize the performance index, J. In BBO we say that a habitat with high HSI has a lot of species, whereas a habitat with a low HSI has few species. Eventually the number of species will help us to decide the immigration rate and emigration rate of each habitat.

3.4. Mutation

Mutation in BBO is considered as SIV mutation, which are K_P, K_I, and K_D values in a habitat. The species count probability is used to determine the mutation rate. A very low HSI and a very high HSI have less chance to mutate when compared to a habitat that has a medium HSI. The reason for this is that a habitat that has a very high HSI or very low HSI is given a chance to further improve the performance, whereas a medium HSI is unlikely to mutate due to the habitat. Elitism is used to save the features of the habitat that has the best K_P, K_I, and K_D values in the BBO process, so even if the mutation ruins its HSI, we can revert back based on the save features.

$$m = m_{\max}\left(1 - \frac{P_S}{P_{\max}}\right) \tag{6}$$

Here,

P_S = probability of each island containing S species; P_{max} = maximum of P_S;

m_{max} = maximum mutation rate (user defined); m = mutation rate.

The ranges of optimized parameters of the PID controller are:

$$K_P^{\min} \leq K_P \leq K_P^{\max} = 0.5 \leq K_P \leq 80$$
$$K_I^{\min} \leq K_I \leq K_I^{\max} = 0.2 \leq K_I \leq 30$$
$$K_D^{\min} \leq K_D \leq K_D^{\max} = 0.1 \leq K_D \leq 15$$

The flow chart shown in Figure 4 explains the BBO algorithm for tuning the PID parameters. The parameters of BBO for tuning the PID controller are given in Table 2.
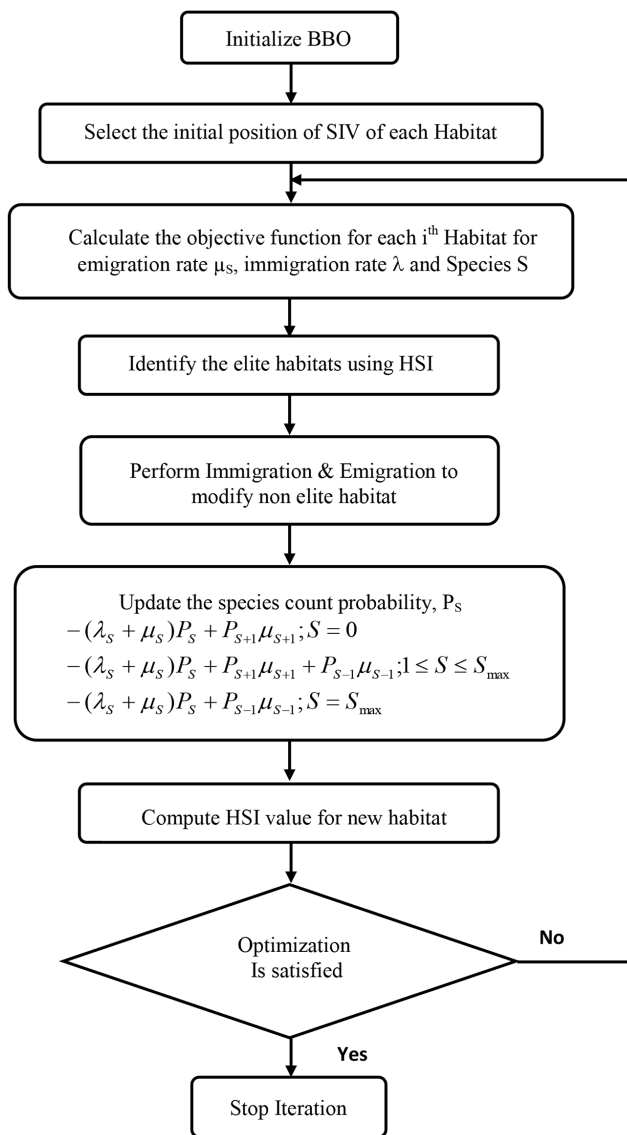

Figure 4. BBO algorithm for optimization.

Table 2. Parameters for tuning PID gains using BBO.

Parameters	Size
Habitat modification probability	1
Population number	50
Mutation rate	0.05
Iteration count	50
Number of elite habitat	4
Max. emigration and immigration rate	1

4. Model of proposed system

The proposed system combines a PID controller with a PSS to provide a better performance for a differing range of operating conditions. Figure 5 shows a block diagram of the proposed system. In the proposed system, a BBO algorithm is used for tuning the PID gains to enhance the stability of the synchronous machine for the wide range of operating conditions. The generator speed deviation ($\Delta\omega$) is given as the input signal to the proposed controller. The PSS provides the electrical damping torque in phase with the speed deviation to improve the damping of the power system. The controller output is given to the excitation system through an automatic voltage regulator. The aim is to control the phase difference between the generator and load. The objective of using a BBO-based PID controller connected with a PSS is to provide a better solution to the stability problem compared with power systems utilizing either PSS or PID controllers alone.
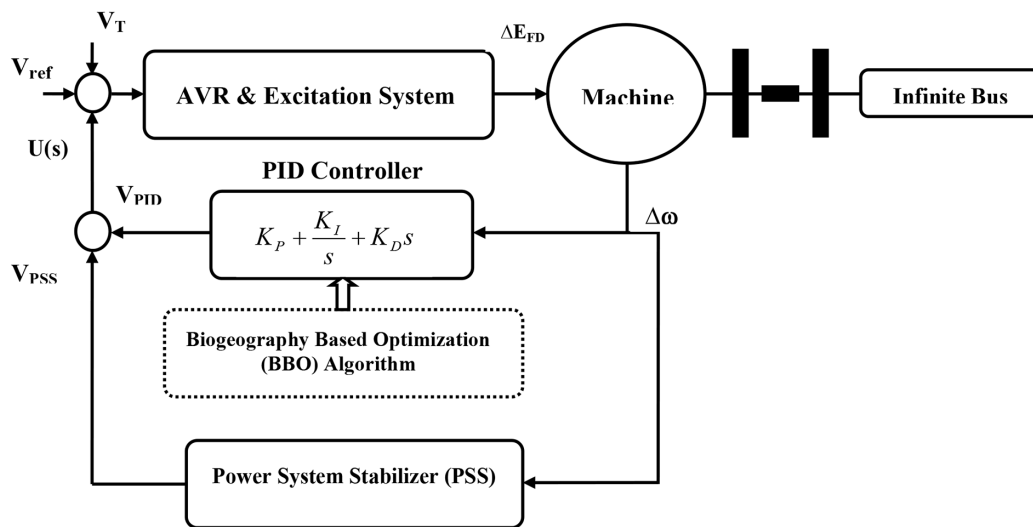

Figure 5. Proposed model.

5. Simulation results

To analyze the performance of the BBO-based coordinated controller, a simulation model was developed using MATLAB/Simulink. The effectiveness of the proposed controller was investigated for various operating conditions using the Simulink model.

The optimized values of the parameters of the generic PSS of the proposed system were [4]: $K_{PSS} = 125$; $T_w = 2$; lead–lag time constants, $T_1 = 5000$, $T_2 = 2000$, $T_3 = 3$ and $T_4 = 5.4$; limiter = –0.5 to 0.5.

The values of the PID controller obtained using 3 methods are presented in Table 3.

The optimization results were computed and the convergence characteristics of the BBO and PSO methods are shown in Figure 6. From the convergence plot, the BBO algorithm has better convergence than the PSO algorithm. The dynamic behaviors and convergence characteristics of the algorithms can be analyzed with the statistical indices mean (M) and standard deviation (σ), which are given by:

$$M = \frac{\sum_{i=1}^{n} f(K_i)}{n} \tag{7}$$

$$\sigma = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(f(K_i) - M)^2} \tag{8}$$

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

Table 3. Parameters obtained using 3 methods.

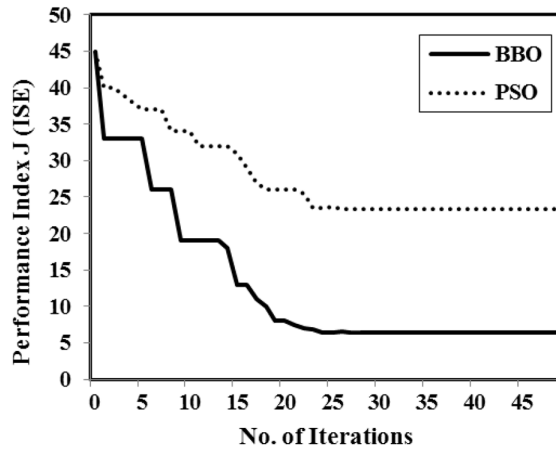| Tuning method		PID gains			Performance
		K_P	K_I	K_D	index (J)
BBO algorithm		52.6	20.2	9.73	6.24
PSO algorithm		5.14	0.9	1.63	23.41
Adaptation law	Normal load with ground fault	−0.264	−1.53	1.24	-
	Normal load with 3φ fault	−0.256	−1.46	1.14	-
	Heavy load with ground fault	−0.261	−1.50	1.21	-
	Heavy load with 3φ fault	−0.25	−1.44	1.12	-

Figure 6. Comparison of fitness function.

The BBO algorithm results in a better fitness value compared to the PSO algorithm, as shown in Table 4.

Table 4. Comparison of computational efficiency of PSO and BBO algorithms.

Optimization methods	Max.	Min.	Range	Mean (M)	Standard. deviation (σ)
PSO	45	23.41	21.59	26.592	5.4904
BBO	45	6.22	38.78	12.363	9.8884

Therefore, the BBO-based PID controller obtains the optimal parameters more quickly and efficiently. The performance of BBO, PSO, AL, and CPSS were simulated and analyzed in the MATLAB/Simulink environment for different operating conditions and the following test cases were considered for simulations.

5.1. Case 1: Normal load (200 MVA) with ground fault

Here the synchronous machine was subjected to a normal load (active power P = 200 MVA; inductive reactive power Q_L = 160 MVA; capacitive reactive power Q_C = 160 MVA) with a ground fault condition in the transmission line. At each transition time, the selected fault breakers opened and closed depending on the

initial state. The ground fault is applied at t = 0.6/60 s and closed at t = 6/60 s in the transmission line. Figures 7 and 8 show the time response of speed deviation and rotor angle deviation for Case 1.
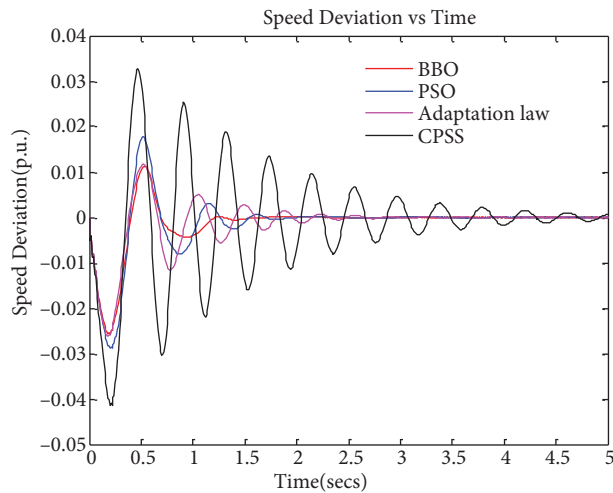

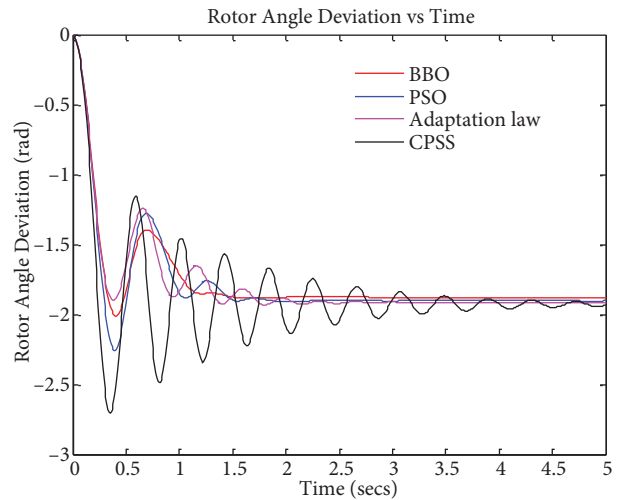**Figure 7.** Speed deviation for normal load with ground fault.

Figure 8. Rotor angle deviation for normal load with ground fault.

5.2. Case 2: Normal load (200 MVA) with 3-phase fault

In this case a 3φ fault was introduced in the transmission line. In a 3φ fault condition, the fault switching of phase A, phase B, and phase C is activated. The initial status of the fault breaker is usually 0 (open). In a 3φ fault condition, the transition time is applied at t = 0.6/60 s and closed at t = 6/60 s in the transmission line, similar to the ground fault. Figures 9 and 10 show the response of speed deviation and rotor angle deviation for Case 2.
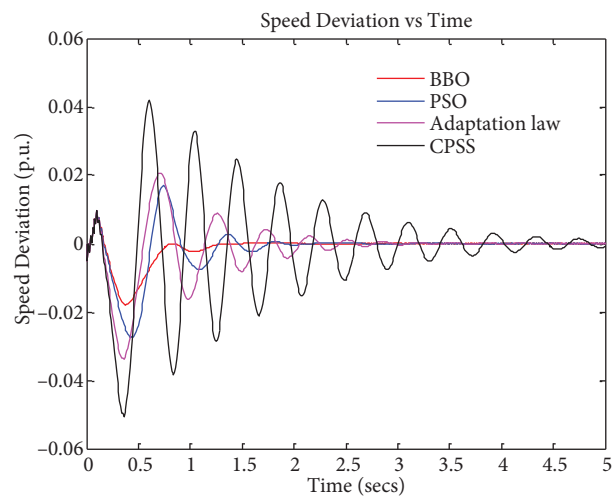

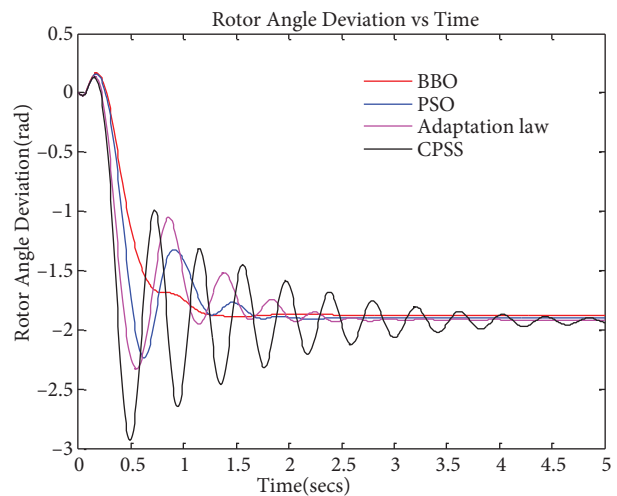**Figure 9.** Speed deviation for normal load with 3-phase fault.

Figure 10. Rotor angle deviation for normal load with 3-phase fault.

5.3. Case 3: Heavy load (600 MVA) with 3-phase fault

In this case, a heavy load (3 times the normal load) of active power P = 600 MVA; inductive reactive power Q_L = 480 MVA; capacitive reactive power Q_C = 480 MVA was introduced to the synchronous machine with ground fault condition in the transmission line. The fault transition time is same as in the previous cases. Speed deviation and rotor angle deviation responses for Case 3 are shown in Figures 11 and 12.
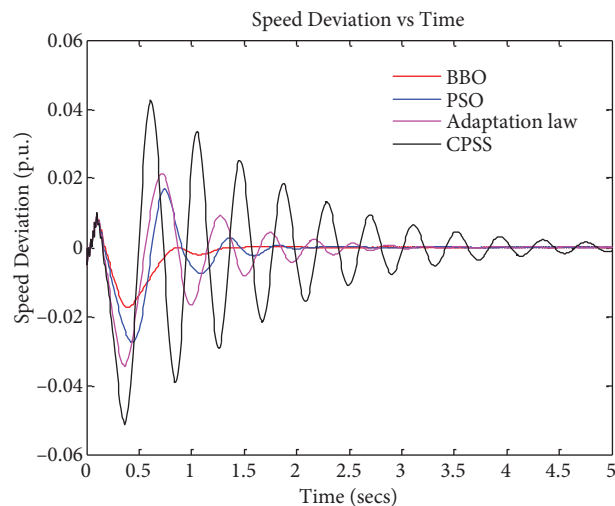

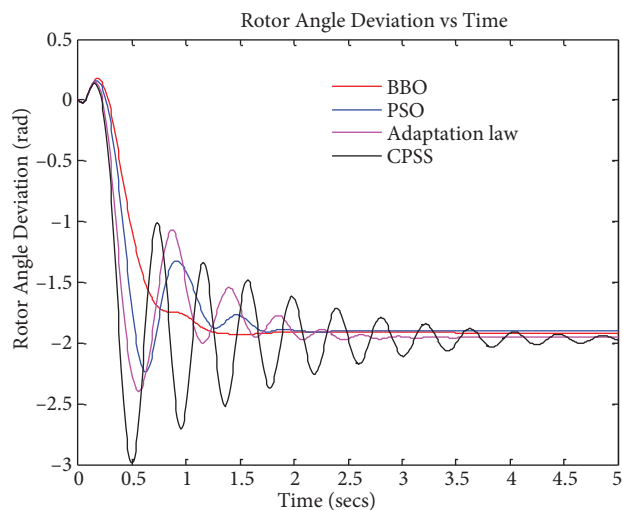**Figure 11.** Speed deviation for heavy load with 3-phase fault.

Figure 12. Rotor angle deviation for heavy load with 3-phase fault.

The above cases clearly illustrate how the proposed controller suppresses the overshoot and settling time to the nominal level. Both the overshoot and settling time obtained by the BBO algorithm are better compared to other methods. It can be clearly observed that the BBO-based PID PSS achieves a steady state faster than the other methods and provides better stability.

6. Conclusion

In this paper, a BBO algorithm was used to tune the parameters of a PID controller connected with a PSS. The design of the PID controller was considered as the optimization problem, which has been solved by the BBO algorithm. The performance of the proposed BBO-based coordinated controller has been compared and analyzed with PSO and AL methods. It was observed that the proposed controller significantly suppressed the electromechanical low frequency oscillations of the rotor speed and power angle. The damping characteristics of the proposed method were good with low-frequency oscillations, and the system stabilized quickly. The proposed idea successfully improves the system stability, efficiency, dynamism, and reliability.

References

[1] Bose A, Canizares C, Hatziargyriou N, Kundur P, Stankovic A, Paserba J, Ajjarapu V, Taylor C, Anderson G, Hill D et al. Definition and classification of power system stability. IEEE T Power Syst 2004; 19: 1387-1401.

[2] Kundur P. Power System Stability and Control. 3rd ed. New York, NY, USA: McGraw-Hill, 1993.

[3] Vijayakumar P, Nagaraj B. A comparative study of PID controller tuning using GA, EP, PSO and ACO. J Autom Mobi Robot Int Syst 2011; 5: 42-48.

[4] Gowrishankar K, Ragavendiran R, Gnanadass R. Modelling and performance analysis of proportional integral derivative controller with PSS using Simulink. In: 4th IEEE International Conference on Computing Applications in Electrical Engineering; 20–21 February 2010; Roorkee, India. pp. 5-8.

[5] Abido MA, Abdel-Magid YL. Hybridizing rule based power system stabilizers with genetic algorithms. IEEE T Power Syst 1999; 14: 600-607.

[6] Duman S, Ozturk A. Robust design of PID controller for power system stabilization by real coded genetic algorithm. Int Rev Electr Eng 2010; 5: 2159-2170.

[7] Hakim E A, Soeprijanto A. Multi-machine power system stabilizer based on optimal fuzzy PID with genetic algorithm tuning. J Energy Pow Eng 2010; 4: 43-50.

[8] Babaei E, Galvani S, Ahmad Jirdehi M. Design of robust power system stabilizer based on PSO. In: IEEE Symposium on Industrial Electronics and Applications; 4–7 October 2009; Kuala Lumpur, Malaysia. pp. 325-330.

[9] Mahmoud MS, Soliman HM. Design of robust power system stabilizer based on particle swarm optimization. Circuit Syst 2012; 3: 82-89.

[10] Abido MA. Optimal design of power system stabilizers using particle swarm optimization. IEEE T Energy Conver 2002; 17: 406-413.

[11] Sheeba R, Jayaraju M, Sundareswaran K. Performance enhancement of power system stabilizer through colony of foraging ants. Electr Pow Compo Sys 2014; 42: 1016-1028.

[12] Kennedy J, Eberhart R. Particle swarm optimization. In: IEEE International Conference on Neural Networks; 27 November–1 December 1995; Perth, Australia. pp. 1942-1948.

[13] Hsu Y, Wu CJ. Design of self-tuning PID power system stabilizer for multi-machine power system. IEEE T Power Syst 1988; 3: 1059-1064.

[14] Simon DJ. Biogeography based optimization. IEEE T Evolut Comput 2008; 12: 702-713.

[15] Brown JH, Riddle BR, Lomolino MV. Bio-geography. 3rd ed. Sunderland, MA, USA: Sinauer Associates, 2009.

[16] Khelfi MH, Salem M. Application of biogeography based optimization in tuning of PID controller for non-linear systems. In: IEEE International Conference on Complex Systems; 5–6 November 2012; Agadir, Morocco. pp. 1-6.

[17] Xiang LC, Jiangtao C, Fuli W. Local search strategy biogeography based optimization algorithm for self-tuning of PID parameters. In: 32nd Chinese Control Conference; 26–28 July 2013; Xian, China. pp. 4306-4310.

[18] Lakshmi P, Karthikeyan K. Optimal design of PID controller for improving rotor angle stability using BBO. Procedia Engineering 2012; 38: 889-902.

[19] Gowrishankar K. Modelling and performance analysis of PID power system stabilizer using adaptation law in Simulink environment. In: IEEE International Conference on Electrical, Computer and Communication Technologies; 12–13 September 2011; Tamil Nadu, India. pp. 83-89.

[20] Gowrishankar K, Jagadeesh P. Tuning of PID controller for a synchronous machine connected to a non linear load. ARPN Journal of Engineering and Applied Sciences 2014; 9: 1659-1668.