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Performance analysis of biogeography-based optimization for automatic voltage regulator system

Uğur GÜVENÇ[1,*], Tuncay YİĞİT[2], Ali Hakan IŞIK[3], İbrahim AKKAYA[1]
[1]Department of Electrical & Electronics Engineering, Faculty of Technology, Düzce University, Düzce, Turkey
[2]Department of Computer Engineering, Faculty of Engineering, Süleyman Demirel University, Isparta, Turkey
[3]Department of Computer Engineering, Faculty of Engineering, Mehmet Akif Ersoy University, Burdur, Turkey

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Abstract: A self-tuning method to determine the appropriate parameters of a proportional-integral-derivative controller for an automatic voltage regulator (AVR) system using a biogeography-based optimization (BBO) algorithm is proposed in this study. The BBO algorithm was developed based on the theory of biogeography, which describes migration and its results. We propose that the BBO algorithm has a high-quality solution and stable convergence characteristics, and thus it improves the transient response of the controlled system. The performance of the BBO algorithm depends on the transient response, root locus, and Bode analysis. Robustness analysis is done in the AVR system, which is tuned by an artificial bee colony (ABC) algorithm in order to identify its response to changes in the system parameters. We compare the BBO algorithm with the ABC algorithm, particle swarm optimization algorithm, and differential evolution algorithm. The results of this comparison show that the BBO algorithm has a better tuning capability than the other optimization algorithms.

Key words: Automatic voltage regulator, biogeography-based optimization, self-tuning control

1. Introduction

The main emphasis in power systems is to control the terminal voltage. In recent power systems, the output voltage of a generator is commonly detected with automatic voltage regulator (AVR) systems. At the same time, it initiates corrective action by adjusting the exciter control in a definite direction [1–3]. The AVR uses the exciter voltage of a generator to handle the terminal voltage. During the past decades, several control methods such as adaptive control and fuzzy control have been studied for better dynamic response in the AVR system [1,3]. Even though these methods have been developed significantly, the proportional-integral-derivative (PID) controller is popularly used in various control applications. The main reason for this situation is that it can be implemented easily and has a robust performance in different operating conditions. The PID tuning control loop is the adjustment of the optimal values for the desired control response. To obtain the desired control response, adjustment of the optimal values is performed with the PID tuning control loop. Unfortunately, PID tuning is a difficult problem and can be hard in practice because many industrial plants have important problems such as time delays, high order, etc. [3]. In the related literature, many classical methods have been proposed for the adjustment of the PID parameters [4], such as the gain-phase margin method and Cohen–Coon method [5]. Unfortunately, it is not easy to identify optimal and near optimal PID parameters using these methods in many industrial plants [3].

*Correspondence: ugurguvenc@duzce.edu.tr

Recently, many researchers have demonstrated the heuristic optimization techniques owing to their capability to find an appropriate solution in PID tuning for AVR systems. In 2004 Gaing [3] and in 2005 Kim and Park [6] reported a particle swarm optimization (PSO)-based self-tuning PID controller and a comparison with the genetic algorithm (GA)-based method for the AVR system. Kim and Cho [7] proposed a hybrid approach that includes the GA and bacterial foraging for tuning the PID controller of an AVR system in 2006. Later on, several methods such as the intelligent particle swarm algorithm [8], chaotic ant swarm optimization [9], and discrete action reinforcement learning automata [10] were suggested. Gozde and Taplamacioglu [1] proposed the artificial bee colony (ABC) algorithm with the aim of improving the performance of the self-tuning PID controller in this system. In the performance analysis, they compared the results with the differential evolution (DE) algorithm and PSO algorithm. On the other hand, there is no definite algorithm to find the appropriate solution for the AVR system.

Hence, studying a new heuristic optimization algorithm to identify the optimal parameters of a PID controller in an AVR system is an observable problem. In this context, Simon [11] proposed a modern optimization concept on the basis of biogeography. He developed a biogeography-based optimization (BBO) algorithm that focuses on the two mechanisms of migration and mutation. In biogeography, mathematical models are defined with the distributing species. They specify how species migrate from one region to another, new species' appearance, and their extinction [12]. The comparisons between the BBO performance and other optimization methods were given on a wide set of benchmarks by Simon [11]. In that study, the results obtained from the BBO method were promising. In addition to this, the BBO method has been successfully applied to different areas, such as aircraft image classification [13], image segmentation [14], power flow problems [15], the economic load dispatch problem [16,17], engine sensor selection [11], robot controllers [18] and the traveling salesman problem [19]. This paper focuses on optimizing the control parameters of the PID controller for the AVR system using the BBO method. The performance of the BBO algorithm is evaluated with transient response, root locus, and Bode analysis. The AVR system is adjusted by the ABC algorithm. To identify the AVR system response in system parameters' change, robustness analysis is also applied to this system. Simulations of self-tuning of the PID controller for the AVR system indicate the performance and robustness of the optimization method. The study consists of 5 sections. Section 2 explains the AVR system model that has a PID controller. In Section 3, we present BBO and the implementation of a BBO-PID controller in the AVR system. Section 4 provides numerical simulations and comparisons. Finally, in Section 5, the conclusion and recommendations of the issue of performance analysis of BBO for AVR systems are presented.

2. Description of an AVR system

The role of an AVR is to control the terminal voltage magnitude of a synchronous generator at a desired level. The AVR system consists of generators, amplifiers, exciters, and sensors, the four major components in an AVR system. To evaluate the performance of the AVR, transfer functions of these components are represented as follows.

2.1. Amplifier

The amplifier model is presented by a gain K_a and a time constant τ_a, where the transfer function is defined as follows:

$$\frac{V_R(s)}{V_e(s)} = \frac{K_a}{s\tau_a + 1}. \tag{1}$$

The typical values of K_a gain change from 10 to 400. The amplifier time constant τ_a often ranges from 0.02 to 0.1 s.

2.2. Exciter model

The transfer function of an exciter model is described by a gain K_e and a single time constant τ_e, where the transfer function is defined as follows:

$$\frac{V_F(s)}{V_R(s)} = \frac{K_e}{s\tau_e + 1}. \tag{2}$$

Typical values of K_e gain change from 10 to 400. The time constant τ_e changes from 0.5 to 1.0 s.

2.3. Generator model

The transfer function of the linearized generator model is defined as follows:

$$\frac{V_t(s)}{V_F(s)} = \frac{K_g}{s\tau_g + 1}, \tag{3}$$

where K_g is the gain and τ_g is the time constant. These values are load-dependent, and K_g may change from 0.7 to 1.0 and τ_g from 1.0 to 2.0 s, from full load to no load [20].

2.4. Sensor model

The sensor model of the system is represented by the following first-order transfer function. The ratio ($V_s(s)$ / $V_t(s)$) is given by:

$$\frac{V_s(s)}{V_t(s)} = \frac{K_s}{s\tau_s + 1}, \tag{4}$$

where τ_s has a small value. This value varies from 0.001 to 0.06 s and K_s is from 1.0 to 2.0.

2.5. PID controller

PID controller is one of the earlier control strategies commonly used in feedback control of industrial control systems [21]. This controller has been successfully used for more than 60 years. The parallel connections of the controller components are used to define the design of the PID controller. It is given in Figure 1. From this diagram, the transfer function of the PID controller is found to be

$$G(s) = \frac{U_C(s)}{E(s)} = K_p + \frac{K_i}{s} + K_d s, \tag{5}$$

where K_p refers to the proportional gain. This gain increases the loop gain. In this way, the system is less sensitive to disturbances, where K_d is the differential gain. It improves transient response by means of high-frequency compensation. K_i is the integral gain and it helps to reduce steady-state errors by means of low-frequency compensation [22].

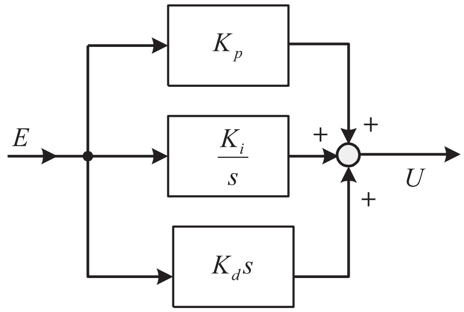

Figure 1. Block diagram of the parallel PID controller.

2.6. The AVR system with the PID controller

The AVR system model can be obtained by the PID controller and its four components. The block diagram representation is given in Figure 2. Here, $\Delta V_s(s)$, $\Delta V_{ref}(s)$, ΔV_s, and $\Delta V_t(s)$ refer to the output voltage of a sensor model, the reference input voltage, the error voltage, and the output voltage by a generator, respectively.

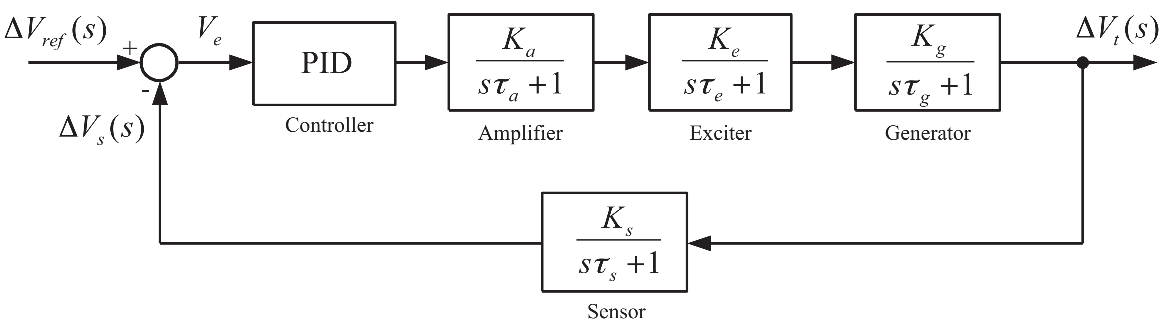

Figure 2. Transfer function model of AVR system with PID controller.

The transfer function of AVR system with the PID controller is described in Eq. (6).

$$\frac{\Delta V_s(s)}{\Delta V_{ref}(s)} = \frac{\left(s^2K_d + sK_p + K_i\right)(K_aK_eK_g)(1+s\tau_s)}{s(1+s\tau_a)(1+s\tau_e)(1+s\tau_g)(1+s\tau_s) + (K_aK_eK_gK_s)(s^2K_d + sK_p + K_i)} \tag{6}$$

3. Biogeography-based optimization algorithm

BBO is a kind of evolutionary algorithm. This algorithm uses the numerical studies of biogeography, which focus on the geographical distribution of all living organisms. The main objective of BBO is to clarify the distribution changes of all species in different environments over the course of time. For instance, it explains how species increase in number or become extinct [23].

Geographical regions that have a high habitat suitability index (HSI) are appropriate for the living space of biological species. The properties of HSI are rainfall, diversity of fauna and flora, topography, and local temperature. The variables identified by habitability are known as suitability index variables (SIVs).

A high HSI has a low rate of species immigration on account of the fact that it has quite a full population. On the contrary, a low HSI has a high rate of species immigration for their sparse populations. Figure 3 describes a model of species abundance in a habitat.

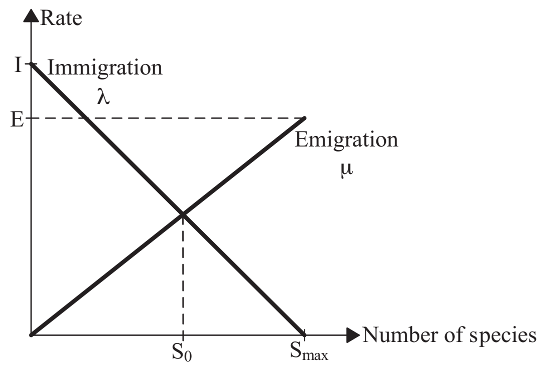

Figure 3. Single habitat's species model [11].

The immigration rate of a habitat is proportional to the number of species in the habitat. The immigration rate will get a maximum value when there are not any species in the habitat. (I) is the maximum immigration rate and S_{max} is the largest possible number of species. When the habitat reaches the maximum species capacity (S_{max}), the maximum emigration rate (E) appears. If the immigration and emigration rates are equal, the equilibrium number of species (S_0) can be obtained. The curve of Figure 3 is a straight line. However, in reality it will be more detailed and complicated. This simplified graphic shows general information about the immigration and emigration process [11].

The equations for the number of species S, the immigration rate λ_s, and the emigration rate μ_s are shown below.

$$\lambda_S = I \cdot \left(1 - \frac{S}{S_{\max}}\right) \tag{7}$$

$$\mu_S = \frac{E \cdot S}{S_{\max}} \tag{8}$$

S_{max} is the probability P_S of a habitat that includes exactly S species; in addition, P_S varies in time t to $(t + \Delta t)$ [11]. It is given by:

$$P_S = (t + \Delta t) = P_S(1 - \lambda_S\,\Delta t - \mu_S\,\Delta t) + P_{S-1}\,\lambda_{S-1}\,\Delta t + P_{S+1}\,\lambda_{S+1}\,\Delta t. \tag{9}$$

This equation holds because one of the following cases must hold for having S species at time $(t + \Delta t)$:

i. There are S species at time t and no immigration or emigration takes place from t to $(t + \Delta t)$;

ii. There are $(S – 1)$ species at time t and one species immigrates;

iii. There are $(S + 1)$ species at time t and one species emigrates.

If Δt is small enough, the probability of more than one emigration or immigration can be ignored. After that, taking the limit of Eq. (9) in the event of $\Delta t \to 0$ gives the equation shown below [4].

$$\begin{array}{l} S = 0 \\ 1 \leq S \leq S_{\max} - 1 \\ S = S_{\max} \end{array} \tag{10}$$

BBO basically depends upon migration and mutation. The numerical and detailed expressions of migration and mutation are explained below.

3.1. Migration

The BBO technique has a population of candidate solutions that is demonstrated with an array of integers. Each integer is regarded as a SIV in the solution array. The HSI of each candidate solution is evaluated by using its SIVs. If candidate solutions are good enough, it has high HSI; otherwise, it has a low HSI. The immigration rate probability decides the modification of each SIV in a related solution. When any SIV in a given solution is selected for modification, emigration rates of the other solutions are found with probability theory. It identifies which of the solutions should migrate a randomly selected SIV to a related solution [11]. It can be seen that the BBO and the recombination approach of evolutionary strategies (ESs) have some similarities.

However, there is a main difference between the two algorithms: the global recombination in ES provides new solutions; on the contrary, the BBO offers changes in the existing solutions. In addition, the BBO has an elitism algorithm for keeping the best solutions. It is prevented from immigration that corrupts the solution.

3.2. Mutation

Natural disasters or some events such as flotsam, disease, etc. can dramatically alter the HSI of a natural habitat and they can affect the equilibrium value of the species. SIV mutation represents this event in BBO. In addition, the mutation rates are identified by a species count probability, which is evaluated by the differential equation shown in Eq. (10). In a population every member has a related probability, which shows the possibility of an existing solution for a given problem [24]. The rate of mutation can be calculated as

$$m(S) = m_{\max}\left(\frac{1 - P_S}{P_{\max}}\right). \tag{11}$$

In this equation, $m(S)$ is the mutation rate, $m_{\max}$ is the maximum mutation rate, and $P_{\max}$ is the maximum probability. A mutation operator supports the increase in diversity of a population, and without this modification, the highly probable solutions are inclined to be more dominant in the population. The BBO uses an elitism approach for keeping the best solutions; therefore, even if a mutation ruins the solution, the previous solution can be replaced with a new one. Thus, mutation has a high probability of both good and bad solutions. It is useful to apply mutation on average solutions, when the average solutions are in stage of advancement [24,25].

3.3. Implementation of a BBO-PID controller in an AVR system

The BBO algorithm is proposed to determine the appropriate parameters of a PID controller for an AVR system through the self-tuning method. In control theory, a self-tuning method is capable of optimizing the PID controller parameters by using tuning variables to maximize or minimize the fulfillment of an objective function. The integral of time weighted squared error (ITSE) function shown in Eq. (12) is selected as an objective function in the AVR system. This objective function is chosen to minimize the settling time due to dependency of errors on time [3]:

$$ITSE = \int_0^t t e^2 (t) \, dt. \tag{12}$$

In this section, finding the appropriate PID controller parameters by using the BBO algorithm is explained while satisfying the limits of the PID controller parameters. The search procedures of the proposed algorithm are shown below:

(1) Initialize the BBO parameters like habitat modification probability, probability of mutation, maximum immigration rate, maximum emigration rate, step size for numerical integration, number of iterations, maximum species count, elitism parameter, number of habitats, and number of SIVs number of controller parameter.

(2) The primary values of controller parameters, i.e. SIVs of each habitat, are randomly selected while satisfying the constraints of the AVR system. Then the habitats' population size has been constituted.

(3) Fitness evaluation, i.e. computation of the HSI value for each habitat of the population set for the given rate of emigration, rate of immigration, and species.

(4) Elite habitats are defined by using the HSI value.

(5) Probabilistically carry out migration operation on each nonelite habitat. After that, modification of each solution set is performed. After modification, each set's HSI is recalculated.

(6) Each species' habitat probability count is updated using Eq. (9). The mutation operation is carried out on the nonelite habitat, and each new habitat's HSI value is computed.

(7) Return to the third step for the next iteration or stop iterations after a predefined number of iterations.

4. Numerical simulations

A self-tuning method to identify the appropriate parameters of a PID controller for the AVR system through the BBO algorithm is proposed in our study. To verify the efficiency of the proposed algorithm, a self-tuning PID controller-based AVR system is shown in Figure 4. The initial values and the range of minimum and maximum values in the AVR system are the same as those of Gozde and Taplamacioglu [1].

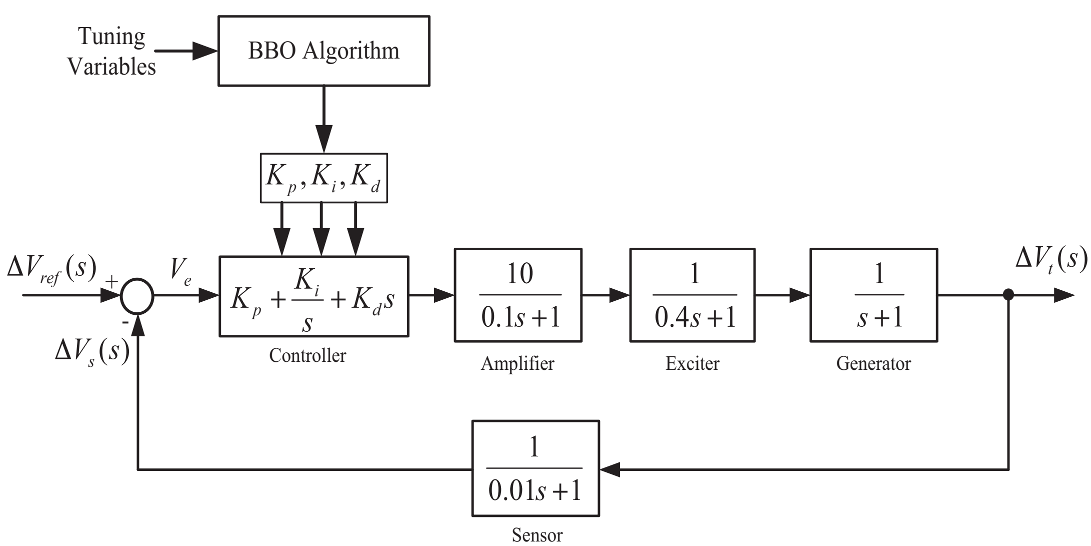

Figure 4. Block diagram of self-tuning PID controller-based AVR system.

To find appropriate solutions through the BBO algorithm, a number of careful experimentations are performed. In this way, the following parameters are obtained. They are the size of habitat, probability of habitat modification, step size for mathematical integration of probabilities, immigration probability bounds per gene, migration rates for different islands, maximum immigration rates for different islands, and mutation probability. Their values are 50, 1, 0.1, 1, 1.1, and 0.005, respectively.

After this simulation, the obtained gains of the controller are as given in Table 1. The transfer function of the AVR system tuned by the BBO approach is given in Eq. (13).

$$\frac{\Delta V_t\,(s)}{\Delta V_{ref}\,(s)} = \frac{0.07363s^3 + 7.507s^2 + 14.5s + 12.21}{0.0004s^5 + 0.0454s^4 + 0.555s^3 + 8.873s^2 + 15.38s + 12.21} \tag{13}$$

Table 1. The PID controller's optimum parameters.

Gain parameters	Proposed	ABC [1]	PSO [1]	DEA [1]
K_p	1.2464	1.6524	1.7774	1.9499
K_i	0.5893	0.4083	0.3827	0.4430
K_d	0.4596	0.3654	0.3184	0.3427

The results obtained for voltage changing curves after the simulation of the GSA are compared with the ABC, PSO, and DE in Figure 5.

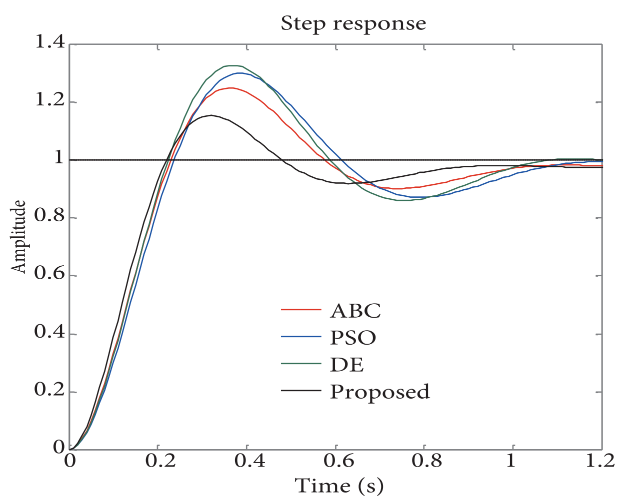

Figure 5. Voltage changing curves of the AVR system.

4.1. Transient response analysis

The performance criteria that are used to characterize the transient response to a unit step input include settling time, maximum overshoot, peak time, and rise time [26]. Here the required time to reach 5% of the step response curve's final value is accepted as the settling time and the rise time is the time required for the response to rise to between 10% and 90% of its final value. To underline the advantages of the proposed BBO-PID controller, the results given after the analysis are compared with the other optimization algorithms. They are represented in Table 2. It is concluded that the BBO algorithm has a better performance for maximum overshoot of 7.5% compared to the ABC algorithm, 12.1% compared to the PSO algorithm, and 14.6% compared to the DE algorithm. For settling time, the proposed BBO algorithm has better results by 20.1% compared to the ABC algorithm, 24.2% compared to the DE algorithm, and 30.5% compared to the PSO algorithm. For rise time, the proposed algorithm has better results by 4.7% compared to the ABC algorithm, 8% compared to the PSO algorithm, and 2% compared to the DE algorithm. When the BBO algorithm is examined in terms of peak time, it has better results by 13.5% compared to the ABC and DE algorithms and 19.8% compared to the PSO algorithm. Thus, the proposed BBO algorithm has better results than the ABC, PSO, and DE algorithms, respectively.

Table 2. AVR system's transient response analysis results.

Algorithm	Maximum overshoots	Settling time (5% band)	Rise times	Peak times
Proposed	1.160	0.766	0.149	0.317
ABC [1]	1.250	0.920	0.156	0.360
DEA [1]	1.330	0.952	0.152	0.360
PSO [1]	1.300	1.000	0.161	0.380

4.2. Root locus analysis

A root locus analysis enables us to compare the stability characteristics of the proposed method to the other optimization methods for the AVR system. The root locus analysis was performed through the MATLAB control system toolbox. The root locus curve is shown in Figure 6 for the proposed method. The closed loop poles and their damping ratios for the ABC, PSO, DE, and BBO methods are also represented in Table 3. If any of these closed loop poles pass into the left-hand plane, we will know that the system is stable. According to the results, optimization algorithms provide stability for all control systems. Table 3 also shows the conjugate poles acquired with the BBO algorithm. They are situated on the left of the s-plane. The BBO algorithm tunes the biggest damping ratio concerning the control system. It is greater than the ABC, PSO, and DE algorithms by as much as 6%, 15%, and 20%, respectively.

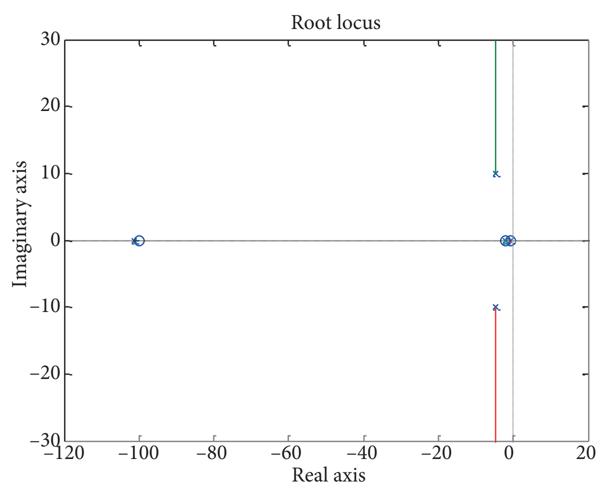

Figure 6. Root locus curve of the AVR system that is set by BBO algorithm.

4.3. Bode analysis

The stability in the control system's frequency response is measured with Bode analysis. It is used to observe the gain and phase of the control loop. In our study, Bode analysis was carried out through the control system toolbox of MATLAB. The Bode analysis curves are given in Figure 7 for the proposed method.

Table 3. The AVR system's poles and damping ratios.

Proposed		ABC [1]		PSO [1]		DEA [1]	
Closed loop poles	Damping ratio	Closed loop poles	Damping ratio	Closed loop Poles	Damping ratio	Closed loop poles	Damping ratio
–100.00	1.00	–100.98	1.00	–100.85	1.00	–100.91	1.00
–4.8 + j10.2	0.427	–3.75 + j8.40	0.40	–3.08 + j7.80	0.36	–3.02 + j8.19	0.34
–4.8 – j10.2	0.427	–3.75 – j8.40	0.40	–3.08 – j7.80	0.36	–3.02 – j8.19	0.34
–2.1	1.00	–4.74	1.00	–6.26	1.00	–6.29	1.00
–0.585	1.00	–0.25	1.00	–0.21	1.00	–0.22	1.00

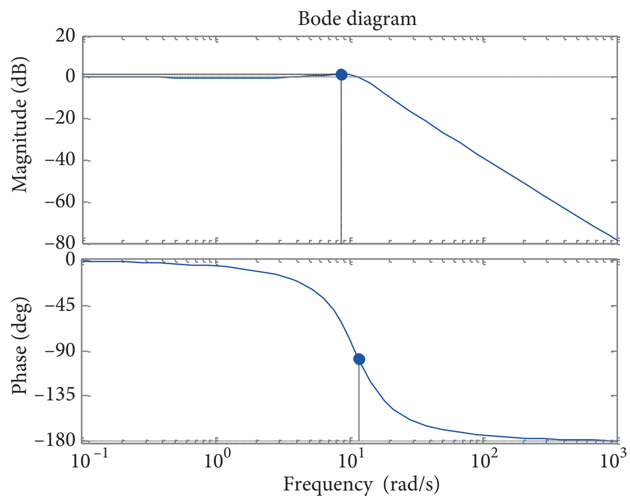

Figure 7. Bode plots of the system set by the BBO algorithm.

The delay margins, the phase margins, and the peak gains calculated from these plots are given in Table 4. This table includes the maximum phase margin, minimum peak gain, maximum bandwidth, and maximum delay margin. They are acquired with the BBO algorithm.

Table 4. Phase margins, peak gains, and delay margins of the AVR system.

Algorithm	Peak gains	Phase margins (deg)	Delay margins	Bandwidths
Proposed	1.56 dB (1.38 Hz)	81.6	0.122 s (1.86 Hz)	14.284
ABC [1]	2.87 dB (1.20 Hz)	69.4	0.111 s (1.74 Hz)	12.880
DEA [1]	4.20 dB (1.21 Hz)	58.4	0.092 s (1.78 Hz)	12.800
PSO [1]	3.75 dB (1.14 Hz)	62.2	0.103 s (1.67 Hz)	12.182

4.4. Robustness analysis

It is seen in Table 5 that the performance results of the proposed algorithm are comparative with the performance of ABC algorithm. In this study, the ITSE performance index is used to set the parameters of the PID controller since the objective function, the gains, and the time constants of the AVR system are considered as given Section 2. However, K_g has been changed from 0.7 to 1.0 in steps of 0.1. T_g has been changed from 1.0 to 2.0 in steps of 0.5. Hence, Table 5 contains 12 different operating conditions of the AVR system. The BBO-based optimization approach represents less maximum overshoot of change in terminal voltage, less settling time of change in terminal voltage, less rise time of change in terminal voltage, and less peak times of change in terminal voltage than the ABC algorithm.

Table 5. Optimized PID gains and transient response parameters under various operating scenarios.

Kg	Tg	Controller	Kp	Ki	Kd	Maximum overshoots	Settling times (5% band)	Rise times	Peak times
0.7	1.0	Proposed	1.5703	0.7278	0.4316	1.14	0.581	0.195	425
		ABC	1.6851	0.6681	0.3759	1.18	1.07	0.202	454
	1.5	Proposed	1.5371	0.6789	0.5235	1.06	0.582	0.248	502
		ABC	1.5165	0.6125	0.4154	1.09	0.769	0.277	582
	2.0	Proposed	1.3571	0.6599	0.5011	1.01	0.487	0.354	732
		ABC	1.3913	0.5967	0.4216	1.05	0.503	0.371	790
0.8	1.0	Proposed	1.5236	0.6895	0.5083	1.15	0.805	0.161	345
		ABC	1.6425	0.6124	0.4561	1.17	0.872	0.167	371
	1.5	Proposed	1.4814	0.6869	0.5126	1.08	0.580	0.223	459
		ABC	1.4783	0.6048	0.4008	1.11	0.749	0.252	547
	2.0	Proposed	1.4514	0.7323	0.5590	1.04	0.379	0.277	557
		ABC	1.4316	0.6354	0.5236	1.04	0.397	0.290	587
0.9	1.0	Proposed	1.3651	0.6424	0.5026	1.15	0.773	0.150	327
		ABC	1.3269	0.6866	0.4125	1.15	0.790	0.170	373
	1.5	Proposed	1.3269	0.6254	0.5687	1.07	0.789	0.195	387
		ABC	1.2887	0.6729	0.4518	1.08	0.587	0.226	466
	2.0	Proposed	1.2758	0.6965	0.5292	1.03	0.368	0.269	537
		ABC	1.2375	0.7239	0.4253	1.06	0.793	0.304	657
1.0	1.0	Proposed	1.2464	0.5893	0.4596	1.16	0.766	0.149	317
		ABC [1]	1.6524	0.4083	0.3654	1.25	0.920	0.156	360
	1.5	Proposed	1.2135	0.5432	0.4863	1.08	0.494	0.200	402
		ABC	1.6034	0.3915	0.3491	1.2	1.170	0.213	489
	2.0	Proposed	1.1964	0.5267	0.5163	1.03	0.347	0.252	485
		ABC	1.5723	0.3689	0.3358	1.17	0.889	0.269	610

5. Conclusion

Today, every system has unique responses for different types of operating conditions. In these conditions, many algorithms are used to optimize the parameters of the system. Within this context, we use the BBO algorithm to optimize the AVR system parameters. This algorithm is proposed to determine the appropriate parameters of a PID controller for an AVR system through the self-tuning method. Moreover, we give the comparative tuning performance analysis results for this algorithm. Well-known analysis techniques such as root locus, transient response, and Bode analysis are used in our study. Obtained results are compared with reference [1] and the ABC, PSO, and DEA algorithms. The robustness analysis of this algorithm is also tested under different working circumstances and compared with the ABC algorithm. For the same control application, our BBO algorithm can acquire the computational efficiency, best convergence characteristics, and more robustness than the other heuristic algorithms. Thus, the results of the BBO algorithm show that this algorithm can be used for the AVR system successfully. In addition, it provides adjusting of the AVR system effectively. Due to these reasons, the BBO method can be used for different types of control applications in the future.

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