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Comparative performance analysis of artificial bee colony algorithm for automatic voltage regulator (AVR) system

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Abstract

In this study, Artificial Bee Colony (ABC) algorithm is applied to the Automatic Voltage Regulator (AVR) system for obtaining optimal control. The tuning performance of this algorithm and its contribution to the robustness of the control system are also extensively and comparatively investigated. In the performance analysis, Particle Swarm Optimization (PSO) algorithm and Differential Evolution (DE) algorithm are used for the purpose of comparison. These analyses are realized by benefiting from different analysis methods such as transient response analysis, root locus analysis, bode analysis and statistically Receiver Operating Characteristic (ROC) analysis. Afterwards, the robustness analysis is applied to the AVR system, which is tuned by ABC algorithm in order to determine its response to changes in the system parameters. At the end of the study, it is shown that the ABC algorithm is successfully applied to the AVR system for improving the performance of the controller and shows a better tuning capability than the other similar population based optimization algorithms for this control application.

1. Introduction

Providing constancy and stability of the nominal voltage level in an electric power network is also one of the main control problems for an electric power system, because all equipments that are connected with this power network have been designed for a certain

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voltage level called rated or nameplate voltage. If the nominal voltage level deviates from that value, the performance of these equipments decreases and their life expectancy drops. In addition to this, the other important reason for this control is that the real line losses depend on real and reactive power flow. In fact, the reactive power flow depends greatly on terminal voltages in the power system. However it is possible to minimize the real line losses by controlling the nominal voltage level. To solve these control problems, which are explained above, an Automatic Voltage Regulator (AVR) system is applied to power generation units [1]. The AVR system is a closed loop control system that provides terminal voltage at the desired value. The configuration of this control system will be investigated in the next section. In the related literature, to realize the AVR system with better dynamic response, a number of different control strategies such as optimal, adaptive, robust control, etc. have been reported by researchers so far. But the self-tuning adaptive control technique is distinguished from the other control techniques because it makes the process, which is under control, less sensitive to changes in process parameters, and in particular it is also simpler to implement than the other modern control techniques. For this purpose, this type of control is applied to the AVR system in this study. Previous works related to the AVR system, which uses the self-tuning methods, initiated in the years of the 1990s. For example, Swidenbank et al. [2] applied the classical self-tuning control techniques to the AVR system in 1999. After this study, Fitch et al. [3] used a generalized predictive control technique as a self-tuning control algorithm in the same year.

Since the conventional self-tuning control techniques containing more mathematical computing may also be unsuitable in some operating conditions due to the complexity of the power system such as nonlinear load characteristics and variable operating points, the usage of artificial intelligence based self-tuning control and optimization techniques was preferred by researchers from the beginning of 2000. For example, Panda and Padhy [4] proposed PSO based optimal design method for STATCOM-based controller with multiple PSS, and they tested the stability of their design in two area power system. After three years, they used the improved genetic algorithm method in order to solve the optimal design problem of flexible AC transmission system (FACTS)-based controller for the power systems [5]. However, self-tuning PID controllers tuned by these optimization methods have also been initiated to be applied to the AVR system frequently in these years. Gaing [6] suggested a PSO based self-tuning PID controller for the AVR system, and he compared the result of his method with that of the genetic algorithm based method in 2004. Two years after, Kim and Cho [7] developed the hybrid method, which contained genetic algorithm and bacterial foraging optimization technique, in order to improve the performance of the self-tuning PID controller in the AVR system. In 2007, Mukherjee and Ghoshal [8] reported the Sugeno fuzzy logic self-tuning algorithm based on crazy-PSO for PID controller, and proposed a novel cost function in this optimization method. They also compared their results with the genetic algorithm based controller. Later on, Zhu et al. [9] suggested a chaotic ant swarm algorithm in order to optimize the gains of PID controller in the AVR system in the year of 2009. In the same year, Zamani et al. [10] designed the particle swarm optimization based fractional order PID controller for the AVR system. They investigated the basic performance and robustness of their controller and compared with that of the classical PID controller. Coelho [11] proposed the chaotic optimization approach for tuning of the PID gains in 2009. Chatterjee et al. [12] also made a comparison between the optimization performance of velocity relaxed and craziness based particle swarm optimization methods on AVR system in 2009.

In this study, it is evaluated that the ABC algorithm may be used as an alternative tuning method due to its superior local and global search capability provided by separate artificial bee colonies such as employees, onlookers and scouts [13,14]. This algorithm was successfully applied first to the different optimization and control processes so far. Some of them are the neural networks training [15], the design of optimum IIR filter [16], the quadratic knapsack problem [17], the parameter extraction of MESFETs [18], the economic dispatch problem for power system [19], clustering [20], the prediction of protein tertiary structure [21] and the load-frequency control for interconnected power system [22].

The aim of this study, which is different from the above literature, is that the ABC algorithm is applied to the AVR system in order to optimize the control parameters of the PID controller, and its tuning performance for the application of optimal AVR system, which is determined comparatively using PSO and DE algorithms. In this way, the optimal voltage control of the power system is provided. All analyses are realized by benefiting from different analysis methods such as the transient response analysis, the root locus analysis, the Bode analysis and the ROC analysis for investigating the results from another point of view. In addition to these aims, the robustness analysis is also applied to the AVR system, which is tuned by the ABC algorithm, in order to determine the contribution of this algorithm to the robustness of the control system.

2. Materials and methods

2.1. Model of AVR system

The AVR system is one of the two main control loops in a power generation unit. Generally, while the Automatic Load-Frequency Control (ALFC) loop, which is one of these loops, provides the constancy and the stability of the global system frequency, the AVR loop, which is simpler and faster than the ALFC loop, provides the constancy and the stability of the local terminal voltage of the generator. A simpler AVR system contains five basic components such as amplifier, exciter, generator, sensor and comparator as depicted in Fig. 1 [1]. In such a system, a terminal voltage is continuously sensed by a voltage level sensor. This signal is rectified and smoothed in order to compare with a DC reference signal in the comparator. Later on, the error voltage obtained from this comparison is amplified and applied to the controller. Finally, the output of the controller is used so as to control the field windings of the generator by means of the exciter.

A small signal model of this system is represented in Fig. 2 and the parameters of this model are depicted in Table 1 [6]. In this study, the PID controller has been preferred for obtaining the control signal $u(s)$ as represented in Eq. (1). The PID control is still a simpler control method, which is used by industries owing to their easy implementation of the hardware and the software. In particular, when the PID controller is applied with self-tuning methods, it gains robustness capability towards changing the different operating conditions:

$$u(s) = \Delta V_e(s)\left(K_p + \frac{K_i}{s} + K_d s\right) \tag{1}$$

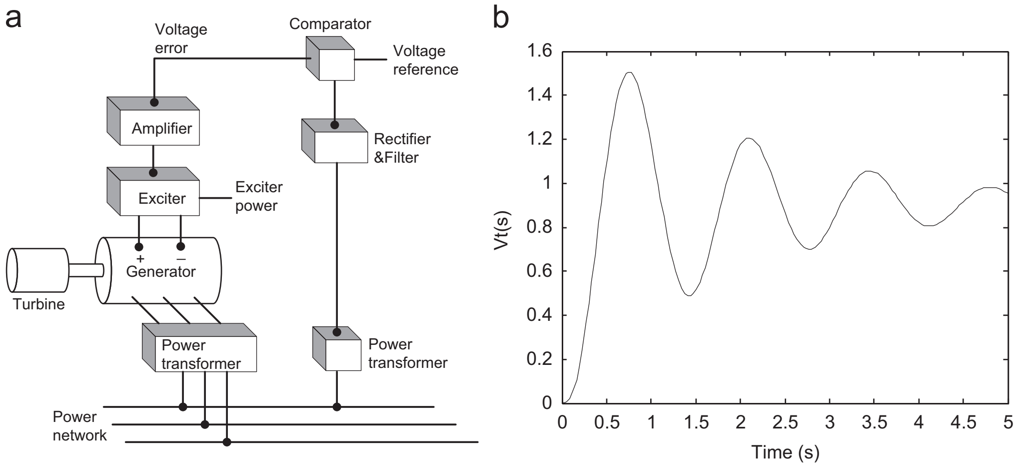

Fig. 1. (a) Real model of AVR system and (b) response of AVR system without control.

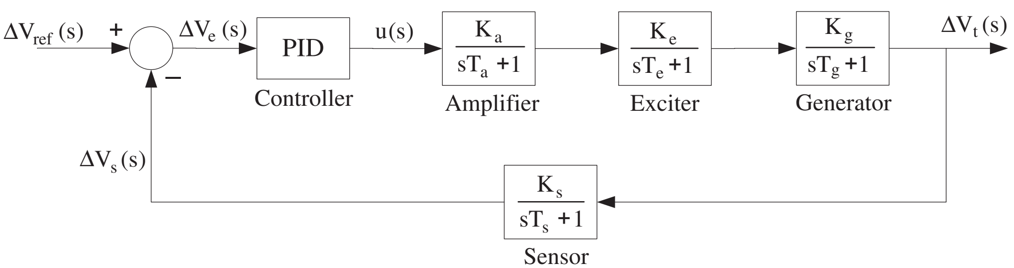

Fig. 2. Transfer function model of AVR system.

Table 1
Transfer function and parameter limits of AVR system.

	Transfer function	Parameter limits	Used parameter values
PID controller	$K_p+(K_i/s)+K_d s$	$0.2 \le K_p,K_i,K_d \le 2.0$	$K_p,K_i,K_d=$ optimum_values
Amplifier	$K_a/(1+sT_a)$	$10 \le K_a \le 40, \quad 0.02 \le T_a \le 0.1$	$K_a=10, \quad T_a=0.1$
Exciter	$K_e/(1+sT_e)$	$1 \le K_e \le 10, \quad 0.4 \le T_e \le 1.0$	$K_e=1, \quad T_e=0.4$
Generator	$K_g/(1+sT_g)$	K_g depends on load (0.7–1.0) $1.0 \le T_g \le 2.0$	$K_g=1, \quad T_g=1$
Sensor	$K_s/(1+sT_s)$	$0.001 \le T_s \le 0.06$	$K_s=1, \quad T_s=0.01$

In addition to these advantages of the PID controller, a reduction of steady-state error and an improvement of the dynamic response of the control system can be provided by this control technique. A steady-state error is zeroed by an integral controller by means of adding a pole to the origin and increasing the system type by one. An improvement of the transient response can also be provided through derivative action, which adds a finite zero to the open loop transfer function of the control system [23]. The transfer function of the entire AVR system is represented in Eq. (2). In fact, this transfer function presents the ratio of the incremental changes of the output (terminal voltage) and the input (reference voltage) of this system [8].

$$\frac{\Delta V_t(s)}{\Delta V_{ref}(s)} = \frac{(s^2K_d + sK_p + K_i)(K_aK_eK_g)(1+sT_s)}{s(1+sT_a)(1+sT_e)(1+sT_g)(1+sT_s) + (K_aK_eK_gK_s)(s^2K_d + sK_p + K_i)} \tag{2}$$

2.2. Self-tuning control

A self-tuning control is an adaptive control technique that changes some controller parameters according to tuning variables related to different operating regions in which the plant works. This control technique particularly deals with nonlinear processes, processes with time variations or situations where the requirements on the control that change with the operating conditions [24].

The main advantage of this control technique is that it is simpler to implement than the other adaptive control techniques and also the controller parameters can be adjusted very quickly in response to the changes in the plant dynamics. A typical block diagram of self-tuning control system is depicted in Fig. 3. In this figure, the tuning variables can be the measured signal, the control signal or an external signal. The control parameters of the controller are computed by a self-tuning algorithm. The algorithm is run for all different operating conditions by automatic tuning. As a tuning algorithm, although the classical tuning methods have been used so far, the population based optimization algorithms are applied increasingly due to their simpler implementation, better performance of converging and less run times at present [24]. Three of these algorithms, which are used in this study, are explained in the following section.

2.3. Optimization algorithms used for parameter tuning

2.3.1. Particle swarm optimization algorithm

Particle Swarm Optimization was first introduced by Kennedy and Eberhart in 1995 [25]. This algorithm provides high quality solutions within shorter calculation time and stable convergence characteristics. It uses particles that represent potential solutions of the problem. Each particle flies in search of space at a certain velocity, which can be adjusted in the light of preceding flight experiences. The projected position of *i*th particle of the

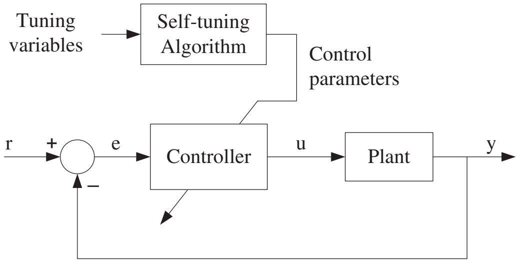

Fig. 3. Block diagram of self-tuning control system.

Table 2
Main steps of PSO algorithm.

Initialization
Repeat
Evaluate the fitness values of particles
Compare the fitness values to determine the p_i and g
Change velocity and position of the particles as to (3) and (4)
***Until** (requirements are met)*

Table 3
Main steps of DE algorithm.

Initialization
Evaluation
Repeat
Mutation
Recombination
Evaluation
Selection
***Until** (requirements are met)*

swarm x_i, and the velocity of this particle v_i at $(t+1)$th iteration are defined by the following two equations:

$$v_i^{t+1} = wv_i^t + c_1 r_1 (p_i^t - x_i^t) + c_2 r_2 (g_i^t - x_i^t) \tag{3}$$

$$x_i^{t+1} = x_i^t + v_i^{t+1} \tag{4}$$

where $i = 1, \ldots, n$ and n is the size of the swarm, w is inertia weight decreased linearly for each iteration, c_1 and c_2 are the positive constants, r_1 and r_2 are the random numbers, which are uniformly distributed in [0,1], t determines the iteration number, p_i represents the best previous position of the ith particle and g represents the best particle among all the particles in the swarm. At the end of the iterations, the best position of the swarm will be the solution of the problem. The basic steps of the algorithm are presented in Table 2 [25].

PSO algorithm has been used for the power system researches such as automatic generation control, automatic dispatch control, optimal power flow control, automatic reactive power/voltage control, power system stabilizers, etc. since the beginning of 2000 [26].

2.3.2. Differential evolution algorithm

Differential Evolution Algorithm was developed by Storn in 1997. This algorithm uses crossover, mutation and selection operatorslike genetic algorithms. The main difference of these algorithms is that while DE algorithm relies on mutation operation, the genetic algorithms rely on crossover. The basic steps of DE algorithm are represented in Table 3 [27]. In DE algorithm, d numbers of parameters are represented by d-dimensional vectors. A population of these vectors is randomly created at the start of the algorithm and is improved by applying mutation, crossover and selection operators. This algorithm has been frequently applied to the power system optimization in recent years.

Table 4
Main steps of ABC algorithm.

Send the scouts onto the initial food sources
Repeat
Send the employed bees onto the food sources and determine their nectar amounts
Calculate the probability value of the sources with which they are preferred by the onlooker bees
Stop the exploitation process of the sources abandoned by the bees
Send the scouts into the search area for discovering new food sources, randomly
Memorize the best food source found so far
***Until** (requirements are met)*

2.3.3. Artificial bee colony algorithm

Artificial Bee Colony Algorithm is one of the more recent population based optimization algorithm for solving the multidimensional optimization problems. It was reported by Karaboğa in 2005 [13,14]. An intelligent behavior of honey bee colony that searches new food sources around their hive was considered to compose the algorithm. This colony of artificial bees consists of three groups of bees called employed bees, onlookers and scouts. While a half of the colony consists of the employed artificial bees, the other half includes the onlookers. There is only one employed bee for every food source. It means that the number of employed bees is equal to the number of food sources around the hive. The main steps of the algorithm are given in Table 4.

Each cycle of the search consists of three steps: moving the employed and the onlooker bees to the food sources, calculating their nectar amounts and determining the scout bees and directing them to the possible food sources. Each food source position represents a possible solution of the problem. The amount of nectar of a food source corresponds to the quality of the solution represented by that food source. Onlookers are placed on the food sources using a probability based selection process. As the nectar amount of a food source increases, the probability value with which the food source is preferred by onlookers increases too. Every bee colony has scouts that are the colony's explorers. The explorers do not have any guidance while looking for food. They are primarily concerned with finding any kind of food source. As a result of such behavior, the scouts are characterized by low search costs and a low average in food source quality. Occasionally, the scouts can accidentally discover rich, entirely unknown food sources. In the case of artificial bees, the artificial scouts could have the fast discovery of the group of feasible solutions as a task.

It is perceived that ABC algorithm has triple search capability. While the local search is realized by employed and onlooker bee phases, global search is realized by scout bee phase in ABC algorithm consecutively and separately. This capability provides better convergence performance to ABC algorithm than other similar optimization algorithms [13,14]. This algorithm is applied to some different optimization processes so far.

3. Results and discussion

The self-tuning PID controller has been preferred for this application due to its superiorities explained before. The gains of the controller are tuned by the optimization algorithms, which have also been mentioned in the preceding sections. During these algorithms, the upper and the lower bounds of the gains are chosen as [0.2, 2]. The number of iteration and the population size are also chosen the same for all algorithms. They are

Table 5
Optimum parameters of the PID controller.

	ABC	PSO	DEA
K_p	1.6524	1.7774	1.9499
K_i	0.4083	0.3827	0.4430
K_d	0.3654	0.3184	0.3427

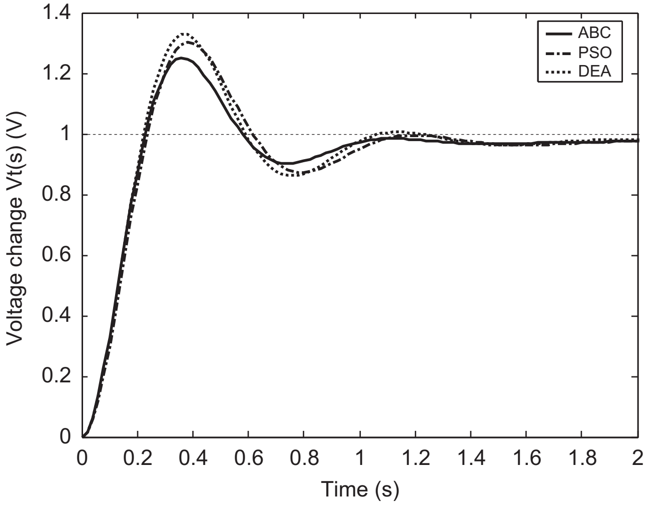

Fig. 4. Voltage changing curves of the AVR system.

taken to be 50 and 300. In addition to these, the scaling factor is taken as 0.02 for DE algorithm. In ABC algorithm, the parameters are chosen in which the colony size is 20, the control parameter in order to abandon the food source is 100 and the number of runs is 3. All simulations are realized on the computer, which includes Core2 of 2 GHz and RAM of 1 GB. As a cost function will be minimized for determining the optimum values of the gains of the controller, the integral of time weighted squared error (ITSE) function, which is represented in Eq. (5), is preferred. This cost function is chosen for minimizing the settling time due to dependency of errors on time [24]:

$$\mathrm{ITSE} = \int_0^t t(u_g)^2 dt \tag{5}$$

As a result, the obtained optimal gains of the controller are represented in Table 5. The transfer functions of the system according to these gains are also represented in Eqs. (6), (7) and (8) for ABC, PSO and DE algorithms, respectively. Also, the obtained voltage change curves $V_t(s)$ according to these transfer functions are shown in Fig. 4:

$$\frac{\Delta V_t(s)}{\Delta V_{ref}(s)} = \frac{0.03654s^3 + 3.819s^2 + 16.56s + 4.083}{0.0004s^5 + 0.0454s^4 + 0.555s^3 + 5.164s^2 + 17.52s + 4.083} \tag{6}$$

$$\frac{\Delta V_t(s)}{\Delta V_{ref}(s)} = \frac{0.03184s^3 + 3.362s^2 + 17.81s + 3.827}{0.0004s^5 + 0.0454s^4 + 0.555s^3 + 4.694s^2 + 18.77s + 3.827} \quad (7)$$

$$\frac{\Delta V_t(s)}{\Delta V_{ref}(s)} = \frac{0.03427s^3 + 3.622s^2 + 19.54s + 4.43}{0.0004s^5 + 0.0454s^4 + 0.555s^3 + 4.937s^2 + 20.5s + 4.43} \quad (8)$$

At the end of the simulations, the tuning superiority of the algorithms according to each other is put forward using time domain, frequency domain and statistical analysis methods as explained below. After determining the tuning method with the best dynamic performance, the robustness of this method is also investigated.

3.1. Transient response analysis

Transient response analysis provides the investigation of the system behavior during the time of the beginning and the steady state [23]. The results obtained at the end of the analysis are represented in Table 6 and Fig. 5. It is seen from Table 6 that ABC algorithm has better results for the settling time as 8.7% than PSO algorithm and 3.5% than DE algorithm. For the maximum overshoots, it also gets better performance as 4% than PSO algorithm and 6.4% than DE algorithm. On the other hand, the peak time of ABC algorithm is same as the peak time of DE algorithm, and both are better than that of PSO

Table 6
Results of the transient response analysis of the AVR system.

	Maximum overshoots	Settling times (5% bant)	Rise times	Peak times
PSO	1.300	1.000	0.161	0.380
DEA	1.330	0.952	**0.152**	**0.360**
ABC	**1.250**	**0.920**	0.156	**0.360**

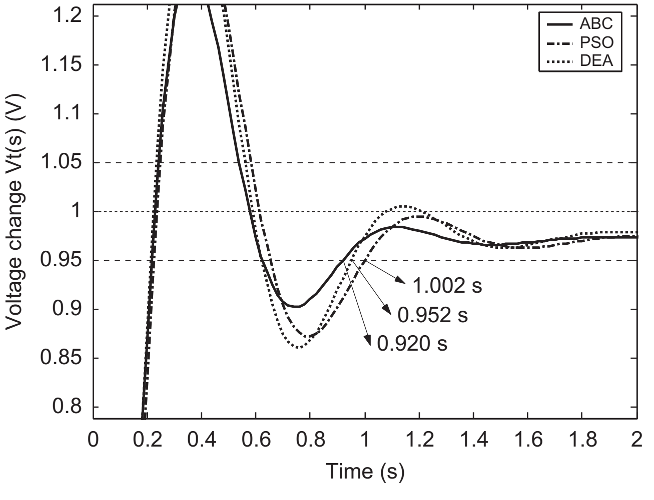

Fig. 5. Zoom of voltage changing curves of the AVR system.

algorithm as much as 5.5%. When the rise time is investigated, it is seen that the best result belongs to DE algorithm and the worst one belongs to PSO algorithm.

3.2. Root locus analysis

Root locus analysis allows the investigation of time domain and stabilization behaviors of the control system [23]. The root locus curves are depicted in Figs. 6, 7 and 8 for ABC, PSO and DE algorithms, respectively. The closed loop poles and their damping ratios are also represented in Table 7. This analysis shows that all closed loop poles of the control

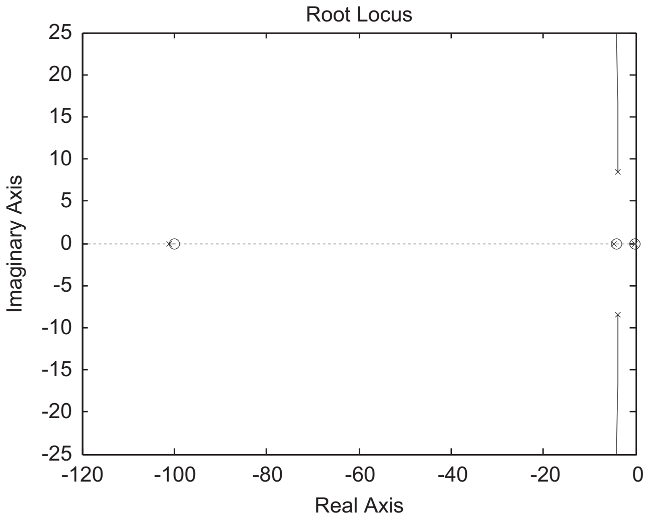

Fig. 6. Root locus curve of the system that is tuned by ABC algorithm.

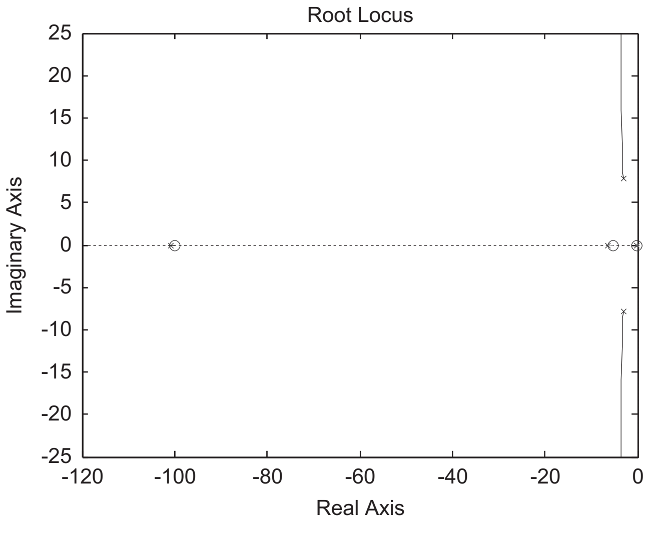

Fig. 7. Root locus curve of the system that is tuned by PSO algorithm.

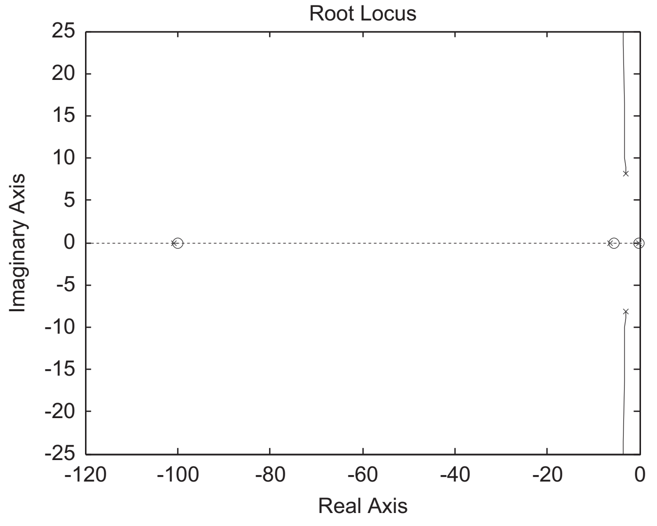

Fig. 8. Root locus curve of the system that is tuned by DE algorithm.

Table 7
Poles and damping ratios of the AVR system.

ABC		PSO		DE	
Closed loop poles	Damping ratio	Closed loop poles	Damping ratio	Closed loop poles	Damping ratio
−100.98	1.00	−100.85	1.00	−100.91	1.00
−3.75+*j*8.40	**0.40**	−3.08+*j*7.80	0.36	−3.02+*j*8.19	0.34
−3.75−*j*8.40	**0.40**	−3.08−*j*7.80	0.36	−3.02−*j*8.19	0.34
−4.74	1.00	−6.26	1.00	−6.29	1.00
−0.25	1.00	−0.21	1.00	−0.22	1.00

system are at the left side of the *s*-plane for all optimization algorithms. It means that all control systems tuned by the optimization algorithms are being stable. In addition to these results, Table 7 presents that the conjugate poles obtained with ABC algorithm are more to the left on the *s*-plane and the biggest damping ratio belongs to the control system tuned by ABC algorithm. It is bigger than that of PSO algorithm as much as 10% and that of DE algorithm as much as 15%.

3.3. Bode analysis

Bode analysis gives information about the frequency response of the control system [23]. The magnitudes and the phase plots obtained from this analysis are depicted in Figs. 9–11. The peak gains, the phase margins and the delay margins computed from these plots are also represented in Table 8. It is seen from this table that the minimum peak gain is obtained by ABC algorithm. In addition to this, the maximum phase margin, maximum delay margin and maximum bandwidth are also provided by ABC algorithm. As a result, it

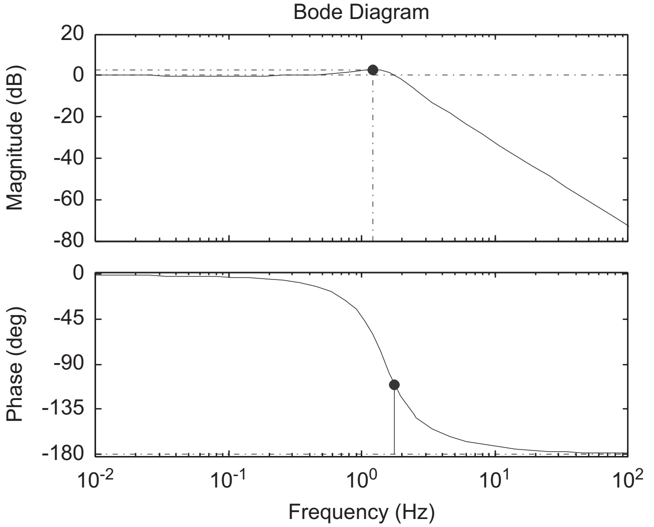

Fig. 9. Bode plots of the system that is tuned by ABC algorithm.

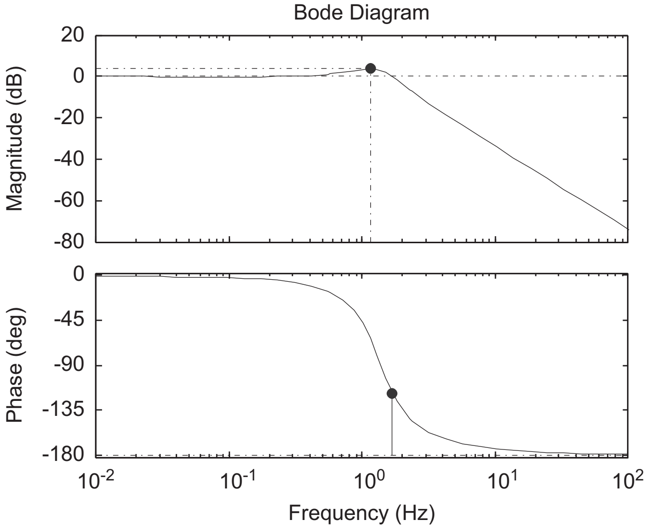

Fig. 10. Bode plots of the system that is tuned by PSO algorithm.

can be said that the best frequency response belongs to the system tuned by ABC algorithm.

3.4. ROC analysis

Although the results obtained above may be sufficient for the control theory, these are statistically investigated through ROC analysis method. In this application, this analysis

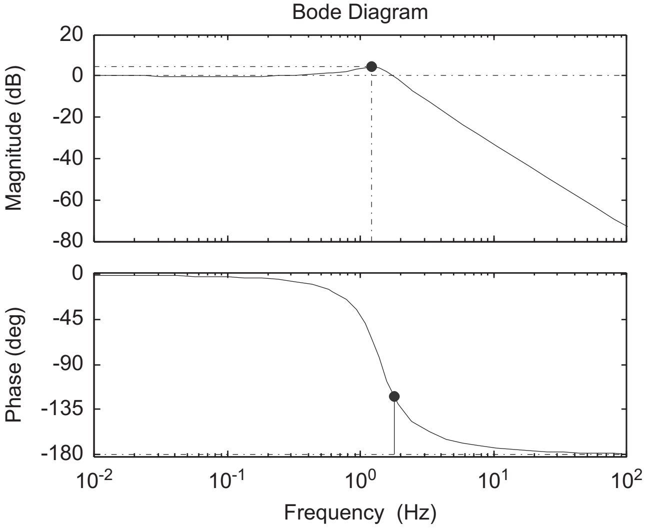

Fig. 11. Bode plots of the system that is tuned by DE algorithm.

Table 8
Peak gains, phase margins and delay margins of the AVR system.

	Peak gains	Phase margins (deg.)	Delay margins	Bandwidths
PSO	3.75 dB (1.14 Hz)	62.2	0.103 s (1.67 Hz)	12.182
DEA	4.20 dB (1.21 Hz)	58.4	0.092 s (1.77 Hz)	12.800
ABC	**2.87 dB (1.20 Hz)**	**69.4**	**0.111 s (1.74 Hz)**	**12.879**

method shows that how many voltage changes approach to the ideal step response in transient and steady-state regions of the curves. This technique was reported by Egan in 1975 [28,29] and has been used in the signal detection theory, analyzing the behavior of the diagnostic systems, medical decision making, machine learning, etc. so far.

In this study, ROC analysis is applied to the unit step response curves depicted in Fig. 4. The sensitivities, the specificities and the regions under the ROC curves are calculated. How the required data have been obtained from Fig. 4 is presented in Fig. 12. Then, the ROC curves plotted with the help of these data are represented in Fig. 13(a)–(c). Finally, the percent ratios of the sensitivity, the specificity and the regions under the ROC curves are represented in Table 9. In addition to these results, the calculated means and the medians for these curves are also presented in this table. According to these results, the sensitivity of the system optimized by ABC algorithm is bigger than that of the systems optimized by DE algorithm as 11.34% and that of the systems optimized by PSO algorithm as 13.9%. The specificity obtained by ABC algorithm is also bigger than the result obtained by DE algorithm as 0.45% and the result obtained by PSO algorithm as 5.9%. For the region under the ROC curves, the region obtained by ABC algorithm is bigger than the region obtained by DE algorithm as 6.06% and the region obtained by PSO algorithm as 6.96%. In addition to these, the median and the mean belonging to the

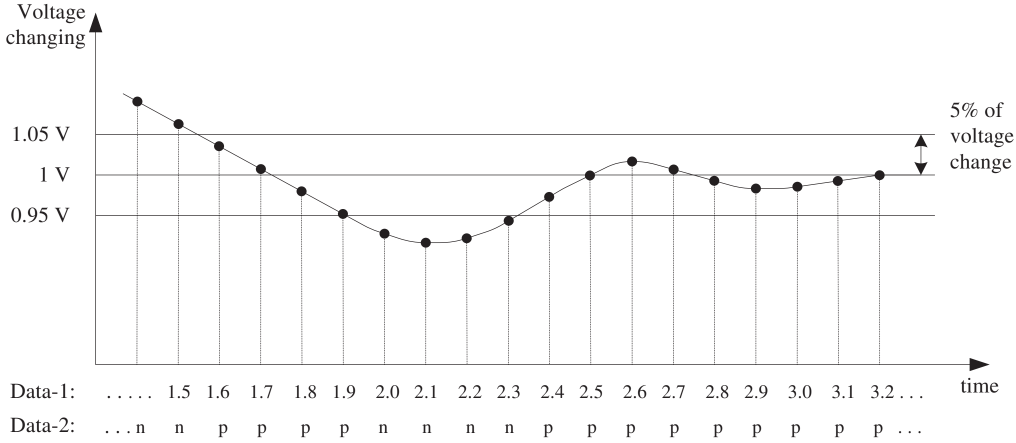

Fig. 12. Classification of the voltage change curve for obtaining confusion matrix.

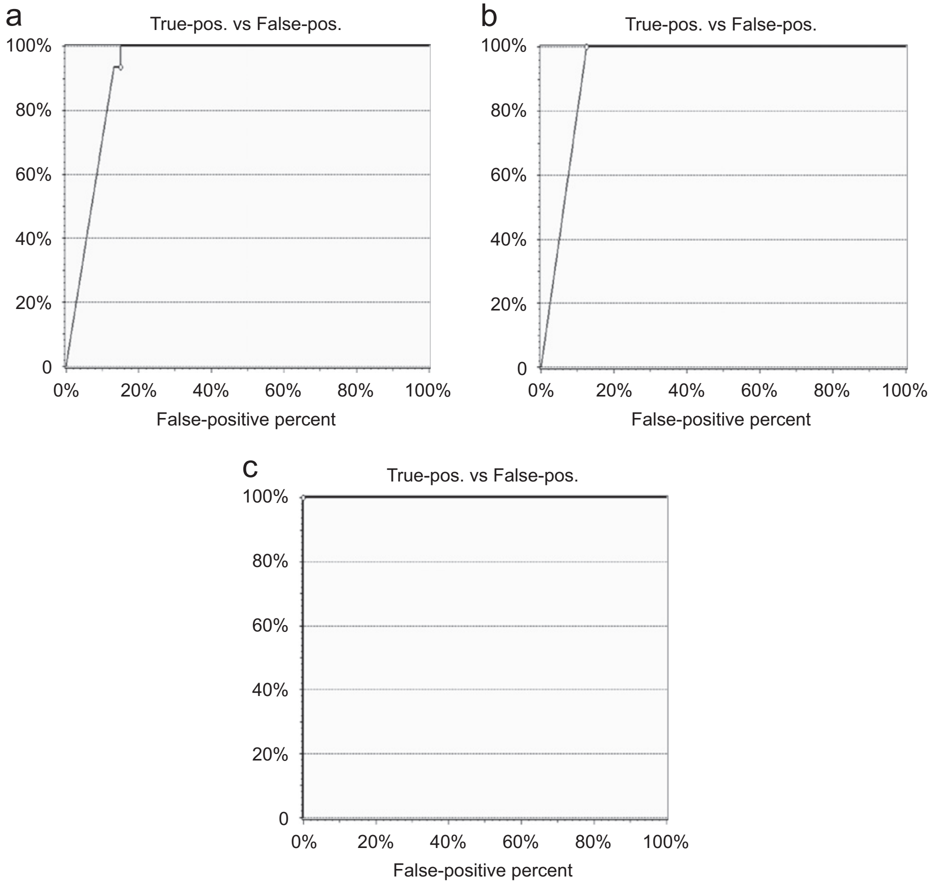

Fig. 13. ROC curves of the voltage change with (a) PSO algorithms, (b) DE algorithms and (c) ABC algorithms.

Table 9
Results of the statistically (ROC) analysis.

	Sensitivity (%)	**Specificity (%)**	**Region under the curve (%)**	**Medians**	**Means**
PSO	84.91	93.62	92.85	0.9749	0.9470
DEA	87.50	99.05	93.75	0.9781	0.9522
ABC	**98.70**	**99.50**	**99.80**	**0.9744**	**0.9458**

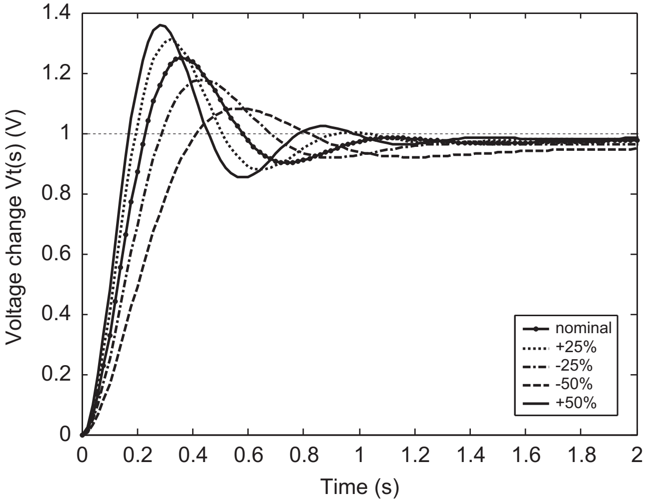

Fig. 14. Voltage change curves ranging from −50% to +50% for the gains of amplifier, exciter, generator and sensor models.

ABC algorithm are smaller than the others. Hence, it is statistically evaluated that the closest curve to the ideal unit step response is achieved through ABC algorithm.

3.5. Robustness analysis

The gains and the time constants which belong to the elements of the model are changed separately in the range of $\pm 50\%$ so as to investigate the robustness of the AVR system tuned by ABC algorithm. The obtained results are presented in Figs. 14–18 and Table 10. In addition, the range of total deviations and the percentage values of maximum deviations are also listed in Table 11. It is seen from this table that all the deviations for the chosen system parameters are in the small ranges generally. In particular, there are almost no deviations for the sensor time constant T_s. On the other hand, the changes of the gains are caused by bigger deviations than those of time constants. For example, the settling time deviates from its nominal value only in the range of 1.528 s, but its maximum deviation is 144.5%. In contrast, for all the time constants, the average deviation of the maximum overshoot is 5.6%, that of the settling time and rise time is 27.5% and that of the peak time is 24.7%. All ranges of the total deviations of these are approximately below 0.5. According to these results, it can be said that the PID controller tuned by ABC algorithm

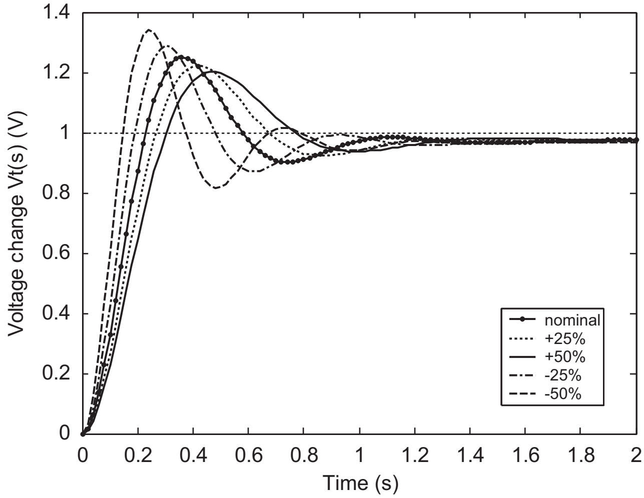

Fig. 15. Voltage change curves ranging from −50% to +50% for T_g.

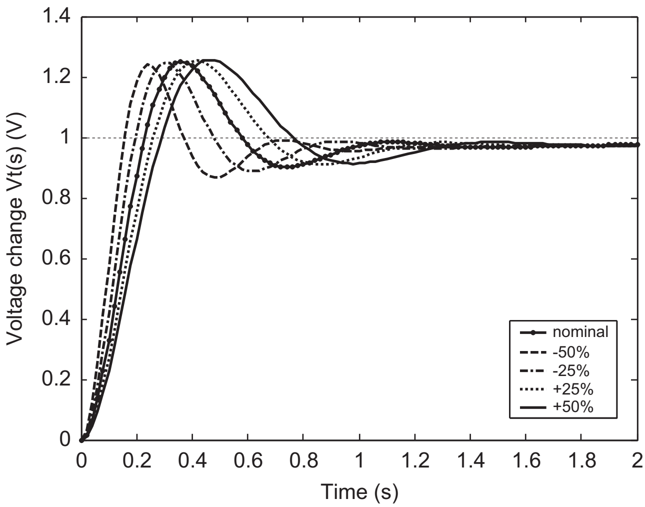

Fig. 16. Voltage change curves ranging from −50% to +50% for T_e.

is robust and provides the desired control behavior without the effect of changes of those parameters in the specified change interval.

4. Conclusion

This study presents both the usage of ABC algorithm as the new artificial intelligence based optimization technique in order to optimize the control problem of AVR system and the comparative tuning performance analysis of this algorithm. To reveal the tuning performance of ABC algorithm on AVR system, artificial intelligence based PSO and DE

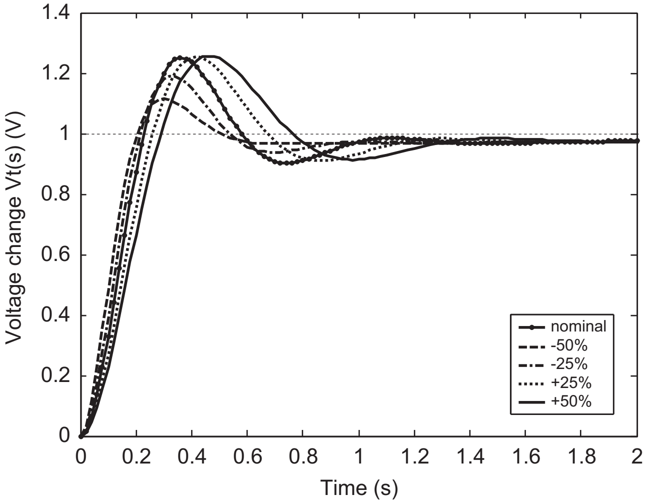

Fig. 17. Voltage change curves ranging from −50% to +50% for T_a.

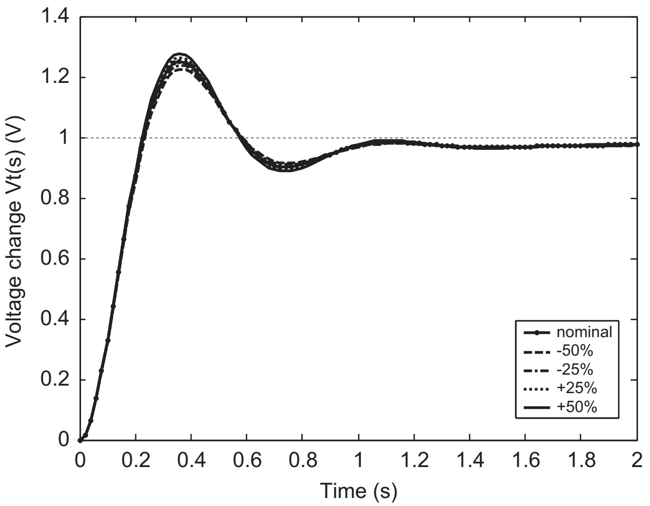

Fig. 18. Voltage change curves ranging from −50% to +50% for T_s.

algorithms are applied to the control system for the purpose of comparison, additionally. The transient response analysis, the root locus analysis and the Bode analysis are used in order to obtain the results. In another point of view for analyzing them, statistical ROC analysis method is also applied to the results. Hereby it is seen that the tuning superiority of ABC algorithm is proved by all analysis techniques. It is evaluated that this result is caused by the triple search capability of the ABC algorithm. As explained in the related sections, the local search is realized by the employed and the onlooker bee phases and global search is realized by the scout bee phase in ABC algorithm consecutively and separately. In contrast, the local and global searches are realized by the same update

Table 10
Results of robustness analysis of the control system tuned with ABC algorithm.

Parameter	Rate of change[a] (%)	Maximum overshoot (V)	Settling time (5% bant) (s)	Rise time (s)	Peak time (s)
K_g, K_a, K_e and K_s	−50	1.080	2.250	0.303	0.559
	−25	1.170	1.140	0.218	0.477
	+25	1.310	0.802	0.151	0.303
	+50	1.360	0.722	0.133	0.275
T_g	−50	1.340	1.050	0.100	0.233
	−25	1.270	0.786	0.148	0.273
	+25	1.220	1.040	0.195	0.388
	+50	1.200	1.130	0.214	0.496
T_a	−50	1.110	0.419	0.159	0.290
	−25	1.190	0.798	0.168	0.322
	+25	1.280	1.010	0.185	0.433
	+50	1.330	1.080	0.192	0.440
T_e	−50	1.240	0.619	0.107	0.244
	−25	1.220	0.777	0.151	0.267
	+25	1.250	1.060	0.191	0.400
	+50	1.260	1.200	0.209	0.458
T_s	−50	1.210	0.918	0.181	0.335
	−25	1.230	0.919	0.179	0.336
	+25	1.260	0.921	0.176	0.339
	+50	1.270	0.922	0.174	0.340

[a] According to the values represented in Table 6.

Table 11
Range of total deviations and percentage of maximum deviations of investigated system.

Parameter	Range of total deviations	Percentage of maximum deviations (%)
K_g, K_a, K_e and K_s		
Maximum overshoot (V)	0.28	13.6
Settling time (s)	1.528	144.5
Rise time (s)	0.17	94.2
Peak time (s)	0.284	55.2
T_g		
Maximum overshoot (V)	0.14	7.2
Settling time (s)	0.085	22.8
Rise time (s)	0.114	37.1
Peak time (s)	0.263	37.7
T_a		
Maximum overshoot (V)	0.22	11.2
Settling time (s)	0.339	54.4
Rise time (s)	0.033	23.1
Peak time (s)	0.15	22.2
T_e		
Maximum overshoot (V)	0.02	0.8

Table 11 (*continued*)

Parameter	Range of total deviations	Percentage of maximum deviations (%)
Settling time (s)	0.581	32.7
Rise time (s)	0.102	33.9
Peak time (s)	0.214	32.2
T_s		
Maximum overshoot (V)	0.06	3.2
Settling time (s)	0.004	0.2
Rise time (s)	0.007	16
Peak time (s)	0.005	6.9

formula in PSO and DE algorithms. On the other hand, the robustness of this algorithm is also shown by the applied method. Accordingly, the AVR system that was optimized by ABC algorithm is affected in adequately small amount by changes of the process parameters in the range of $\pm 50\%$. Consequently it is seen from this study that ABC algorithm can be applied to the AVR system successfully, and it allows to control this system optimally and robustly. In addition to this, it can be evaluated that this control technique obtained using ABC algorithm is also applied to different control applications.

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