Enhanced Artificial Bee Colony Algorithm to Optimize PID-AVR Controller

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Abstract — **A controller generates suitable control signals for exhibiting desired response of any physical system. Control of electrical power generators has always remained very critical in power systems' operation and control. The continuously changing load demand at the generators terminals and restructuring of power systems have immensely increased the need of an optimally tuned controllers. Automatic Voltage Regulator (AVR), mounted on the generators plays pivotal role in power systems' smooth operation during steady-state and transient mode as well. Proportional integral and derivative (PID) controller is the most commonly used controller for AVR. Bio-inspired optimization algorithms have been reported to give revolutionary results in field of power systems operation and control. This research work has used Enhanced Artificial bee colony (EABC) optimization algorithm to optimally tune PID-AVR. EABC capitalizes on three different mutation equations simultaneously to yield the optimal solution of an optimization problem. This research work has compared the performance of EABC with other ABC variants for optimizing PID-AVR using five different fitness functions. The results show the best convergence of EABC algorithm.**

Keywords—Enhanced ABC, PID-AVR optimization, Optimization algorithms, Evolutionary computing, Power systems.

I. INTRODUCTION

The trend of planning to operate power systems at ever lesser margins - to maximize the profit in the era of restructured power systems - has put the system stability at stake [1, 2]. Stability of a power system can be explained as its ability to regain a state of operating equilibrium after being subjected to a physical disturbance [3]. The stability of a power system is related to stability of a synchronous generator [4]. Automatic Voltage Regulators (AVRs), mounting on the generator play pivotal role in smooth running of the power systems [5, 6]. AVR keeps terminal voltage constant at preset voltage level. Deviation of terminal voltage from rated voltage eminently affects the performance of all equipments associated with the system, not only in terms of efficiency but also from equipments' life perspective as well [7, 8]. Therefore AVRs are of immense importance during transient as well as steady state operation of power systems [3, 5, 9]. Proportional Integrator Derivative (PID), a linear controller is the most commonly used controller to regulate outputs of AVR.

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Various advanced control methodologies such as conventional control, neural control and fuzzy control have been studied and applied [4, 6, 10-12]. PID controller is a linear controller and is the most widely used controller in industry even today owing to its important features such as wide operating range, fewer parameters to tune, elimination of steady-state offset and anticipation of the future [2, 13]. Despite very few tuning parameters, it is difficult to tune PID gains properly because of higher order industrial plants, time delays and nonlinearity [14]. An experimental study has revealed that more than 40% of installed controllers in industry are poorly tuned [13]. Ziegler-Nichols (ZN) is the most commonly used classical method for PID controller tuning. However, it is often difficult to get optimal or near optimal PID gains using ZN method [15, 16].

On the other hand, bio-inspired optimization algorithms are well known for producing optimal solutions of numerous engineering problems [10, 13, 15-17]. Nevertheless application of bio-inspired optimization algorithms for online tuning of controllers is limited due to lesser convergence speed [18]. Furthermore, the review of intelligent systems based solutions to enhance power system stability has revealed that due to speedy response and error resilience, intelligent systems produce better performance than conventional systems [2].

Artificial Bee Colony (ABC) is a bio-inspired optimization algorithm which has captured much attention due to its superior convergence and lesser number of control variables [19-21]. ABC algorithm emulates foraging phenomenon of honeybees to generate solutions of complex problems and has been proposed in 2005 [19]. Nonetheless, ABC algorithm suffers from slow convergence [22], poor exploitation capability [23, 24] and prone to local optima traps [25]. To overcome the flaws, various researchers have proposed different amendments [17, 22, 24-30]. A variant of ABC optimization algorithm was proposed by the authors [25]. The proposed variant was named Enhanced ABC (EABC) algorithm. The proposed variant had been rigorously compared with various existing ABC variants on a few high dimensional benchmark functions. The results have proved significantly improved performance of EABC.

The objective of this research work is to analyze the performance of EABC on a real world application i.e. PID-AVR optimization. The performance of EABC has been compared with a number of existing ABC variants. PID-AVR system used in this research work has been adapted from research works published in reputable journals. Afterword different fitness functions, proposed in reputable journals, have been collected to thoroughly analyze the performance of the optimization algorithms. An optimization algorithm may exhibit different performance as the fitness function changes.

This paper has been organized in seven sections. The immediate section presents model of PID-AVR which has been optimized in this research work. The third section discusses EABC optimization algorithm. The fourth section describes the simulation set-up and parameters setting of the compared optimization algorithms. The fifth section discusses the results. The sixth section compares the performance of the optimized PID-AVR models and finally conclusion is presented in the conclusion section.

II. PID-AVR MODEL

Model of PID-AVR which has been used to assess the performance of the optimization algorithm is depicted in Figure 1. This model has also been used by [10, 14-16]. The transfer-functions and gain-values of the model components are given in Table 1.

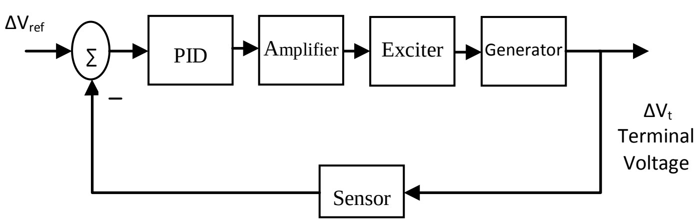

Figure 1. Block diagram of PID-AVR model used in this research.

Table 1. Transfer function of the PID-AVR model their values.

Components	**Transfer Function**	**Parameter Values**
Amplifier	$TF_{Amplifier} = K_a/1+\tau_a s$	$K_a = 12$ $\tau_a = 0.1$
Exciter	$TF_{Exciter} = K_e/1+\tau_e s$	$K_e = 1$ $\tau_e = 0.4$
Generator	$TF_{Generator} = K_g/1+\tau_g s$	$K_g = 1$ $\tau_g = 1$
Sensor	$TF_{Sensor} = K_s/1+\tau_s s$	$K_s = 1$ $\tau_s = 0.01$
Controller	$TF_{Controller} = (k_p s+k_i+k_d s^2)/s$	

As illustrated in Figure 1, the controller generates control-signal on the basis of error-signal (ΔV_e) [32-34]. The error-signal is deviation of generator's output voltage from the preset-voltage. Function of the proportional (P) controller is to minimize the magnitude of the error-signal [32]. The steady-state-error is reduced by the integral (I) component of the controller [33]. Furthermore, the derivative (D) element of controller is to damp out the oscillations [34].

Fitness functions which have been used by different researchers [10, 14-16, 31] to optimize PID-AVR are presented in Table 2. The first, second and third fitness functions carry correlated objectives and hence, the fitness are difficult to optimize. The fourth and fifth fitness functions are known as Integral of Time-weighted Square Error (ITSE) and Integral of Time-weighted Absolute Error (ITAE) respectively. ITSE and ITAE are the commonly used fitness functions for PID controller optimization. In Table 2, O_{sh} is an overshoot, E_{ss} represents a steady-state error, t_s is the settling time, t_r shows the rise-time, max_dev represents the maximum-deviation of voltage, e(t) shows the difference between calculated and desired value, β=1.5 and max(t)=1sec.

Table 2. Fitness functions to optimize PID-AVR.

Label	**Fitness function**	**Reference**
f_1	$(1 - e^{-\beta}) \times (O_{sh}+E_{ss}) + e^{-\beta}(t_s - t_r)$	[14, 16]
f_2	$\dfrac{e^{-\beta} \times \dfrac{t_s}{\max(t)}}{(1-e^{-\beta}) \times \left\lvert 1-\dfrac{t_r}{\max(t)} \right\rvert} + e^{-\beta} \times O_{sh} + E_{ss}$	[15]
f_3	$(O_{sh} \times 10000)^2 + t_s^2 + \dfrac{0.001}{(max\_dev)^2}$	[10]
f_4	$\int_{t=0}^{t=t_{max}} t \times (e(t))^2 dt$	[31]
f_5	$\int_{t=0}^{t=t_{max}} t \times \lvert e(t) \rvert\, dt$	[15]

III. ENHANCED ARTIFICIAL BEE COLONY (EABC) OPTIMIZATION ALGORITHM

EABC algorithm simulates foraging phenomenon of honeybees similar to the standard ABC algorithm [35]. Flow chart of EABC algorithm is given in Figure 1. EABC algorithm divides the population of honeybees into three different classes. One is called employed-bees, which are assigned randomly-initialized food-sources at the start of the algorithm. The employed-bees assess nectar amount and neighborhood of the assigned food-sources. Later on, the bees pass the information to onlooker-bees. The nectar-amount of a food-source symbolizes the fitness of a possible-solution. The second type of honeybees is named onlooker-bees. Onlooker-bees explore neighborhood of only high-quality food-sources. The neighborhood of the food-sources is explored by a mutation equation.

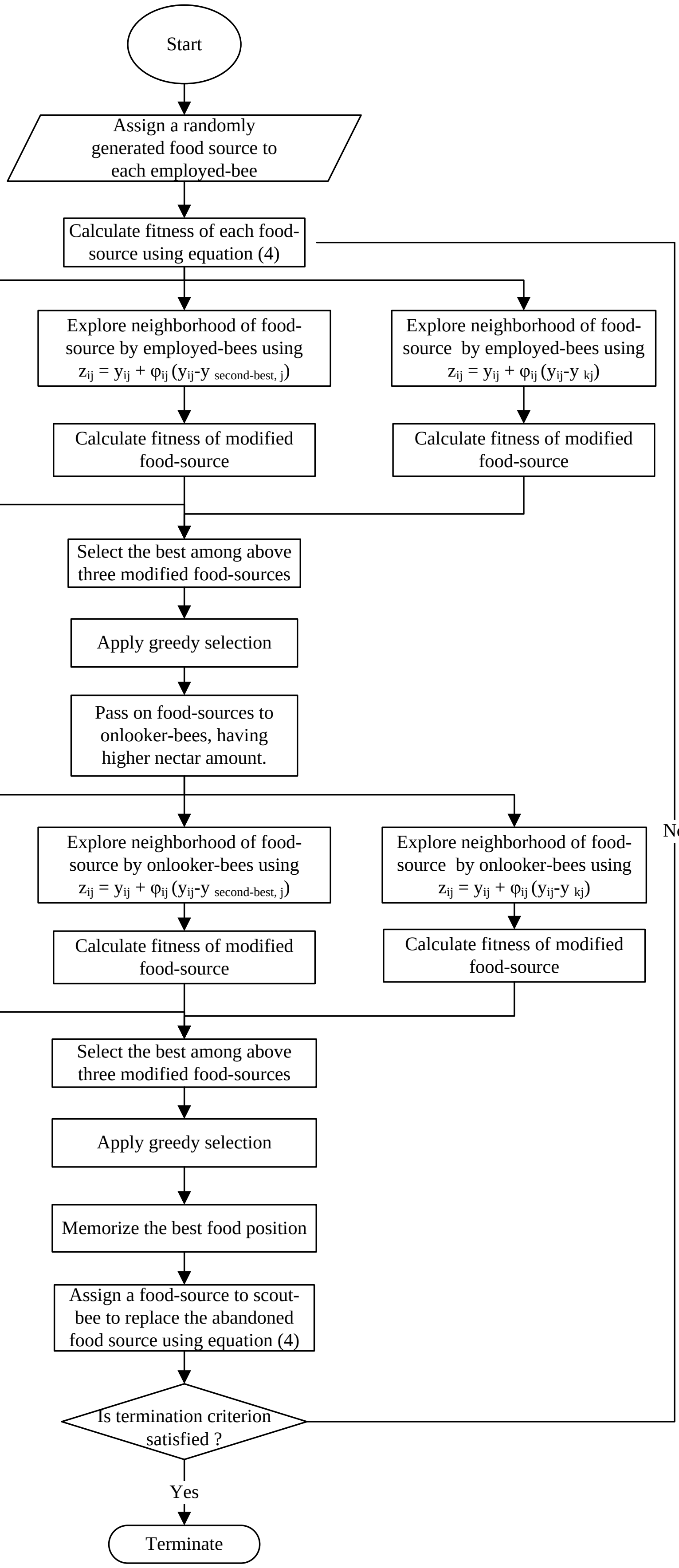

Figure 2 Flow chart of Enhanced Artificial Bee Colony Optimization Algorithm (EABC)

Mutation equation of an optimization algorithm determines its performance. On the other hand, no free lunch theorem states that no single mutation equation can yield equally-better performance on different types of optimization problems. Mutation equation of an optimization algorithm set rules of engagement among honeybees. Besides, the interaction among the population elements emerges self-organized patterns. Additionally, the neighborhood exploration of any food-source using the gbest food-source increases convergence rate however, it may lead towards premature convergence. On other hand, the neighborhood exploration of any food-source based on a randomly chosen food-source curtails convergence rate but, it inducts capability to avert local optima. Therefore, EABC algorithm capitalizes on three different mutation-equations to avail benefits of each mutation-equation, unlike the standard ABC algorithm. The mutation-equations of EABC are given below;

$$z_{ij} = y_{ij} + \varphi_{ij}\,(y_{ij}-y_{best,\,j}) \tag{1}$$

$$z_{ij} = y_{ij} + \varphi_{ij}\,(y_{ij}-y_{second\text{-}best,\,j}) \tag{2}$$

$$z_{ij} = y_{ij} + \varphi_{ij}\,(y_{ij}-y_{k\,j}) \tag{3}$$

where y_{ij} symbolizes j_{th} dimension of i_{th} food-source, y_{kj} represents j_{th} dimension of k_{th} food-source, z_{ij} corresponds to candidate-solution of j_{th} dimension of i_{th} food-source, $y_{best,\,j}$ is the j_{th} index of the global-best (gbest) food-source, $y_{second\text{-}best,\,j}$ is the j_{th} index of the global-second-best food-source, *i* and *k* are the mutually-exclusive food sources, j Є [1,2,…. D], *D* is the dimension of search space, *j* and *k* are randomly chosen numbers and φ is a random number within [-1, 1].

Equations (1) and (2) capitalize on the gbest and the second-gbest food-source for the neighborhood exploration of a food-source, respectively. Hence, the proposed algorithm capitalizes on multiple gbest food-sources. This way, the proposed algorithm explores around multiple so-far best-found areas of a search-space. Hence, EABC algorithm has the ability to converge faster while avoiding local-optima traps. Moreover, equation (3) capitalizes on a randomly chosen food-source and it further strengthen local-optima avoiding capability of the proposed algorithm. The proposed algorithm explores the neighborhood of every food-source based on the three equations (1), (2) and (3). After calculating nectar amount of the three new food-sources, the best among the three is selected for further processing. Thus the proposed algorithm uses three different mutation-equations however, it updates every food-source only twice in an iteration similar to the standard ABC algorithm.

The third type of bees is known as scout-bees. If nectar amount of any food-source is sucked then, the associated employed-bee becomes scout-bee. The scout-bee directly goes to the dancing area of a hive where employed-bees share the information, with onlooker-bees, of the evaluated food-sources. The scout-bee collects information about the gbest food-source then, the scout-bee directly flies to the food-source for exploring its neighborhood. EABC algorithm assigns a food-source to scout-bee using the following equation;

$$Z_{nj} = (y_{best,\,j}) \times \beta_{nj} \tag{4}$$

where z_{nj} is the j_{th} dimension-magnitude of the newly assigned food-source, $y_{best,j}$ is the j_{th} dimension-magnitude of the gbest food-source, j Є [1,2,…. D], *D* is the dimension of search space and β_{nj} is random number within [0.90, 1.10].

The limits of β are chosen keeping in view that the transformation process may not distort the gbest food-source much. The other stages of EABC and the standard ABC algorithm are similar. For further explanation, please refer to [25].

IV. Simulation Set-Up and Parameter Settings

The performance of the optimization algorithms has been analyzed using PID-AVR model presented in Figure 1. PID-AVR model has been optimized using fitness functions presented in Table 2. The algorithms have been run for 30 generations with population-size equal to 10. The value of *"limit"* control variable has been limited to 15. As these are the common control variables therefore, their values have been set to the same value for all algorithms for unbiased comparison. *P* for IABC has been set to 0.25 and *ASF* for MABC has been set to 0.90. These are algorithm specific control variables and their values have been set according to the suggestions given in their respective research works.

The performance of EABC has been analyzed in comparison to ABC [19], BABC [28], IABC [27], MABC [22] and BSFABC [26] algorithms. Each algorithm has been run 30 times on each fitness function to analyze the robustness and the convergence of the optimization algorithms. The performance of the algorithms has been analyzed on the basis of the average convergence over thirty runs and standard deviation among thirty outputs. Afterword, PID-gains yielding the least fitness function value, among thirty runs, have been taken to compare the performance of the controller optimized by the algorithms. The PID-AVR components are given in Table 1 and the values are well within limits specified in [10, 14, 16].

V. Results and Discussion

Figures 3 to 7 show convergence rates of the optimization algorithms on the five fitness functions (f_1, f_2, f_3, f_4 and f_5). The presented plots clearly show that BSFABC and MABC have resulted in inferior convergence than the standard ABC algorithm. Mutation equation employed by BSFABC during onlooker-bees stage is highly local in nature whereas MABC suffers from poor neighborhood exploration. On the other hand, BABC and IABC have resulted in better convergence on f_1 and f_2 initially. However, the algorithms could not converge more on the fitness functions as, the algorithms generates new solutions around gbest possible solution. Any algorithm which heavily relies upon the gbest possible solution for the convergence similar to BABC may exhibit superior convergence on benchmark functions. However, the performance of such algorithm deteriorates on real world applications.

From the presented plots of convergence rates, it can be deduced that EABC optimization algorithm has resulted in the best convergence on all the fitness functions. On f_3, f_4 and f_5, EABC has successfully averted local optima traps where other algorithms could not converge beyond a certain level. It shows that EABC algorithm is an appropriately balanced algorithm in terms of exploration and exploitation.

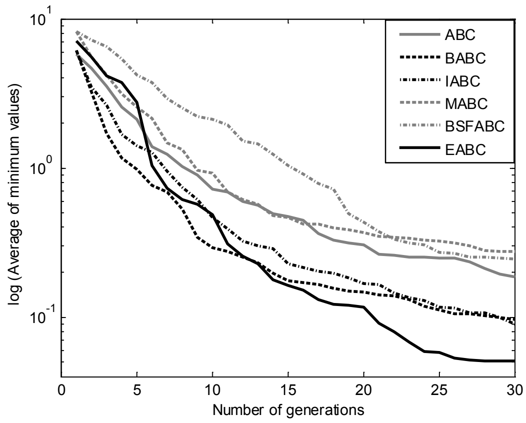

Figure 3. Convergence rates of the algorithms on f_1.

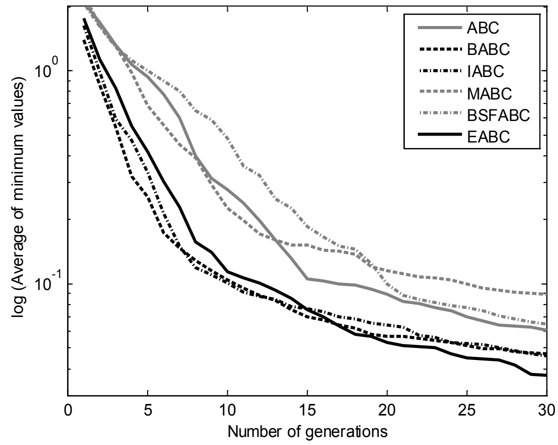

Figure 4. Convergence rates of the algorithms on f_2.

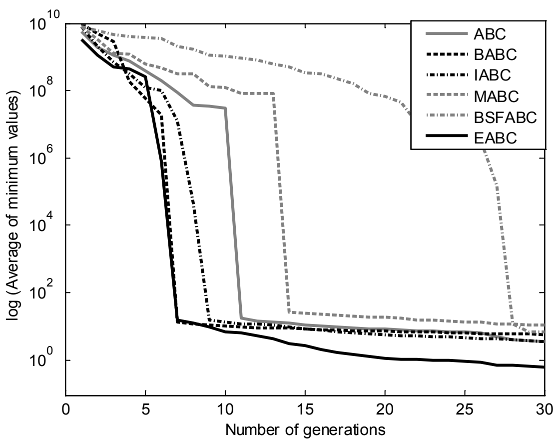

Figure 5. Convergence rates of the algorithms on f_3.

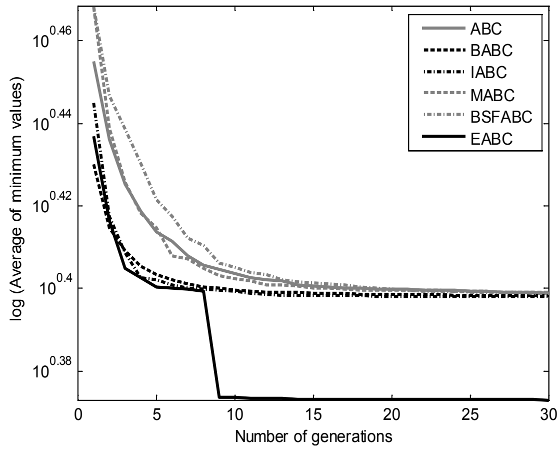

Figure 6. Convergence rates of the algorithms on f_4.

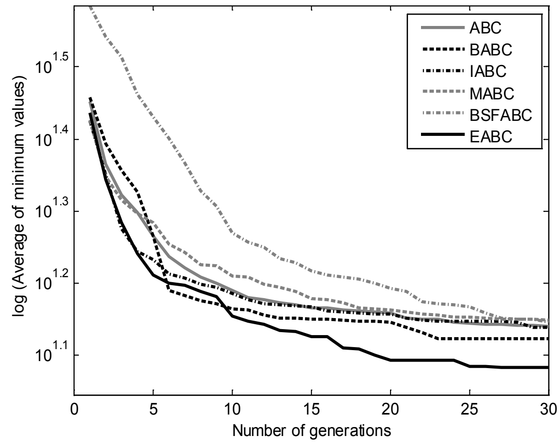

Figure 7. Convergence rates of the algorithms on f_5.

Table 3 presents the convergence results of the optimization algorithms on the fitness functions used to optimize PID-AVR model. The results prove that EABC algorithm has resulted in the least value of average convergence among all the optimization algorithms. Furthermore, EABC has also produced the least value of standard deviation on all the fitness functions. It shows that the algorithm is the most robust among the compared algorithms.

Table 3 also presents rank of the algorithms on each fitness function. The table gives overall rank of every algorithm at the end. The presented results suggest that BSFABC algorithm has performed better than MABC algorithm. Moreover, the standard ABC algorithm has performed better than MABC and BSFABC algorithms. Between IABC and BABC algorithms, IABC algorithm has performed marginally better than BABC algorithm. Among the existing ABC variants, GABC algorithm has exhibited the best convergence results. Moreover, the proposed algorithm has outperformed all the compared optimization algorithms in optimizing PID-AVR controller mounted on synchronous generator. This shows that EABC algorithm possesses well balanced exploration and exploitation capabilities among compared ABC variants.

Table 3 Convergence results of the optimization algorithms.

Label	Algorithm	Average	Std Deviation	Rank
f_1	**EABC**	**0.0506**	**0.0267**	**1**
	GABC	0.0586	0.0256	2
	IABC	0.0900	0.0599	3
	MABC	0.2745	0.1615	7
	BSFABC	0.2455	0.1524	6
	BABC	0.0972	0.1247	4
	ABC	0.1850	0.0732	5
f_2	**EABC**	**0.0371**	**0.0136**	**1**
	GABC	0.0388	0.0144	2
	IABC	0.0460	0.0159	3
	MABC	0.0898	0.0317	7
	BSFABC	0.0648	0.0262	6
	BABC	0.0473	0.0201	4
	ABC	0.0607	0.0228	5
f_3	**EABC**	**0.6935**	**0.8775**	**1**
	GABC	1.2499	1.6372	2
	IABC	3.4096	3.3025	3
	MABC	11.0155	9.5893	7
	BSFABC	6.6881	11.3777	6
	BABC	5.5139	7.7941	5
	ABC	3.5842	3.4841	4
f_4	**EABC**	**2.3841**	**0.2665**	**1**
	GABC	2.4190	0.3097	2
	IABC	2.5006	0.0009	3
	MABC	2.5063	0.0044	7
	BSFABC	2.5055	0.0111	5
	BABC	2.5022	0.0043	4
	ABC	2.5059	0.0146	6
f_5	**EABC**	**12.1103**	**2.6303**	**1**
	GABC	12.6085	2.8296	2
	IABC	13.7538	1.7386	4
	MABC	14.1060	1.8577	7
	BSFABC	14.0094	2.4470	6
	BABC	13.2784	2.4697	3
	ABC	13.8078	1.7273	5
Overall Rank of Algorithms		**EABC**	**5**	
		GABC	10	
		IABC	16	
		MABC	35	
		BSFABC	29	
		BABC	20	
		ABC	25	

VI. Performance Analysis of Optimized PID-AVR

In this section, the PID gains yielding the least fitness function value among thirty runs have been taken for comparing the performance of optimized PID-AVR. PID gains yielding the least value are called the best convergence. Hence, this section compares the performance of the best convergence of each algorithm on each fitness function. Performance of PID-AVR gains, optimized using different algorithms, has been analyzed using time-domain analysis. Time-domain analysis considers four different parameters for assessing the performance of the controller i.e. rise-time (*RT*), settling-time (*ST*), overshoot (O_{sh}) and steady-state-error (*SSE*). The terms are defined below;

1. *Rise-time*: The time required to increase the value from 10% to 90% of final value.
2. *Settling-time*: The time required to damp out oscillations with 2% or 5% of final value. In this research work 2% of oscillations have been considered to calculate settling time.
3. *Overshoot*: The amount of system output response proceed beyond the desired response. Normally overshoot is given in percentage values.
4. *Steady State Error*: The difference between output value and real output at final time. Steady-state-error in this research work has been calculated at ten seconds.

Table 4 gives the time-domain-analysis results obtained using all the considered optimization algorithms. On f_4 MABC has resulted in the best optimized PID-AVR. However, on the rest of the fitness-functions, MABC has failed to produce even satisfactory PID-AVR gains. Moreover, the average convergence shown in Figure 7 is considerably inferior to EABC algorithm. The proposed algorithm (EABC) has yielded satisfactory results on f_4 whereas on the rest of the fitness-functions, EABC has produced the best response among all the compared algorithms.

Table 4 Time domain analysis results of PID-AVR model.

Label	Algorithm	RT	ST	O_{Sh}	SSE
f_1	**EABC**	**0.3131**	**0.4917**	**0**	**1.65E-07**
	IABC	0.3436	0.5372	0	7.05E-07
	MABC	0.4967	0.7943	0	1.98E-05
	BSFABC	0.3486	0.5520	0	5.75E-07
	BABC	0.3225	0.5019	0	8.00E-07
	ABC	0.4246	0.7041	0	3.48E-06
f_2	**EABC**	**0.3178**	**0.5001**	**0**	**5.51E-07**
	IABC	0.3284	0.5108	0	4.86E-07
	MABC	0.4138	0.6742	0	8.41E-06
	BSFABC	0.3497	0.5525	0	5.36E-07
	BABC	0.3253	0.5058	0	8.01E-07
	ABC	0.3481	0.5526	0	4.43E-07
f_3	**EABC**	**0.3242**	**0.5102**	**0**	**3.26E-07**
	IABC	0.3792	0.6098	0	4.96E-06
	MABC	0.5314	1.0017	0	3.08E-05
	BSFABC	0.4111	0.6619	0	1.47E-05
	BABC	0.3241	0.5138	0	6.96E-07
	ABC	0.4464	0.7097	0	4.43E-05
f_4	**EABC**	**0.1124**	**0.7733**	**21.2852**	**4.94E-07**

	IABC	0.0958	0.945	28.448	3.85E-06
	MABC	**0.1227**	**0.7099**	**23.7873**	**2.51E-07**
	BSFABC	0.0964	0.948	27.9845	4.79E-06
	BABC	0.0956	0.9504	28.4668	3.12E-06
	ABC	0.0961	0.9496	28.3742	2.91E-06
f_5	**EABC**	**0.1193**	**0.7007**	**17.0385**	**3.63E-07**
	IABC	0.1308	0.7314	24.052	9.20E-08
	MABC	0.1495	0.7832	22.5297	2.02E-08
	BSFABC	0.1354	0.7472	22.6767	1.07E-07
	BABC	0.1884	0.9189	10.4254	4.14E-07
	ABC	0.1227	0.7115	23.1991	3.32E-07

VII. Conclusion

This research work has compared the performance of six variants of ABC optimization algorithm on PID-AVR model optimization. The performance of the algorithms has been evaluated on five different fitness functions. PID-AVR model and the fitness functions have been adapted from research works published in reputable journals. The performance analysis reveals that BSFABC and MABC algorithms have produced inferior average convergence than the standard ABC algorithm. BABC and IABC are prone to local optima traps, as the algorithms have initially shown better convergence on *f1* and *f2* but could not converge more on the functions. Moreover, on the other fitness functions BABC and IABC algorithms could not exhibit superior convergence. On the other hand, EABC algorithm which was proposed by the authors in reference [25] has shown superior convergence on all the fitness functions. This shows that the algorithm possesses properly balanced exploration and exploitation capabilities. Proper balancing of the capabilities is the prime condition for an optimization to yield equally-well performance over a wide range of optimization problems.

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