Enhanced ABC Variant (JA-ABC4) in Optimizing Economic Environmental Dispatch (EED)

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Abstract: - Artificial bee colony (ABC) optimization algorithm has been successfully applied to solve various optimization problems. ABC is a kind of bio-inspired algorithm (BIAs) that has attracted the attention of optimization researchers. ABC imitates the foraging behaviour of honeybees, thus it can be classified into swarm-intelligence-based (SI) algorithm; one of the prominent classes in BIAs. ABC has shown tremendous results in comparison with other optimization algorithms such as Genetic Algorithm (GA), Differential Evolution (DE) algorithm and Particle Swarm Optimization (PSO) algorithm. Moreover, the advantages of ABC include it is simple and flexible. Despite of these advantages, ABC has been found to be trapped in local optima on multimodal functions and exhibited slow convergence speed on unimodal functions. Motivated by these, researchers have proposed various ABC variants but none of them are able to solve both problems simultaneously. Thus, this paper proposes a new modified ABC algorithm referred to as JA-ABC4 with the objectives to robustly find global optimum and enhance convergence speed. The proposed algorithm has been compared with the standard ABC and other existing ABC variants on twenty-four commonly used benchmarks functions. The performance results have shown that the proposed algorithm has yielded the best performance compared to the standard ABC and two other good ABC variants (BABC1 and IABC) in terms of convergence speed and global minimum achievement. For further justification, JA-ABC4 has been tested to optimize economic environmental dispatch (EED) on 10-unit generator system. The results obtained have also illustrated the robust performance of JA-ABC4 in solving complex real-world problems.

Key-Words: - Artificial bee colony, swarm-intelligence-based algorithm, convergence speed, economic environmental dispatch

1 Introduction

Inspired by the behaviours of nature, bio-inspired algorithms (BIAs) have been applied to solve various optimization problems as shown by works of [1-4]. BIAs are metaheuristic method that has promising results in solving those problems [5]. They have been implemented to overcome the problems of high computational cost and premature convergence tendency faced by numerical methods have faced [3].

BIAs basically consist of several classes and among the most prominent classes are swarm-intelligence-based (SI) algorithms. SI algorithms such as Ant Colony Optimization (ACO) algorithm [6] and Particle Swarm Optimization (PSO) algorithm [7] have been found to show tremendous performance in solving various problems such as the travelling salesman problem [8], power loss minimization [9], voltage profile improvement [10], environmental economic dispatch [11, 12], stability enhancement for multi-machine power system [13] and many more. One SI method that has recently attracted the attention of optimization researchers is Artificial Bee Colony (ABC) algorithm.

ABC was proposed by Karaboga in 2005 [14]. It is a computational method inspired from the foraging behaviour of honeybees [15]. Many optimization researchers show their interest in this algorithm because it has shown efficiency in solving various optimization problems as well as demonstrated excellent performance in comparison with other prominent optimization algorithms such as Genetic Algorithm (GA), Differential Evolution (DE), Particle Swarm Optimization (PSO) algorithms and few others [15-17]. Apart from that, tuning of its control parameters is easy and the implementation of its algorithm is simple and flexible [15].

In spite of its excellence in performance, it actually suffers from few limitations. Among the main limitations are premature convergence tendency on multimodal functions due to local minima trappings and slow convergence speed on unimodal functions [18, 19]. ABC is known to be good in exploration but poor in exploitation. In addition, it portrays extreme self-reinforcement that made ABC has less capabilities in exploitation. Hence, many researchers have come out with the proposal of various ABC variants [18-24] with the aims to solve these problems. However, none of them are able to solve all the problems simultaneously [18, 19, 21]. This is due to the difficulties in balancing exploration and exploitation processes for the algorithm to perform well and maintain its robustness [22-24]. Thus, this work proposes a modified ABC variant named JA-ABC4. Few modifications have been done to the standard ABC algorithm to balance out the exploration and exploitation capabilities of the algorithm. The effects are for the algorithm to persistently avoid local optima trapping and show faster convergence speed, simultaneously.

Economic environmental dispatch (EED) is one of the crucial power systems-based problems that need to be solved as it is related to the emission of toxic gases from fossil fuels as a result of combustion of fossil fuels during electricity generation. The effects of combustion fossil fuels create the worst pollution in major cities; dying forest, increase in global temperature due to excessive carbon dioxide (CO_2) release into the atmosphere and emission of acidic gases such as sulfur oxides (SO_x), nitrogen oxides (NO_x) as well as carbon dioxide (CO_2). The emission of toxic gases into the atmosphere has become a concern to many people due to its hazardous effects. Thus, an efficient solution is vital to solve the matter [25-27].

Basically, EED serves to determine the committed generating units in order to meet the demand while utilizing minimum operating cost and emitting minimum toxic gases. All the matters above are subjected to the system constraints such as power balance and active power lower and upper limit [26, 27]. EED is known to be a constrained-based multi-objective problem [11]. Moreover, the objectives of the problem are contradicted to each other, making the problem to be complex and hard to solve.

In the effort to solve it, researchers have used various types of techniques such as goal-programming techniques [28], multi-objective differential evolution [11] and many more. Nonetheless, most the techniques have evaluated the objectives individually, which required assumption to be made [29]. Although there are techniques that evaluated EED as multiobjective problem, but there are actually found to be computationally intensive and time consuming [11, 30].

2 Artificial Bee Colony

2.1 Standard ABC algorithm

ABC algorithm is a population-based optimization algorithm. Thus, it has three performance-deciding phases to complete each generation. These phases are phases where the population of the bees are interacting with each other. They are employed-bees, onlooker-bees and scout-bee phases. The standard algorithm starts when the employed-bees have been randomly assigned with food sources available around the hive or search-space. Food sources represent the possible solution for the problems. Then, the nectar-amount of food sources which is the fitness of the possible solution is being calculated. After that, employed-bees explore the neighbourhood of food sources associated to it and update its food source using mutation equation or solution search equation given as:

$$z_{ij} = y_i + \phi(y_{ij} - y_{kj}) \tag{1}$$

where z_{ij} represents the candidate solution of *i*-th food source with *j*-th dimension. y_{ij} is *j*-th dimension of *i*-th food source and y_{kj} represents *j*-th dimension of *k*-th food source. Subscripts i and k are the mutually exclusive food sources, $j \in [1,2,\ldots D]$ and D is the dimension of search space. Subscripts j and k are randomly chosen numbers and ϕ is a random number within [-1,1]. The equation directs the interaction among the possible solutions which results in a new possible solution called candidate solution. This candidate solution will be evaluated together with the old possible solution using greedy-selection mechanism, which selects the fitter possible solution between the candidate solution and the old possible solution. Once the fitter possible solution has been chosen, the employed-bees associated with this potentially fitter possible solution share it with the onlooker-bees, in the onlooker-bees phase. Onlooker-bees use fitness-proportion selection scheme in choosing the possible solutions to be updated. The action of onlooker-bees is also dependent upon the probability value, *P*i:

$$P_i = fit_i / \sum_{i=1}^{SN} fit_i \qquad (2)$$

where P_i is the probability of *i*-th food source, fit_i is the fitness value of *i*-th food sources and *SN* represents the number of food sources. Then, the onlooker-bees explore the neighborhood of the selected-possible solution and update it using equation (1). Later, greedy-selection mechanism is applied to choose fitter possible solutions. Finally, in scout-bee phase, the possible solution which has become exhausted and can no longer be improved over a user-defined control parameter *limit* [22] will be abandoned [24]. The employed-bees associated with this possible solution will become scout-bees and will take subsequent flight to discover a new possible solution to replace the abandoned possible solution. This is done by randomly searching the search space [12] using the equation:

$$y_i^j = y_{\min}^j + rand(0,1)(y_{\max}^j - y_{\min}^j) \qquad (3)$$

where y^j_{min} and y^j_{max} is the lower and upper limit of the search space, respectively. *rand (0, 1)* is a function which randomly generates numbers within [0,1]. More details of ABC can be found in [15].

The standard ABC algorithm is known to be good in exploration but poor in exploitation [19, 22-24] resulting the inefficiency of ABC to solve premature convergence tendency and slow convergence speed problems.

2.2 ABC Variants

G-best guided ABC (GABC) algorithm has been proposed by Zhu and Kwong in 2010 [24]. It uses the information of global best possible solution (g-best) in the solution search equation. Thus, it has the capability to improve exploitation. The proposed solution search equation has enhanced the exploitation of the algorithm by driving the candidate solution towards a global best solution. Hence, the candidate solution becomes fitter with each generation. Nevertheless, the algorithm has been found to be slow in convergence rates [19].

Best-so-far ABC (BsfABC) algorithm has been proposed by Banharnsakun *et al.* in 2011 [20]. It has incorporated new solution search equation for the onlooker-bees to improve convergence rate and increase the performance of the algorithm. Nevertheless, it seems to be computationally intensive and the solution search utilized during onlooker bee phase is found to be local in nature. Thus, the possibility to be trapped into local optima is high. This has made BsfABC insufficient in solving complex optimization problems [18, 19].

Improved ABC (IABC) algorithm has been introduced by Gao and Liu in 2011 [21]. Two improved solution search equations have been proposed in this work together with the chaotic systems and the opposition-based learning method during initialization. Besides that, parameter *p* has been introduced to control the emergence of both solution search equations. Nonetheless, this variant is actually poor in exploitation. This is proven when the algorithm is not capable in dealing with Rosenbrock function [21].

Gao *et al.* [22] have recommended global best ABC (BABC) in 2012. They have incorporated new modified solution search equation into the standard ABC to replace the old one, creating two BABC algorithms named BABC1 and BABC2. The solution search equation for BABC1 has driven the new solution around the best solution while the solution search equation of BABC2 explores the search space randomly around the best solution. However, the algorithm has suffered from insufficient in exploration. This limitation leads the variant to premature convergence when solving complex multimodal optimization problems [19].

Enhanced ABC (EABC) has been recommended by Abro and Mohamad-Saleh in 2013 [31]. They introduced new mutation equations during employed, onlooker and scout-bees phases. The proposed mutation equation has been enhanced so that it is balanced in exploration and exploitation capabilities. Besides, a novel Elite-update (EU) stage with the aims to enhance the fitness of the selected gbest possible solution has been proposed. However, they algorithm might suffer from slow convergence speed [32].

An analysis has been carried out and the results have shown that IABC, EABC and BABC1 exhibit the best performances among all. Thus, these three have been chosen as the compared algorithms in this work.

Although the above-mentioned variants aim to overcome these, they are actually not capable to solve the limitations of standard ABC algorithm as discussed previously. Thus, this paper proposes a new ABC variant referred to as JA-ABC4 as the problem solver. This new ABC variant basically is the extension of the variant that has been proposed in the work of [33].

3 Enhanced ABC Variant (JA-ABC4)

The inefficiency of the standard ABC is due to equation (1) which directs the interaction between y_{ij} and y_{kj}. y_{ij} is the possible solution to be updated while y_{kj} is a random possible solution. It means that the random possible solution is being chosen regardless of its fitness value. Hence, in any case, if fitter random possible solution (y_{kj}) is selected, the candidate solution would be fitter as well. The problem arises when the equation simply chooses any poor possible solution for the interaction. The produced candidate solution would be dragged close to the poor possible solution. Hence, the candidate solution would be poor and drifted away from the global minimum.

To overcome the problem, this work has suggested modifications of the standard ABC algorithm. The modifications made are the highlighted steps in Fig. 1. The first step is inserting new stages before the employed-bee phase. These new stages have directed the algorithm to identify few poor possible solutions and then update the solution around global best (gbest) solution using the mutation equation inspired from [22]:

$$z_{ij} = y_{best,j} + \phi(y_{pj} - y_{kj}) \qquad (4)$$

where z_{ij} represents the candidate solution of *i*-th food source with j_{th} dimension. $y_{best,j}$ is the best food source, y_{pj} represents *j*-th dimension of *p*-th food source and is randomly chosen. Subscripts *i*, *k* and *p* are mutually exclusive food sources and the rest of the parameter are the same as equation (1).

Equation (4) generates candidate possible solution which is definitely fitter than the previous one and it substitutes the poor possible solution. This will create a fitter population since employed-bees and onlooker-bees would then update these fitter possible solutions in the next phases. Thus, the entire population becomes fitter yet diverse. By doing so, the convergence speed of the algorithm has been increased.

Since the population now is a fitter population it means that the solution space becomes more complex and hence, there is a possibility for the algorithm to be trapped in local optima. To avoid this, the mutation equation of the employed-bees in employed-bees phase is also modified. This modifications are inspired by the mutation equations found in [21] and [18]. The mutation equation of JA-ABC4 now becomes:

$$z_{ij} = y_{r1,j} + \phi(y_{r2,j} - y_{r3,j}) + \psi(y_{r4,j} - y_{best,j}) \qquad (5)$$

where $y_{r1,j}$, $y_{r2,j}$, $y_{r3,j}$ and $y_{r4,j}$ are *r1, r2, r3* and *r4-th* food sources with j_{th} dimension. Subscripts *r1, r2, r3* and *r4* refer to the mutually exclusive food sources, Ψ is a random number within [0,T], where

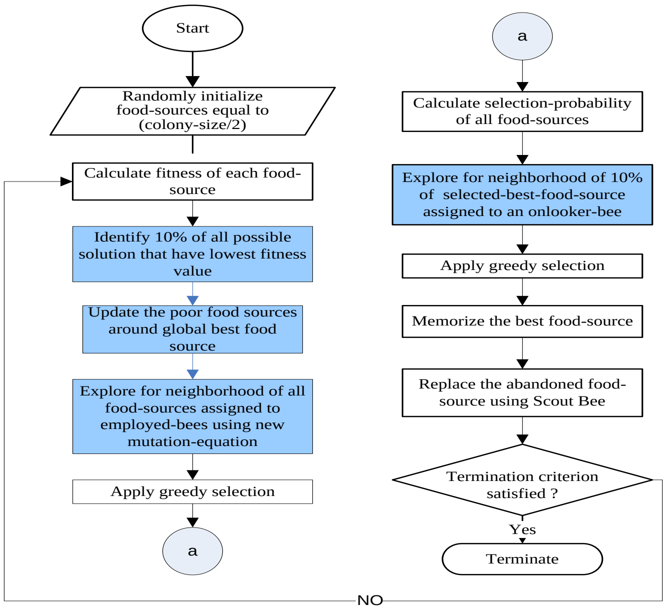

Fig. 1 The flowchart of JA-ABC4

T is a user defined number and the rest of the parameter are the same as equations (1) and (4).

The first two terms of equation (5) are inspired from the equation proposed in [21]. This equation aims to enhance the exploration capabilities of the algorithm as the equation is known for its randomness [21]. Thus, this will cater the possibility for premature convergence tendency of the algorithm. The last term of the equation targets to balance out the exploration and exploitation capabilities of the algorithm [31]. The overall equation simultaneously exhibits faster convergence speed as well as efficient local minima avoidance.

The next modification is to make sure that the overall algorithm demonstrates balanced exploration and exploitation capabilities. This is done by directing the onlooker-bees to update only few (10%) most-fit selected-possible solutions. With only few possible solutions to be updated, the exploitation capability of onlooker-bees has been enhanced and the algorithm is expected to converge faster.

4 Economic Environmental Dispatch (EED)

Economic environmental dispatch (EED) is a multi-objective optimization problem with targets to minimize operating cost of electricity generation and emit minimum amount of toxic gases to the atmosphere [11]. The general mathematical formulation of a multi-objective problem can be written as follow:

$$\begin{aligned} &\text{Min} && (f(x)) \\ &\text{Such that} && g(x) = 0 \\ & && h(x) \leq 0 \end{aligned} \tag{6}$$

where $f(x)$ is the objective function to be minimized, $g(x)$ is the equality constraints and $h(x)$ is the inequality constraints.

Based on the EED objectives, the mathematical formulation of the multi-objectives; operating cost and toxic gases emission and the constraints are being formulated in the following subsection.

2.1 Cost

The mathematical formulation of the operating cost is as follows:

$$F_i(P_i) = \sum_{i=1}^{N} \left[a_i P_i + b_i P_i + c_i \right] \tag{7}$$

where P_i is the power generated by i-th generator unit, a_i, b_i and c_i are the cost coefficients of i-th generator unit and N is the total number of generator unit.

In this work, the effect of valve point is taken into consideration. Valve point effect occurs due to the wire drawing effects that happen when each of the steam admission valves starts to open. The result is a ripple that can cause the objective function to have higher order nonlinearity and become non-smooth [34]. In order to solve the valve point effect, the following equation is formulated:

$$F_i(P_i) = \sum [a_i P_i + b_i P_i + c_i + | d_i \sin\{e_i (P_i^{\min} - P_i)\} |] \tag{8}$$

where d_i and e_i are the fuel coefficients of i-th generator unit that show the valve point effect. The rest of the parameters are the same as equation (7).

2.2 Emission

The mathematical formulation of the toxic gases emission is as follows:

$$F_i(P_i) = \sum_{i=1}^{N} \left[\gamma_i P_i^2 + \beta_i P_i + \alpha_i + \left| \eta_i \exp(\delta_i P_i) \right| \right] \tag{9}$$

where P_i is the power generated by i-th generator unit, α_i, β_i, γ_i, δ_i and η_i are the emission coefficients of i-th generator unit and N is the total number of generator unit.

The abovementioned equation expressed the total summation of the toxic gases released by the generators. The gases such as sulfur oxides (SO_x), nitrogen oxides (NO_x) and carbon dioxide (CO_2) have caused harm to living this, thus need to be minimized.

2.1 Constraints

To minimize both cost and emission, the control variables of the system need to be optimized within their limits while satisfying the equality and inequality constraints. The control variables for EED problem are the power generated by each of the committed generator unit. Thus, the power generated need to satisfy the following constraints which are being presented in the following sub-subsection.

2.2.1 Equality constraint

The equality constraint of EED is active power balance. The active power balance stated that the total active power generated by the committed generating units must be balanced with the power demand and the active power losses of the transmission lines. The equation of the power balance is as follows:

$$\sum_{i=1}^{N} P_i - P_D - P_L = 0 \tag{10}$$

where P_i is the power generated by i-th generator unit, P_D is the active power demand and P_L is the transmission line losses. The rest of the parameters are the same as equation (7).

2.2.2 Inequality constraint

The inequality constraint of EED has limited the active power generated at each committed generating units within their upper and lower limit. The limit is as follows:

$$P_i^{\min} \leq P_i \leq P_i^{\max} \quad i = 1,\ldots,N \qquad (11)$$

where P_i^{min} is the lower limit of active power generated by ***i***-th generator unit, P_i^{max} is the upper limit of active power generated by ***i***-th generator unit and the rest of the parameters are similar to equation (7).

2.3 Penalty function

Penalty function is derived prior to converting multi-objective function with equality and inequality constraints to a single objective function. For that purpose, penalty terms have been added to the objective function and the final equation of the objective function in the form of penalty function is given as:

$$P(x) = \sum_{i=1}^{N} F_i(P_i) + \sum_{i=1}^{N} E_i(P_i) + K \times \left\{ (\sum_{i=1}^{N} P_i) - P_L - P_D \right\}^2$$

where F_i is the cost function, E_i is the emission function, P_i is the active power generated at *i*-th generator unit, K is the penalty term of the penalty function, P_L is the power losses of the transmission lines and P_D is the power demand.

5 Experimental Setup

The proposed algorithm, JA-ABC4 has been simulated on twenty-four commonly used benchmark functions as listed in Table 1. Its performance has been compared with the standard ABC (ABC) [15] and the best-performed ABC variants, i.e. global best ABC (BABC1) [22], enhanced global-best ABC (EBABC) improved ABC (IABC) [21] and.

The simulation and testing process have been done in Matlab 2010a programming language and Intel Core i7 CPU 2.80 GHz computer.

Table 1 Benchmark functions

Function	Function Name	Initialization Range
f1	Griewank	*±600*
f2	Rastrigin	*±15*
f3	Rosenbrock	*±15*
f4	RS Ackley	*±32*
f5	Schwefel	*±500*
f6	Himmelblau	*±600*
f7	RS Sphere	*±600*
f8	Step	*±600*
f9	Bohachevsky 2	*±100*
f0	RS Schwefel 2.22	*±100*
f11	RS Schwefel Ridges	*±100*
f12	RS Schwefel Ridges with Noise	*±15*
f13	RS Elliptic	*±100*
f14	Zekhelip	*±15*
f15	Non-continuos Rastrigin	*±15*
f16	Michalewicz	*0-180*
f17	First Expanded Function	*±15*
f18	Second Expanded Function	*±15*
f19	Third Expanded Function	*±15*
f20	Fourth Expanded Function	*±500*
f21	Fifth Expanded Function	*±100*
f22	Sixth Expanded Function	*±100*
f23	Seventh Expanded Function	*±15*
f24	Eighth Expanded Function	*±100*

For all algorithms, the dimension of the benchmark function has been set to 30, the population size has been set to 50, number of generation has been limited to 1000 and the parameter *limit* has been set as *D*×*SN*, where *D* represents the dimension of the search space and *SN* is the number of food sources. The *T-value* for JA-

ABC4 has been set to 0.5 [18] and the *p-value* of IABC has been set to 0.25 [21]. As for global solution validation, each of the compared algorithms including JA-ABC4 has been set to simulate for 30 times on each benchmark function [18]. All these values follow those used and recommended in the literature [15, 16, 18, 21-24].

For the purpose of optimizing the EED problem, 10-unit generator system has been used as the test system. The data for the test system can be found in [11]. For the comparison purpose, the performance of JA-ABC4 in solving EED problem has been compared with again two best-performed ABC variants; IABC and BABC1 as well as with other optimization algorithms available in the work of [11].

6 Results and Discussion

Figs. 2 to 9 show the performance results of the proposed algorithm, JA-ABC4 in comparison with the standard ABC and two best-performed ABC variants i.e. BABC1 and IABC.

The performance results have shown the superiority of JA-ABC4 compared to other algorithms in terms of convergence speed and global minimum. Figs. 3, 4 and 8 have depicted that the standard ABC and BABC1 have failed to reach the optimum solution on *f*2, *f*5 and *f*20. Although IABC did reach the global optimum on *f*2 and *f*20 but the convergence speed of JA-ABC4 is faster than IABC. Moreover, JA-ABC4 has efficiently reached global minimum for *f*5 whereas other algorithms have been trapped in local optima. Figs. 2, 4, 5, 6 7 and 9 show that JA-ABC4 exhibits faster convergence speed than other compared algorithms while the rest of the graphs have also illustrated the superb performance of JA-ABC4 compared to other algorithms in terms of convergence speed and avoiding local minima trapping.

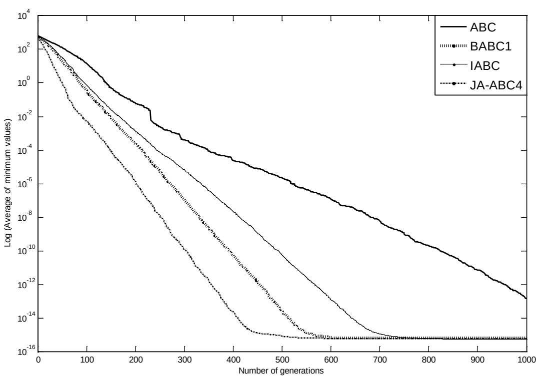

Fig. 2 Performance result of JA-ABC4 on *f*1

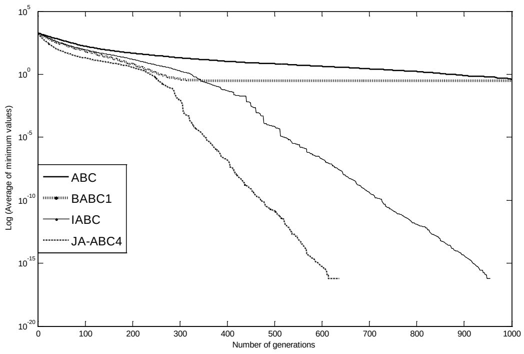

Fig.3 Performance result of JA-ABC4 on *f*2

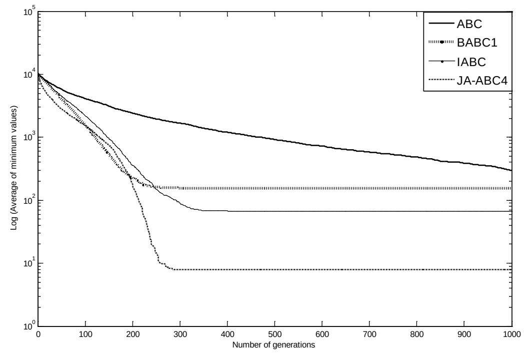

Fig.4 Performance result of JA-ABC4 on *f*5

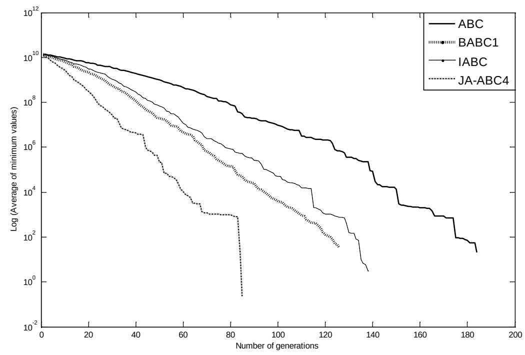

Fig.5 Performance result of JA-ABC4 on *f*6

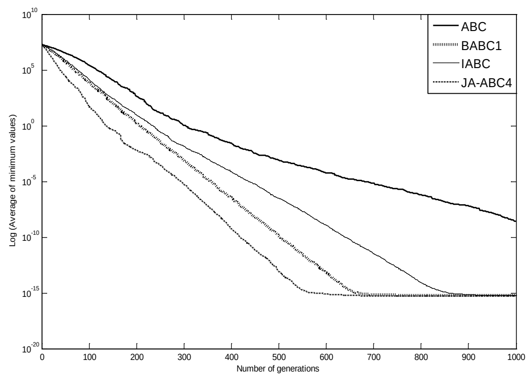

Fig.6 Performance result of JA-ABC4 on *f*11

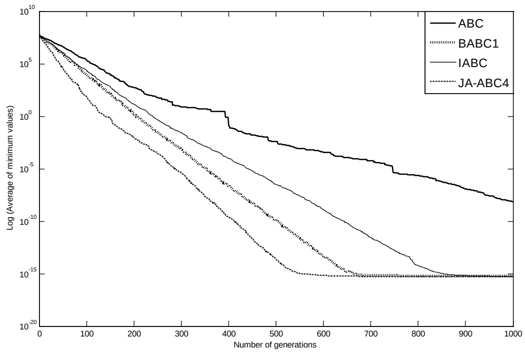

Fig.7 Performance result of JA-ABC4 on *f*13

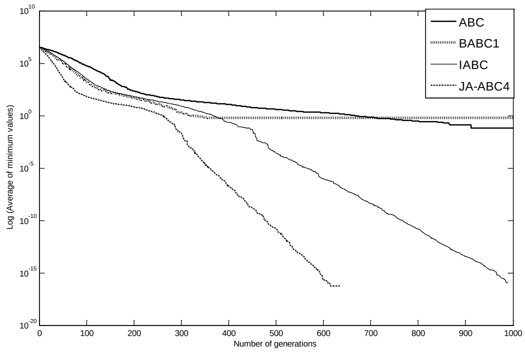

Fig.8 Performance result of JA-ABC4 on *f*20

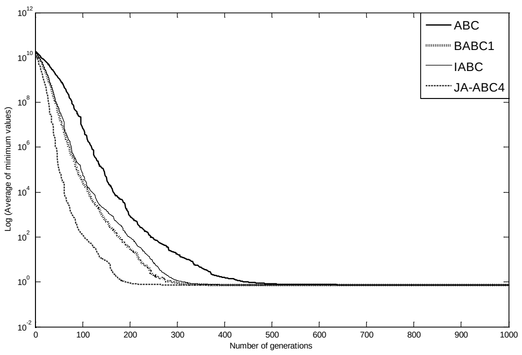

Fig.9 Performance result of JA-ABC4 on *f*24

Meanwhile, Table 2 shows the performance of the compared algorithms in minimizing operating cost and toxic gases emission. The optimum values of the each committed generating units have also been tabulated. The results have shown that JA-ABC4 performs better than the compared existing ABC variants.

Table 2 Performance results of compared ABC variants in minimizing EED on 10-unit generator system

Variables	Algorithms			
	ABC (MW)	IABC (MW)	BABC1 (MW)	**JA-ABC4** (MW)
P_{G1}	46.5130	50.1551	55.0000	55.0000
P_{G2}	80.0000	80.0000	79.4886	80.0000
P_{G3}	110.9106	118.2991	96.1012	119.0620
P_{G4}	111.7598	99.6486	102.3848	101.3351
P_{G5}	79.3592	109.5674	100.3286	82.1131
P_{G6}	113.7011	70.0000	90.6135	76.6806
P_{G7}	263.2133	294.8604	299.8829	300.0000
P_{G8}	340.0000	329.4802	339.9922	331.9996
P_{G9}	470.0000	470.0000	470.0000	470.0000
P_{G10}	470.0000	463.6977	451.8173	470.0000
EED (105)($(lb))	1.1737	1.1693	1.1686	**1.1677**

In the meantime, Table 3 has been presented to show the performance of JA-ABC4 in comparison with other optimization algorithms which are multi-objective differential evolution (MODE), pareto differential evolution (PDE), nondominated sorting genetic algorithm-II (NSGA-II) and strength pareto evolutionary algorithm 2 (SPEA2) algorithms. The results have clearly depicted that JA-ABC4 requires least amount of operating cost and emits least toxic gases in comparison with other ABC variant and optimization algorithms.

Table 3 Performance results of compared optimization algorithms in minimizing EED on 10-unit generator system

Algorithm	EED (10^5)($(lb))
MODE	1.1760
PDE	1.1762
NSGA-II	1.1767
SPEA2	1.1763
ABC	1.1737
IABC	1.1693
BABC1	1.1686
JA-ABC4	**1.1677**

Thus, from the performance results that have been illustrated by the graphs and the tables, they have vividly proved that the proposed ABC algorithm, JA-ABC4 is the reliable optimization algorithm to solve any other complex optimization problems.

7 Conclusion

This paper proposes JA-ABC4, a new ABC variant with the objectives to enhance the performance of ABC algorithm in terms of avoiding premature convergence and improving the convergence speed. Modifications were made to the standard ABC algorithm, producing JA-ABC4 which has balanced exploration and exploitation capabilities leading to better convergence and local trap avoidance. This is proved as the performance results obtained clearly exhibited the excellent performance of the JA-ABC4 as compared to others on various commonly used benchmark functions.

The performance proposed algorithm is further analyzed by implementing it to optimize economic environmental dispatch (EED) problem. JA-ABC4 has shown tremendous results in solving this complex real-world problem. Hence, this has suggested that the proposed algorithm is a robust optimization algorithm which has exhibited the ability to solve complex optimization problems.

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References:

[1] Y. Hendrawan and H. Murase, "Bio-inspired feature selection to select informative image features for determining water content of cultured Sunagoke moss," *Expert Systems with Applications,* vol. 38, pp. 14321-14335, 2011.

[2] H. A. Kurid, T. S. Alnusairi, and H. S. Almujahed, "OBAME: Optimized Bio-inspired Algorithm to Maximize Search Efficiency in P2P Databases," *Procedia Computer Science,* vol. 21, pp. 60-67, 2013.

[3] M. Rocha, R. Mendes, O. Rocha, I. Rocha, and E. C. Ferreira, "Optimization of fed-batch fermentation processes with bio-inspired algorithms," *Expert Systems with Applications,* vol. 41, pp. 2186-2195, 2014.

[4] B. B. Youssef, "Parallelization of a Bio-inspired Computational Model for the Simulation of 3-D Multicellular Tissue Growth," *Procedia Computer Science,* vol. 20, pp. 391-398, 2013.

[5] S. Binitha and S. S. Sathya, "A Survey of Bio inspired Optimization Algorithms," *International Journal of Soft Computing and Engineering (IJSCE), ISSN,* pp. 2231-2307, 2012.

[6] M. Dorigo, V. Maniezzo, and A. Colorni, "Ant system: optimization by a colony of cooperating agents," *Systems, Man, and Cybernetics, Part B: Cybernetics, IEEE Transactions on,* vol. 26, pp. 29-41, 1996.

[7] J. Kennedy and R. Eberhart, "Particle swarm optimization," in *Neural Networks, 1995. Proceedings., IEEE International Conference on*, 1995, pp. 1942-1948 vol.4.

[8] C. Ding, Y. Cheng, and M. He, "Two-level genetic algorithm for clustered traveling salesman problem with application in large-scale TSPs," *Tsinghua Science and Technology,* vol. 12, pp. 459-465, 2007.

[9] H. Tehzeeb-Ul-Hassan, R. Zafar, S. A. Mohsin, and O. Lateef, "Reduction in power transmission loss using fully informed particle swarm optimization," *International Journal of Electrical Power & Energy Systems,* vol. 43, pp. 364-368, 2012.

[10] I. Musirin, N. D. M. Radzi, M. M. Othman, M. K. Idris, and T. K. A. Rahman, "Voltage Profile Improvement Using Unified Power Flow Controller via Artificial Immune System," *WSEAS Transaction on Power Systems,* vol. 3, pp. 194-204, 2008.

[11] M. Basu, "Economic environmental dispatch using multi-objective differential evolution," *Applied Soft Computing,* vol. 11, pp. 2845-2853, 2011.

[12] K. S. Kumar, V. Tamilselvan, N. Murali, R. Rajaram, N. S. Sundaram, and T. Jayabarathi, "Economic Load Dispatch with Emission Constraints using Various PSO

Algorithms," *WSEAS Transaction on Power Systems,* vol. 3, pp. 598-607, 2008.

[13] A. Oonsivilai and B. Marungsri, "Stability Enhancement for Multi-machine Power System by Optimal PID Tuning of Power System Stabilizer using Particle Swarm Optimization," *WSEAS Transaction on Power Systems,* vol. 3, pp. 465-474, 2008.

[14] D. Karaboga, "An Idea Based on Honey Bee Swarm For Numerical Optimization," *Technical Report-TR06,* 2005.

[15] D. Karaboga and B. Akay, "A comparative study of Artificial Bee Colony algorithm," *Applied Mathematics and Computation,* vol. 214, pp. 108-132, 2009.

[16] D. Karaboga and B. Basturk, "A powerful and efficient algorithm for numerical function optimization: artificial bee colony (ABC) algorithm," *Journal of Global Optimization,* vol. 39, pp. 459-471, 2007/11/01 2007.

[17] D. Karaboga and B. Basturk, "On the performance of artificial bee colony (ABC) algorithm," *Applied Soft Computing,* vol. 8, pp. 687-697, 2008.

[18] A. G. Abro and J. Mohamad-Saleh, "Enhanced Global-Best Artificial Bee Colony Optimization Algorithm," in *Computer Modeling and Simulation (EMS), 2012 Sixth UKSim/AMSS European Symposium on,* 2012, pp. 95-100.

[19] A. G. Abro and J. Mohamad-Saleh, *An Enhanced Artificial Bee Colony Optimization Algorithm*: WSEAS Press, 2012.

[20] A. Banharnsakun, T. Achalakul, and B. Sirinaovakul, "The best-so-far selection in Artificial Bee Colony algorithm," *Applied Soft Computing,* vol. 11, pp. 2888-2901, 2011.

[21] W. Gao and S. Liu, "Improved artificial bee colony algorithm for global optimization," *Information Processing Letters,* vol. 111, pp. 871-882, 2011.

[22] W. Gao, S. Liu, and L. Huang, "A global best artificial bee colony algorithm for global optimization," *Journal of Computational and Applied Mathematics,* vol. 236, pp. 2741-2753, 2012.

[23] W.-f. Gao and S.-y. Liu, "A modified artificial bee colony algorithm," *Computers & Operations Research,* vol. 39, pp. 687-697, 2012.

[24] G. Zhu and S. Kwong, "Gbest-guided artificial bee colony algorithm for numerical function optimization," *Applied Mathematics and Computation,* vol. 217, pp. 3166-3173, 2010.

[25] P. Breeze, *Power Generation Technologies*: Elsevier Science, 2005.

[26] C. Po-Hung and C. Hong-Chan, "Large-scale economic dispatch by genetic algorithm," *Power Systems, IEEE Transactions on,* vol. 10, pp. 1919-1926, 1995.

[27] N. Sinha, R. Chakrabarti, and P. K. Chattopadhyay, "Evolutionary programming techniques for economic load dispatch," *Evolutionary Computation, IEEE Transactions on,* vol. 7, pp. 83-94, 2003.

[28] J. Nanda, D. P. Kothari, and K. S. Lingamurthy, "Economic-emission load dispatch through goal programming techniques," *Energy Conversion, IEEE Transactions on,* vol. 3, pp. 26-32, 1988.

[29] A. Farag, S. Al-Baiyat, and T. C. Cheng, "Economic load dispatch multiobjective optimization procedures using linear programming techniques," *Power Systems, IEEE Transactions on,* vol. 10, pp. 731-738, 1995.

[30] D. B. Das and C. Patvardhan, "New multi-objective stochastic search technique for economic load dispatch," *Generation, Transmission and Distribution, IEE Proceedings-,* vol. 145, pp. 747-752, 1998.

[31] A. G. Abro, "Performance Enhancement of Artificial Bee Colony Optimization Algorithm," in *School of Electrical &*

Electronic Engineering. vol. PhD Nibong-Tebal: Universiti Sains Malaysia, 2013.

[32] N. Sulaiman, J. Mohamad-Saleh, and A. G. ABRO, "A Modified Artificial Bee Colony (JA-ABC) Optimization Algorithm," in *Proceedings of the International Conference on Applied Mathematics and Computational Methods in Engineering*, Rhodes Island, Greece, 2013, pp. 74-79.

[33] S. Noorazliza, M.-S. Junita, and A. G. Abro, "A Modified Artificial Bee Colony (JA-ABC) Optimization Algorithm," in *Proceedings of the International Conference on Applied Mathematics and Computational Methods in Engineering*, Rhodes Island, Greece, 2013, pp. 74-79.

[34] L. d. S. Coelho and V. C. Mariani, "An efficient cultural self-organizing migrating strategy for economic dispatch optimization with valve-point effect," *Energy Conversion and Management*, vol. 51, pp. 2580-2587, 2010.