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

NOORAZLIZA SULAIMAN¹, JUNITA MOHAMAD-SALEH²*, ABDUL GHANI ABRO³
¹,²School of Electrical & Electrical Engineering
Universiti Sains Malaysia
Nibong-Tebal, Penang
MALAYSIA
³College of Engineering
King Saud University Al Muzahimiyah Campus
Riyadh, Saudi Arabia
noorazlizasulaiman@gmail.com, jms@usm.my*, ghaniabro@gmail.com

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)
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:

$$z_{ij} = y_{ij} + \phi(y_{ij} - y_{kj})$$  \hspace{1cm} (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 $\phi$ 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, $P_i$:

$$P_i = \frac{fit_i}{\sum_{j=1}^{SN} fit_j}$$ (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:

$$y'_i = y'_{\text{min}} + \text{rand}(0,1)(y'_{\text{max}} - y'_{\text{min}})$$ (3)

where $y'_{\text{min}}$ and $y'_{\text{max}}$ is the lower and upper limit of the search space, respectively. $\text{rand}(0, 1)$ 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 Gao and Liu in 2011 [21]. It uses a modified solution search equation 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 \(y_{ik}\) and \(y_{kj}\). \(y_{ik}\) 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]:

\[
z_{ij} = y_{best,j} + \phi(y_{pj} - y_{kj})
\]  

(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 will 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:

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

(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, \(\Psi\) is a random number within \([0,T]\), where

\(T\) 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:

\[
\begin{align*}
\text{Min} & \quad f(x) \\
\text{Such that} & \quad g(x) = 0 \\
& \quad h(x) \leq 0
\end{align*}
\]  

(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:

\[
F_i(P_i) = \sum_{i=1}^{N} \left[ \alpha_i P_i^2 + \beta_i P_i + \gamma_i \right]
\]  

(7)

where \(P_i\) is the power generated by \(i\)-th generator unit, \(\alpha_i\), \(\beta_i\) and \(\gamma_i\) 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:

\[
F_i(P_i) = \sum_{i=1}^{N} \left[ \alpha_i P_i^2 + \beta_i P_i + \gamma_i + d_i \sin\{e_i(P_i^{\text{min}} - P_i)\} \right]
\]  

(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:

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

(9)

where \(P_i\) is the power generated by \(i\)-th generator unit, \(\alpha_i\), \(\beta_i\), \(\gamma_i\), \(\delta_i\) and \(\eta_i\) 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-section.

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:

\[
\sum_{i=1}^{N} P_i - P_D - P_L = 0
\]  

(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:

\[ P_{i}^{\text{min}} \leq P_i \leq P_{i}^{\text{max}} \quad i = 1, \ldots, N \quad (11) \]

where \( P_{i}^{\text{min}} \) is the lower limit of active power generated by \( i \)-th generator unit, \( P_{i}^{\text{max}} \) 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 (BABC) [22], enhanced global-best ABC (EBABC) and 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>
<thead>
<tr>
<th>Function</th>
<th>Function Name</th>
<th>Initialization Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>f1</td>
<td>Griewank</td>
<td>±600</td>
</tr>
<tr>
<td>f2</td>
<td>Rastrigin</td>
<td>±15</td>
</tr>
<tr>
<td>f3</td>
<td>Rosenbrock</td>
<td>±500</td>
</tr>
<tr>
<td>f4</td>
<td>RS Ackley</td>
<td>±32</td>
</tr>
<tr>
<td>f5</td>
<td>Schwefel</td>
<td>±600</td>
</tr>
<tr>
<td>f6</td>
<td>Himmelblau</td>
<td>±600</td>
</tr>
<tr>
<td>f7</td>
<td>RS Sphere</td>
<td>±600</td>
</tr>
<tr>
<td>f8</td>
<td>Step</td>
<td>±100</td>
</tr>
<tr>
<td>f9</td>
<td>Bohachevsky 2</td>
<td>±100</td>
</tr>
<tr>
<td>f10</td>
<td>RS Schwefel 2.22</td>
<td>±100</td>
</tr>
<tr>
<td>f11</td>
<td>RS Schwefel Ridges</td>
<td>±100</td>
</tr>
<tr>
<td>f12</td>
<td>RS Schwefel Ridges with Noise</td>
<td>±15</td>
</tr>
<tr>
<td>f13</td>
<td>RS Elliptic</td>
<td>±100</td>
</tr>
<tr>
<td>f14</td>
<td>Zekhelip</td>
<td>±15</td>
</tr>
<tr>
<td>f15</td>
<td>Non-continuos Rastrigin</td>
<td>±15</td>
</tr>
<tr>
<td>f16</td>
<td>Michalewicz</td>
<td>0-180</td>
</tr>
<tr>
<td>f17</td>
<td>First Expanded Function</td>
<td>±15</td>
</tr>
<tr>
<td>f18</td>
<td>Second Expanded Function</td>
<td>±15</td>
</tr>
<tr>
<td>f19</td>
<td>Third Expanded Function</td>
<td>±15</td>
</tr>
<tr>
<td>f20</td>
<td>Fourth Expanded Function</td>
<td>±15</td>
</tr>
<tr>
<td>f21</td>
<td>Fifth Expanded Function</td>
<td>±15</td>
</tr>
<tr>
<td>f22</td>
<td>Sixth Expanded Function</td>
<td>±15</td>
</tr>
<tr>
<td>f23</td>
<td>Seventh Expanded Function</td>
<td>±15</td>
</tr>
<tr>
<td>f24</td>
<td>Eighth Expanded Function</td>
<td>±100</td>
</tr>
</tbody>
</table>

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 \( D \times SN \), 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 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.
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

<table>
<thead>
<tr>
<th>Variables</th>
<th>Algorithms</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>ABC (MW)</td>
</tr>
<tr>
<td>P_{G1}</td>
<td>46.5130</td>
</tr>
<tr>
<td>P_{G2}</td>
<td>80.0000</td>
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<tr>
<td>P_{G3}</td>
<td>110.9106</td>
</tr>
<tr>
<td>P_{G4}</td>
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</tr>
<tr>
<td>P_{G5}</td>
<td>79.3592</td>
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<tr>
<td>P_{G6}</td>
<td>113.7011</td>
</tr>
<tr>
<td>P_{G7}</td>
<td>263.2133</td>
</tr>
<tr>
<td>P_{G8}</td>
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<td>P_{G9}</td>
<td>470.0000</td>
</tr>
<tr>
<td>P_{G10}</td>
<td>470.0000</td>
</tr>
</tbody>
</table>

EED (10^5)($/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

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>EED (10^5)($/lb))</th>
</tr>
</thead>
<tbody>
<tr>
<td>MODE</td>
<td>1.1760</td>
</tr>
<tr>
<td>PDE</td>
<td>1.1762</td>
</tr>
<tr>
<td>NSGA-II</td>
<td>1.1767</td>
</tr>
<tr>
<td>SPEA2</td>
<td>1.1763</td>
</tr>
<tr>
<td>ABC</td>
<td>1.1737</td>
</tr>
<tr>
<td>IABC</td>
<td>1.1693</td>
</tr>
<tr>
<td>BABC1</td>
<td>1.1686</td>
</tr>
<tr>
<td>JA-ABC4</td>
<td>1.1677</td>
</tr>
</tbody>
</table>
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.

Acknowledgments
The authors acknowledge the Ministry of Higher Education (MOHE) FRGS Grant No: 203/PELECT/6071371 and Universiti Sains Malaysia for the financial and facilities support.

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