Enhanced Hybrid XOR-based Artificial Bee Colony Using PSO Algorithm for Energy Efficient Binary Optimization

Yakubu S. Baguda†
ysoleman1@kau.edu.sa
Information Systems Department, Faculty of Computing and Information Technology,
King Abdulaziz University, Rabigh, Kingdom of Saudi Arabia.

Summary
Increase in computational cost and exhaustive search can lead to more complexity and computational energy. Thus, there is need for effective and efficient scheme to reduce the complexity to achieve optimal energy utilization. This will improve the energy efficiency and enhance the proficiency in terms of the resources needed to achieve convergence. This paper primarily focuses on the development of hybrid swarm intelligence scheme for reducing the computational complexity in binary optimization. In order to reduce the complexity, both artificial bee colony (ABC) and particle swarm optimization (PSO) have been employed to effectively minimize the exhaustive search and increase convergence. First, a new approach using ABC and PSO has been proposed and developed to solve the binary optimization problem. Second, the scout for good quality food sources is accomplished through the deployment of PSO in order to optimally search and explore the best source. Extensive experimental simulations conducted have demonstrate that the proposed scheme outperforms the ABC approaches for reducing complexity and energy consumption in terms of convergence, search and error minimization performance measures.

Key words: Swarm intelligence, artificial bee colony, binary optimization, PSO, convergence, computational complexity

1. Introduction

With increasing demand for energy efficient systems and applications to reduce computational cost and power consumption, highly efficient techniques are needed. Swarm intelligent optimization techniques have continued to play an important role in highly computational cost and efficient exhaustive search to determine optimal solution. This collective phenomenon of organisms has been applied in different fields and specializations – ranging from engineering to computing. The swarm intelligent algorithms can solve complex problems with high degree of precision and accuracy. This is mainly due to their simplicity, scalability, robustness and self-organization capability. It is very important to note that swarm intelligent optimization techniques are part of the intelligent optimization approaches [1] family, but can solve problems which are difficult to be solved by classical optimization techniques with relative ease and sophistication [2].

Several research works have demonstrated that by improving the searching and information exchange capability in ABC algorithm can yield better performance. In [3], a modified searching technique has been proposed in order to achieve best solution and optimal performance. The key fundamental problem of trapping into local optima should be avoided to effectively enhance the overall performance and exploitation capability of ABC. This eventually lead to the introduction of crossover operator in [4] to substantially improve the information exchange amongst the artificial bees while sharing information about forage. More importantly, [5] has demonstrated an improved version of ABC which primarily used local search. Ultimately, it has been reported in [6] that the forward neighborhood search technique can improve the ABC's searching capability.

Additionally, it is known fact that ABC is based on the swarm intelligent behavior of honey bees [7-9]. It has less parameters when compared to other algorithms and can be implemented easily [10]. It has been applicable in estimation and analysis fields. ABC optimization can anticipate problem of uneven distribution of initial solution as reported in [11-13]. This leads to instability and reduces the robustness of the algorithm. To tackle the aforementioned problem, there is need to enhance the global search, effective information exchange and avoiding trapping into local optima. Hybrid swarm intelligent algorithms and techniques to successfully accomplish the above mentioned primary goals.

Furthermore, it is observed that the basic ABC algorithm concept has its own drawback [14] – it requires more modification to efficiently tackle its exploration problem which hinders its performance. Therefore, several hybrid ABC algorithms have been proposed to tackle the aforementioned shortcomings. [15] has proposed a genetic selection searching approach which support ABC algorithm to solve dynamic clustering problem by automatically determining the number of clusters to enhance the searching

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capability. Maximum fitness was used in conjunction with global ABC search to accomplished optimal performance in [16]. A self-adaptive strategy has been used in [17] for generating the food resources to adapt with the discrete space. In [18], it clearly shows that improving the local search can lead to improvement in local exploration – hence the convergence speed can be varied using the control parameter. It has been demonstrated in [19] that the Hamiltonian path can be determine using combinatorial ABC algorithm at relatively low cost and high performance. A hybrid ABC algorithm which utilizes scale-free network to enhance the optimization performance and efficiency is reported in [20].

Recently, there has been a major concern on how to detail with complexity and reducing energy consumption in different areas. Reducing exhaustive search and fast convergence will reduce the complexity to minimum and enhance the overall performance. This paper proposes a new ABC base scheme which utilizes the PSO to reduce the exhaustive search in order to achieve optimal performance while solving binary optimization problems.

The rest of the paper is organized as follows. Section 2 will cover the concept of ABC and PSO. In section 3, the hybrid ABC-PSO algorithm and its improvement has been covered. Experimental simulation, comparison and discussion of the results of the proposed scheme are presented in Section 4. Finally, Section 5 concludes this paper and highlights the future works.

2. Artificial Bee Colony & Particle Swarm Optimization Review

2.1 Artificial Bee Colony

This section briefly introduces the basic concept of Artificial bee colony algorithm in order to have a clear understanding of its fundamental principle. ABC is swarm intelligent based algorithm which mimic the behavior of honey bees. Honey bees can collect nectar from different sources with high efficiency and perfection. More interestingly, the bees adapt with the changes in different environment and condition. Their ability to collect the nectar through division of labor with high coordination has made it a potential tool for solving optimization problems. Effective information sharing and cooperation amongst the honey bees is extremely important to the bee colony. ABC algorithm was developed in 2005 by Karabora. It has been designed primarily to solve numerical optimization problems. Also, ABC algorithm has been employed to solve multidimensional numerical problems. More importantly, this has led to the application of ABC in different fields and specialization.

Basically, ABC has employer and unemployed bees in which each perform a special task. The employer bees mainly search and measure the quality of the food sources – each employer bee is a potential food source. It searches for the good food sources near the original food sources. While the unemployed bees comprise of onlookers and scout bees. The onlooker bees primarily use the information provided by the employed bees to select the food sources. The scout bees are meant to search for new potential food source if certain food sources have not been considered as result of their low quality. These are the key fundamental steps for achieving optimal solution in ABC. It is very important to note that conducting these steps in an effective and efficient way can enhance the performance of the scheme especially reducing the exhaustive search and convergence time.

In addition, there is need to clearly express the aforementioned procedure mathematically for better understanding of the whole process. Let's assumed that the number of the sources is represented by **S**. The bee colony is search **N** rounds in order to determine the best source. As the bee colony is searched, the positions of the old sources have been replaced with new sources which are better than the previous sources. This process continuously selects best sources and discard the sources which are considered low nectar quality sources. Neighboring sources are searched as well to ultimately explore other potential sources to achieve optimal result. The food sources are randomly generated using the mathematical expression shown in equation (1) below:

$$X_i = X_{min} + \beta(X_{max} - X_{min}) \tag{1}$$

where X_i is the rich food source close to the original food source. The values of i range from 1 to N. β is random value [0,1]. More importantly, the food sources are chosen based on their fitness. The fitness function is the criteria used to measure the quality of the food (nectar) collected from the sources since it is very important to determine the quality of the food content based on their sources. This assists in identifying high and low quality food sources. Intuitively, each selected food source is expected to have better quality when compared with the previous sources. The fitness of food source can be computed mathematically using the equation as follows:

$$Fit_i = \begin{cases} \dfrac{1}{1+F_i}, & if\ F_i \geq 0 \\ 1 + |F_i|, & if\ F_i < 0 \end{cases} \tag{2}$$

The fitness is determine based on the criteria described in equation (2). As it can be notice that the fitness value depends greatly on whether F_i is greater or equal to zero, or entirely less than zero.

In addition, the employed bees on regular basis improved the information about the food sources within its neighborhood using the equation described in equation (3) which is as follows:

$$\vartheta_{i,j} = X_{i,j} + \alpha_{i,j}\left(X_{i,j} - X_{k,j}\right), \quad i = 1, 2, \dots, N;\ j = 1, 2, \dots, D \tag{3}$$

The ith candidate solution is represented by $\vartheta_{i,j}$. While the dimension of ith employed bee and kth neighbor employed bee are represented by $X_{i,j}$ and $X_{k,j}$ respectively. The value of $\alpha_{i,j}$ is generated randomly between -1 and +1.

The selection probability of k_{th} employee bee can be determine based on equation (4) shown below

$$P_k = \frac{Fit_k}{\sum_{j=1}^{N} Fit_j} \tag{4}$$

P_k is the selection probability of k_{th} employee bee and Fit_k represents the fitness of k_{th} employee bee. The selection process and capability should be able to select best optimal solution within shortest possible time. Hence, this will improve the performance while solving optimization problems. More importantly, it has been noticed that using PSO can yield better performance when it come searching and fast convergence. This leads to the introduction PSO in ABC algorithm in order to enhance the overall performance. The fundamental basic concept of PSO algorithm is covered in the section 2.2.

2.2 Particle Swarm Optimization

Particle swarm optimization was developed to simulate the behavior of birds to solve optimization problems. Its fundamental way of operation is based on the biological inspiration principles. The flock of birds systematically work and cooperative together in effective way to search for food base on the previous experience. This approach has been adopted in solving several complex optimization problems. It has been applicable in solving scheduling, planning, identification, networking, imaging, optimization and processing problems. Each individual bird represents a particle which follows certain behavior or rules to accomplish the target goal [21]. The particle shares and exchange information to adapt with the changing environment. In addition, the initial behavior of the particles is random, but the swarm continuously organize and coordinated themselves as the time elapse. Interestingly each particle has its own velocity and position at a particular time in the random space. The velocity and position of each particle is updated as they search for optimal solution within the domain.

Initially, lets assumed that there are N particles within the search domain. The velocity of the particles can be represented as $V_i = \{V_1, V_2, \ldots\ldots V_N\}$, while their position represented as $P_i = \{P_1, P_2, \ldots\ldots\ldots P_N\}$. In general, the velocity and position of any at a time t+1can be determine using equation (4) and (5) presented as follows:

$$V_i(t+1) = \omega V_i(t) + C_1\left(P_{lb} - X_i(t)\right) + C_2\left(P_{gb} - X_i(t)\right) \tag{5}$$

$$X_i(t+1) = X_i(t) + V_i(t+1) \tag{6}$$

where $V_i(t+1)$ and $X_i(t+1)$ are the velocity and position of the particle i at a time (t+1). While $V_i(t)$ and $X_i(t)$ represents the velocity and position of the particle i at a time (t). C_1 and C_2 are the social and cognitive coefficient respectively, and they have been set to the same value. The local and global best are represented by P_{lb} and P_{gb}.

3. Hybrid ABC & PSO Binary Optimization Algorithm

This section mainly focuses on the proposed hybrid ABC-PSO scheme to minimize the computational cost and increase convergence. In order to successfully achieve that, there is need to deploy fast convergence and highly efficient searching strategy based on PSO. As it has been known that PSO is simple, robust, distributive and it converges very fast when compared to other swarm intelligence optimization schemes [22,23]. Intuitively, these PSO features when integrated into ABC will yield better performance and reduce the complexity.

3.1 Problem Formulation

To understand the basics of binary optimization, there is need to discuss the general fundamental of binary optimization problem. It is important to note that binary optimization problems are difficult to solve, but continuous approach can be used in tackling such problems. This can be achieved by relaxing the constraint and rounding the result to the nearest integer value. Consequently, it will result in solution which is unfeasible and at the same time it violated the constraints attached to the optimization problem. In general, the binary optimization can be express mathematically as describe in equation (7) shown below:

$$\min_{x} f(x) \quad \textit{Subject to:}\ x \in \{-1, 1\}^n,\ x \in \Omega \tag{7}$$

where $f : R^n \rightarrow R$ is convex and it represent the objective function with convex set $\mathbf{\Omega}$. Additionally, the convexity of the problem can be affected by the constraints. To strategically accomplish the binary optimization, it is assumed that the intersection of $\{-1, 1\}^n$ and $\boldsymbol{\Omega}$ not equal to $\emptyset$. In order to deploy the ABC algorithm to perform the binary operation, the basic ABC scheme used in [24] has been adapted and improved. The employed bees are generated randomly and for each problem, the numbers are represented in form of binary numbers. This eventually reduces the complexity of how the problem can be represented in binary and subsequently optimized. Initially, the binary optimization to be used in solving the XOR problem is formulated and presented. Hence, the probability can be express in matrix form as follows:

$$P_i = \begin{bmatrix} P(X_i = 1) \\ P(X_i = 0) \end{bmatrix} = \begin{bmatrix} p \\ 1-p \end{bmatrix} \quad (8)$$

where p is the probability and its value ranges from 0 to 1. For values greater than 0.5 are considered as 1 and vice visa.

$$X_i = \begin{cases} 1, & if\ t_i \geq p \\ 0, & if\ t_i < p \end{cases} \quad (9)$$

X_i is the dimension of the employee bee and *ti* represents the random trials values which are generated. The equation (5) and (6) can be represented in a form in which the binary optimization can be solved. Therefore, the two equations (5 & 6) can re-written as follows:

$$\vartheta_{i,j}(t+1) = X_{i,j} \oplus \left(C_1 \otimes \left(L_{best} \ominus X_{i,j}\right)\right) \oplus \left(C_2 \otimes \left(G_{best} \ominus X_{i,j}\right)\right) \quad (10)$$

$$X_{i,j}(t+1) = X_{i,j} \oplus \vartheta_{i,j}(t+1) \quad (11)$$

where i = 1, 2,…….N and j = 1,2,……D. G_{best} is the best solution amongst all the food sources available in a particular time. C_1 and C_2 represents the social and cognitive constants - all have been set to unity. While for the onlooker bees, equation (10) has been used as searching equation once the food source is generated. It can be notice that both the global and local optimal best solutions have been considered in order to ultimately enhance the performance of the proposed ABC-PSO algorithm. Consequently, this has greater impact on the capability of the proposed scheme in terms of fast convergence, searching and low complexity. The initialization and searching for the global best amongst the food sources is discussed in the next sections.

3.2 Initialization

In order to initialize the algorithm, the number bees have been set to a fixed value and solution for each employed bee is based on equation (1). The number of bees is assumed to be the same as the number of particles. At the initialization step, the feasible solution obtained from employer and their limit tested to ensure that they are within the boundary. The random solution established within D-dimensional space. Let's assumed that the solutions are represented by **S**. The set of available solutions are represented by **S** = $\{S_1, S_2, \ldots\ldots\ldots S_N\}$. These solutions have randomly been spread over the search space with dimension *i* by *j*.

3.3 Searching for Global Best

The strategy deployed in searching for the global best amongst the food sources is very important and crucial toward achieving optimal performance. Therefore, the PSO equations have been used in enhancing the performance of the ABC scheme when solving the binary optimization problem. The key fundamental issue considered involves modifying how the social and cognitive parts can effectively assist toward convergence. The employed and scout bee equations have been modified based on equation (10) and (11). The employed bees determine the new solutions within close to their previous old solution based on equation (12). It has been assumed that the new solution is represented by $\boldsymbol{\vartheta} = \{\boldsymbol{\vartheta_1}, \boldsymbol{\vartheta_2}, \ldots \boldsymbol{\vartheta_N}\}$. The best solution amongst the solutions in $\boldsymbol{\vartheta}$ is selected as the global best solution using PSO. More importantly, the solutions obtained in $\boldsymbol{\vartheta}$ are assumed to be subset of S.

$$\boldsymbol{\vartheta}_i = \begin{cases} \boldsymbol{\vartheta}(t+1), & if\ \boldsymbol{\vartheta}(t+1) \geq \boldsymbol{\vartheta}(t) \\ \boldsymbol{\vartheta}(t), & \text{otherwise} \end{cases} \quad (12)$$

The best optimal solutions in a particular time $\boldsymbol{\vartheta(t+1)}$ iteration is tracked and compared with the previous best solution $\boldsymbol{\vartheta(t)}$. If the current solution is better than the previous solution, the current solution is maintained and vice visa. Using this strategy adapted from PSO, the scheme continuously progress and subsequently achieved optimal best global solution.

3.4 Hybrid Bee Information Update

The bee information update plays an important role toward obtaining the optimal performance while searching for the better bee food sources. Therefore, the strategy employed in PSO for information update is deployed to tremendously benefit from the unique key features of PSO algorithm which have been mentioned in the previous section.

First, the information update for the ABC-PSO algorithm is purely based on the mechanism used by PSO to update the parameter under examination. Both the quality and proximity of the nectar are considered while choosing the best solution. This information is shared amongst the bees on regular basis to ultimately ensures that the information about the foods sources is shared and track by the honey bees within the colony.

In the standard ABC algorithm, the employee normally searches for the nectar based on the procedure mentioned above. Searching for global solution in a random space is complex which requires more efficient approach to achieve better performance. Hence, the performance of the traditional ABC can be optimized by keeping track of the nectar quality information. More importantly, the global search capability of the ABC algorithm has been improved with the introduction of the global best term which assists greatly in enhancing its exploration.

Algorithm 1: Hybrid ABC-PSO Searching & Information Update

```
Initialize the food sources using equation (9)
Input: Food sources (S1, S2, …….SN)
Output: Global best food source
if Si is within the neighborhood and has good quality
better than the existing then
Si is the best within the neighborhood;
    else
    keep searching for better solution close to the
neighborhood;
end if
while Si is far away from the neighborhood do
        if Si quality and better than the previous global
        best then
        update Si with PSO;
        else
        keep searching;
        end if
end while
```

Using the steps listed in the algorithm above, the exploration and exploitation capability of the standard ABC has been effectively optimized and its performance varied in the next section.

4. Numerical Experiments and Performance Analysis

In this section, the numerical experimentation and performance evaluation of the standard ABC and Hybrid ABC used for the binary optimization problem have been juxtaposed to experimentally verify the performance of each scheme. The results obtained for the experimentations are critically analyzed and compared in order to measure the improvement accomplished by deploying the hybrid ABC scheme. Several experimental scenarios were used to evaluated the performance of the proposed algorithm. More importantly, the performance of the two schemes have been investigated by adjusting different parameters to determine their impact on the different performance metrics.

4.1 Experimental Setup

The implementation and experimentation of the two schemes to be tested were conducted on MATLAB simulation environment. More importantly, it is very important to note that the performance evaluation and testing was carried out by a computer with 2.7GHz processor speed and 8GB RAM capacity. In addition, the impact of increasing parameters such as number of runs and iterations on different parameters have been investigated and observed. Table 1 shows the setting for the parameters used for the experimentation.

Table 1: Parameters Setting

Parameter	Value
Population size	60
Number of Iterations	100
Inertia	1
Learning factors	1

In order to effectively and fairly compare the two algorithms, XOR binary optimization problem was used in the development and the experimentation. The parameters and setting described in Table 1 have been used in investigating and evaluating the performance of the proposed hybrid scheme to determine its proficiency when compared to the standard ABC.

4.2 Performance Comparison

This section presents the evaluation and analysis of the proposed scheme when compared to the standard ABC which was reported in [24]. The proposed hybrid ABC has been compared with the standard ABC algorithm in terms of fitness, mean error, computational complexity and convergence. These performance metric parameters have been considered primarily because they are applicable in evaluating and analyzing the capability of different optimization algorithms in different research works. Both the two schemes under experimentation were subjected to the same test condition, and their performance measured and compared. The primary goal is to reduce the computational complexity by enhancing the searching capability which in turns improves the energy efficiency and utilization as well. Reduction in error leads to good exploration and exploitation while searching for the optimal global best solution to effectively solve the binary optimization problem. The results for the performance evaluation using the aforementioned metrics are presented in the next sections.

4.2.1 Mean Error Minimization

The mean error and standard deviation for both standard ABC and the hybrid ABC schemes have been critically examined to determine which of the scheme has the best performance in terms of mean error. It is important to note that the primary objective of the optimization is to reduce minimize the mean error. The population size and number of runs were used in the experimentation. First, the impact of increasing the population size and runs on mean error were observed and evaluated. Most importantly, rapid decrease in mean error will have dramatic impact on the standard deviation error as well. This can be achieved with the increase in population size and the number run. Subsequently, the scheme convergence can be significantly increase. Initially, the population size was varied from 20 to 10 at an interval of 20 as it has been presented in Table 2. As can be seen, the mean error for the hybrid ABC is relatively low when compared to the standard ABC. This is an indication that the proposed scheme converges faster to minimum. As the population size for both the schemes increases, the mean error reduces as well. Consequently, the deviation reduces with the decrease in the mean error due to an increase in the population size.

Table 2: Mean error & standard deviation comparisons

	Mean Error		Standard Deviation	
Population Size	**ABC**	**ABC+PSO**	**ABC**	**ABC+PSO**
20	0.00082	0.00032	0.00104	0.00035
40	0.00052	0.00011	0.0005	0.000039
60	0.00015	0.0000635	0.00012	0.0000044
80	0.00010	0.0000623	0.000004 7	0.00000395
100	0.000057	0.000057	0.000004 6	0.000000934

Additionally, the deployment of PSO in ABC has resulted in decrease in both the mean error and standard deviation. The rapid decrease in the mean error leads to fast convergence in the hybrid ABC algorithm. Ultimately, the convergence speed of the hybrid ABC has been significantly increase as demonstrated in section 4.2.2. It is known fact that increase in population size enhances the searching capability, convergence and overall performance. As it can be seen that the error and standard deviation are relatively low when the population size has been set to 100 compared to the scenario when the population size is 20. There is dramatic need to balance between the population size and computational cost. Absolutely, the computational time may increase with increase in population size. The mean error and deviation for both the hybrid ABC and standard ABC have been measured and compared. In summary, increase in the number of population size reduces the mean error and the deviation of the hybrid ABC compared to the standard ABC.

4.2.2 Convergence Comparison

Convergence has been one of the key fundamental way for testing optimization algorithms. The rate of convergence indicates how fast an optimization algorithm can be able to determine the best optimal solution. The capability of an optimization scheme to converge toward the global optimal value is extremely important – it clearly indicated its proficiency. Converging toward a local optimal value should be avoided in order to achieve optimal performance. The standard and hybrid ACB algorithms were tested and compared based on their convergence capabilities. Fig 1 shows the output obtained from each algorithm. As it can be seen that the hybrid ABC converges faster when compared to the standard ABC algorithm.

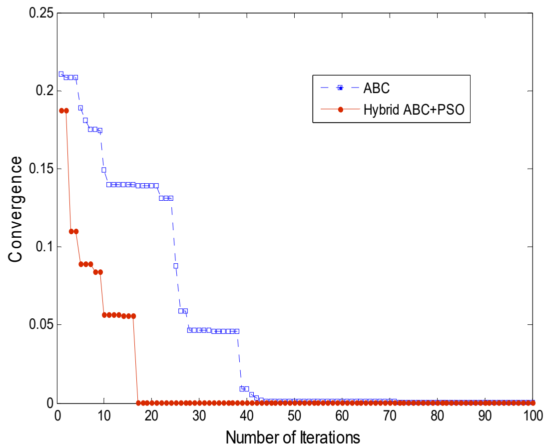

Fig 1. Hybrid and Standard ABC Convergence Comparison

The graph presented in fig 1 indicated that the hybrid ABC has been able toward to zero after 17th iterations while the standard ABC achieved convergence after 44th iteration. This clearly show how with the introduction of PSO has readily change the searching capability of ABC and it subsequently lead to fast convergence. It has been accomplished primarily due to the PSO features which were discussed in section 1. More importantly, the fast convergence ability of the hybrid ABC reduces the amount of energy needed to determine the optimal solution. Hence, the proposed scheme is energy efficient and it ensures effective utilization resources. Based on the experimental result achieved, the convergence of the standard ABC has significantly been improved by 61% as a result of hybridization of PSO features into it. This capability of the proposed hybrid ABC scheme has profound impact on the computational cost and the overall performance. This remarkable achievement has primarily been achieved by enhancing the searching and interactivity capability of the standard ABC. Therefore, the proposed scheme has provided better searching and updating mechanism which improves the overall convergence.

4.2.3 Fitness Solutions & Objective Value

The nature of how the fitness solutions have been distributed over the dimensional space were observed in the performance analysis experimentation. The fitness solutions from the algorithms were observed and presented in fig 2. The fitness values for each scheme at different iteration were observed and noted. Statistically, the relationship between two variables is extremely important piece of information – it measures the strength between correlating coefficients. More importantly, it assists greatly in establishing association or relationship between quantities. Very strong relationship occurs when the slope is unity. This indicates the variables increases with the same quantity at any particular point. the results presented shows clearly correlation between the fitness solution and the number of iterations.

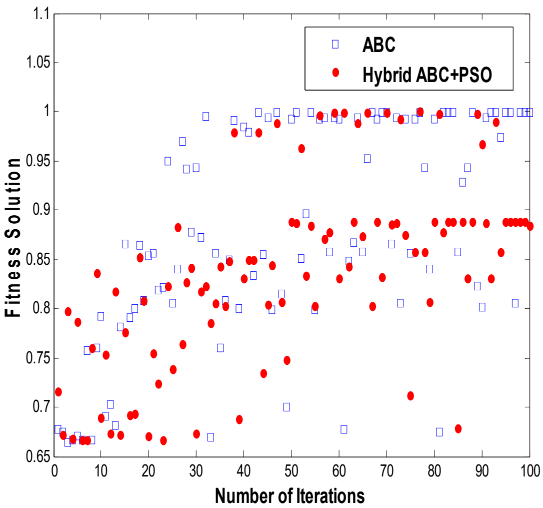

Fig 2. Fitness Solutions Comparison

Furthermore, it can be seen from fig 2 that there is relationship between the fitness solution and the number of iteration. Both the fitness solution and number of iterations seems to have some correlation with, but the relationship seems not very strong. It is very obvious that the fitness solutions move in positive direction with the increase in the number of iteration. Also, it can be noted that the fitness of both algorithms are entirely different and disproportionate when compared to one another.

More importantly, the objective function values for the two schemes have been studied. The objective function primarily defines the objective of the optimization problem. As it has been known that the primary object of the XOR optimization is to minimize the objective function. To achieve that, the objective values of the standard ABC and hybrid ABC were measured as the number of times (runs) was increase from 1 to 5 at an interval of 1. Fig. 3 shows the graphical representation of the objective values of the schemes as the number of runs increases. In each run, the algorithm is executed 100 times depending on the value the maximum number of cycles has been set – this is primarily because of the fact that the maximum number of cycles is 100.

Initially, when the run has been set to 1, the objective values was observed and recorder. There is clear difference between the standard ABC and hybrid ABC in terms of their objective value at the initial stage. The objective value for the hybrid ABC scheme is relatively low compared to the standard ABC. This can be noticed that as the number of run increases, the objective values for both schemes reduce to minimum. Interestingly, the rate at which the hybrid ABC decreases more linearly when compared to the standard ABC. In both the two schemes, the objective value minimization is negligible when the number of runs was set to 1, 2, and 3. More specifically, the objective value start to decreased rapidly from 4th to 5th runs – in both the standard and hybrid ABC scheme. Therefore, it clearly indicated the robustness and reliability of the proposed hybrid ABC scheme compared to the standard ABC scheme. Additionally, the standard ABC scheme requires more runs for it converge toward to the minimal objective value as indicated in fig 3.

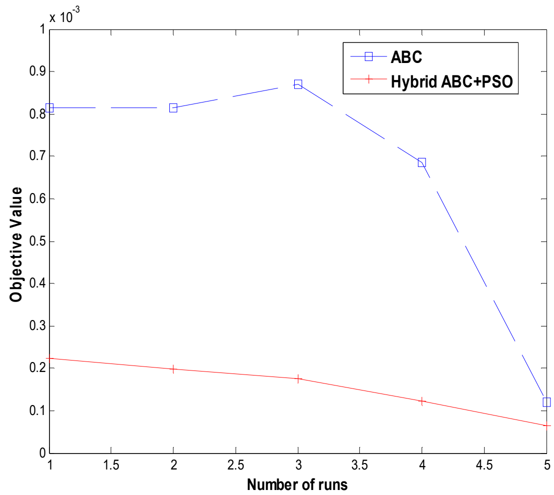

Fig 3. Objective Value Comparison

4.2.4 CPU time Comparison & Analysis

The computational time has been considered to measure and compare the complexity of the enhanced ABC-PSO and the ordinary ABC. As it has already been described the experimentation was conducted in MATLAB simulation environment. The algorithms to be tested were executed by 2.7GHz processor, 8 GB RAM and 64-bit computer. Both schemes were subjected to the same rigorous test under the same setting, condition and simulation environment. The period of time taken for a particular scheme to converge has relationship with its computational complexity. In a nutshell, the higher the complexity, the higher CPU time and vice visa. The primary goal is to reduce the computational complexity which in turn reduce the amount of energy needed to accomplish the task.

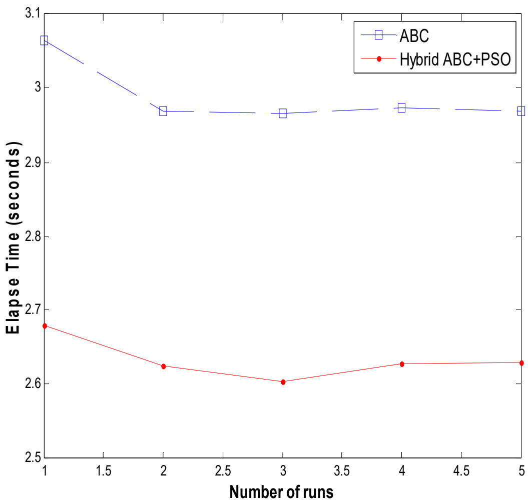

Fig 4. Elapse Time Comparison

The run time for the standard ABC and the hybrid ABC were critically evaluated to determine the computational energy consumed by each of the schemes. The comparison is graphically represented in fig. 4. It shows that the run time for the proposed hybrid ABC and the standard ABC progressively decreases with the increase in the number of runs – between the 1st and 2nd run. It is very important to note that the elapse time for the two schemes are relatively steady between the 2nd and 5th run. Most importantly, the run time for the proposed scheme is relatively low when compared to the standard ABC. Hence, it is obvious that the high run time will ultimately lead to high energy consumption and vice visa. Additionally, the CPU utilization can be reduced with decrease in run time. The elapse time of the standard ABC has been reduced by 11% with the introduction of PSO. This clearly shows that the hybrid ABC has low computational complexity and energy consumption, and better resource utilization when compared to the standard ABC.

5. Conclusions

In this paper a hybrid artificial bee colony and particle swarm optimization scheme for efficient binary optimization has been proposed. The primary goal of the scheme has successfully been achieved by using PSO searching and update capability to reduce computational cost and enhance performance in ABC. More importantly, the proposed scheme was compared with the standard ABC to evaluate the performance of the enhanced hybrid scheme in terms of convergence, error reduction, complexity and fitness. The simulation results obtained shows more promising performance while using the hybrid ABC-PSO scheme in solving the binary optimization problem. Furthermore, the analysis of the CPU times has shown clearly that the proposed ABC–PSO algorithm reduce the computational time and exhaustive searching time in ABC algorithm. The propose scheme can be applied to other areas where ordinary ABC was used to enhance their performance and reduce complexity. On a final note, this paper has provided an avenue through which ABC exploration, exploitation and selection capability can be optimally enhanced. With the integration of PSO into the standard ABC, balance between exploration and exploitation has been accomplished which yielded better performance with relatively low energy consumption and higher proficiency. Our future work will focus on exploring the hybridization of ABC with other schemes to improves its capability and applicability.

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Yakubu S. Baguda (M'05–SM'18) was born in Kano, Nigeria. He received the B.Eng in Electrical Engineering from Bayero University, Nigeria, in 2001. He received an MSc in Information Systems from the Robert Gordon University, Aberdeen, U.K. in 2003 and PhD degree in Electrical Engineering with distinction from the University of Technology, Malaysia, in 2010. From 2011 to 2012, he was a postdoctoral researcher at the UTM-MIMOS Centre of Telecommunication Excellence, Malaysia. He is currently an Assistant Professor with the Faculty of Computing & Information Technology, King Abdulaziz University, Saudi Arabia. He is the author of more than 30 journal and conference articles. His research interests include game theory, e-healthcare system, cross layer design and optimization, energy-efficient schemes, system modeling & prediction, intelligent decision systems, cognitive radio systems, resource allocation & management, network optimization and performance analysis, bioinspired optimization algorithms, wireless multimedia communication and networking. Dr. Yakubu received the chartered engineer (CEng) award from the UK Engineering Council in 2017. He is currently a senior member of both IEEE and ACM.