PERFORMANCE ENHANCEMENT OF ARTIFICIAL BEE COLONY OPTIMIZATION ALGORITHM

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PERFORMANCE ENHANCEMENT OF ARTIFICIAL BEE COLONY OPTIMIZATION ALGORITHM

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With the name of ALLAH SWT, the most merciful, the most gracious and the most compassionate. I feel immense pleasure while writing this page as some time ago I started to accomplish a task and it is about to end. Shukur Alhamdulillah Rabb-il-Aallameen.

PhD! It is a lone journey in a desert with seemingly no end where scorching sun makes difficult to travel during day and night is immensely dark. It is a journey where depleting resources drive you to the finish point and diminishing energies compel you to surrender with every passing day. It is a journey where a person chases another mirage with every moving step in the hope that the day is about to come. However, I was fortunate enough to have support of incalculably cooperative, extremely diligent and highly competent people which made the journey considerably simpler.

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LIST OF ABBREVIATIONS

ABC	Artificial bee colony algorithm
ABC-BSF	Best-so-far scout-bee guided ABC optimization algorithm
ACO	Ant colony optimization algorithm
ANN	Artificial neural network
BA	Bee algorithm
BABC	Global-best ABC
BFO	Bacterial foraging optimization
CABC	Chaotic ABC
CES	Canonical evolution strategy
CEC05	Conference on evolutionary computing 2005
CI	Computational intelligence
CMA-ES	Covariance matrix adaptation evolution strategy
CPSO	Chaotic PSO
DE	Differential evolution
EA	Evolutionary algorithms
EABC	Enhanced Artificial Bee Colony
EP	Evolutionary programming
EPS-ABC	Enhanced Probability-Selection Artificial Bee Colony
ES	Evolution strategy
ESLAT	Evolution strategy learned with automatic termination
EU	Elite Update
EUMR	Elite Update Mutation Rate
FES	Fast evolution strategy
FFEs	Fitness function evaluations
FL	Fuzzy logic
GA	Genetic algorithm
GABC	Gbest-guided ABC
Gbest	Global-best

GRABC	Gbest-influenced Random Artificial Bee Colony
HS	Harmony search
HBMO	Honey Bee Mating Optimization
IABC	Improved ABC
IIR	Infinite impulse-response digital filter
InABC	Interactive ABC optimization algorithm
ISABC1	First intelligent scout-bee based ABC algorithm
ISABC2	Second intelligent scout-bee based ABC algorithm
ISGABC1	First intelligent scout-bee based GABC algorithm
ISGABC2	Second intelligent scout-bee based GABC algorithm
MC-CDMA	Multi-carrier code division multiple access
MABC	Modified ABC
MBABC	Multiple Gbest-guided Artificial Bee Colony
ModABC	Modified ABC
OFDM	Orthogonal frequency division multiplexing
PID	Proportional integral derivative controller
PS-ABC	Probability-Selection ABC optimization algorithm
PS-EA	Particle swarm inspired evolutionary algorithm
PSO	Particle swarm optimization algorithm
RABC	Rosenbrock-ABC algorithm
RBF	Radial basis function ANN
Ridor	Ripple down rule
SA	Simulated annealing
SF	Scale-factor
TS	Tabu-search
VFI	Voting feature interval

PENINGKATAN PRESTASI ALGORITMA PENGOPTIMUMAN KOLONI LEBAH TIRUAN

ABSTRAK

Algoritma Koloni Lebah Buatan (ABC) adalah algoritma pengoptimuman berinspirasikan biologi terkini yang mensimulasi fenomena pencarian makanan oleh lebah. Walaupun kajian terdahulu telah menunjukkan kehebatan algoritma ABC ke atas banyak fungsi penanda aras dan aplikasi dunia sebenar, namun algoritma ABC yang asal and varian-variannya telah dikenalpasti mengalami masalah seperti kadar penumpuan yang lambat, terdedah kepada perangkap optima setempat, keupayaan mengeksploitasi yang lemah dan keupayaan menggantikan penyelesaian berpotensi yang lemah. Untuk mengatasi masalah-masalah ini, penyelidikan ini telah mencadangkan beberapa varian ABC yang baharu dan terubahsuai; algoritma *Gbest-Influenced Random ABC* (GRABC) yang mengeksploitasi dua persamaan mutasi yang berlainan secara sistematik untuk mengeksplorasi dan mengeksploitasi ruang carian dengan cara yang sesuai, algoritma *Multiple Gbest-guided ABC* (MBABC) yang meningkatkan keupayaan untuk mencari optima global dengan mengeksploitasi kawasan terbaik pada ruang carian yang dijumpai, algoritma *Enchanced ABC* (EABC) yang mempercepatkan eksplorasi untuk penyelesaian yang optima berdasarkan ruang carian yang terbaik dijumpai dan algoritma *Enchanced Probability-Selection ABC* (EPS-ABC), versi algoritma *Probability-Selection ABC* terubahsuai yang menggunakan tiga persamaan mutasi yang berlainan secara serentak untuk menentukan optima global. Semua varian ABC yang dicadangkan telah digabungkan dengan skim lebah-pengakap pintar yang dicadangkan, manakala MBABC dan EABC menggunakan skim kemaskini elit yang baharu. Kadar penumpuan varian-varian ABC yang dicadangkan telah dibandingkan dengan varian-varian ABC sedia ada dan algoritma pengoptimuman yang lain menggunakan dua puluh lima fungsi penanda aras. Prestasi algoritma pengoptimuman yang dicadangkan juga telah dianalisis ke atas tiga aplikasi; penganggaran parameter untuk motor aruhan, pengoptimuman gandaan pengawal PID untuk mengawal pengatur voltan automatik dan pengoptimuman kos pengeluaran elektrik dengan penjadualan unit-unit penjanaan kuasa. Keputusan selanjutnya telah dianalisis menggunakan ujian-t and ujian statistik *wilcoxon-signed-rank.* Analisis telah menunjukkan bahawa algoritma-algoritma pengoptimuman yang dicadangkan telah menghasilkan keputusan yang ketara lebih baik berbanding algoritma pengoptimuman yang lain. Secara keseluruhannya, prestasi kadar menumpuan terbaik yang dicapai oleh GRABC, MBABC dan EABC adalah lebih daripada dua kali ganda cepat daripada saingan kedua terbaik mereka. Prestasi kadar penumpuan terbaik algoritma EPS-ABC pula adalah hampir dua kali ganda lebih cepat berbanding algoritma PS-ABC.

PERFORMANCE ENHANCEMENT OF ARTIFICIAL BEE COLONY OPTIMIZATION ALGORITHM

ABSTRACT

Artificial Bee Colony (ABC) algorithm is a recently proposed bio-inspired optimization algorithm, simulating foraging phenomenon of honeybees. Although literature works have revealed the superiority of ABC algorithm on numerous benchmark functions and real-world applications, the standard ABC and its variants have been found to suffer from slow convergence, prone to local-optima traps, poor exploitation and poor capability to replace exhaustive potential-solutions. To overcome the problems, this research work has proposed few modified and new ABC variants; Gbest Influenced-Random ABC (GRABC) algorithm systematically exploits two different mutation equations for appropriate exploration and exploitation of search-space, Multiple Gbest-guided ABC (MBABC) algorithm enhances the capability of locating global optimum by exploiting so-far-found multiple best regions of a search-space, Enhanced ABC (EABC) algorithm speeds up exploration for optimal-solutions based on the best so-far-found region of a search-space and Enhanced Probability-Selection ABC (EPS-ABC) algorithm, a modified version of the Probability-Selection ABC algorithm, simultaneously capitalizes on three different mutation equations for determining the global-optimum. All the proposed ABC variants have been incorporated with a proposed intelligent scout-bee scheme whilst MBABC and EABC employ a novel elite-update scheme. The convergence rates of the proposed ABC variants have been compared with a number of existing ABC variants and other optimization algorithms on twenty five benchmark-functions and on three optimization applications; estimation of induction motor parameters, optimization of PID controller gains for controlling automatic voltage regulator and optimization of electricity production cost by scheduling power generating units. The results of the optimization algorithms have been further analyzed using t-test and wilcoxon-signed-rank statistical tests. The analysis has shown that the proposed optimization algorithms have produced significantly better results than the existing optimization algorithms. Overall, the best performances of GRABC, MBABC and EABC have exhibited more than twice faster convergence than their second best competitors. The best performance of EPS-ABC algorithm has exhibited almost twice faster convergence than PS-ABC algorithm.

CHAPTER 1

INTRODUCTION

1.1 Bio-Inspired Optimization Algorithms

In our everyday lives, we encounter with numerous optimization problems such as optimizing fuel-usage, distance travelled and daily expenses. Optimization is a process to either minimize or maximize output results by systematically rejecting unfeasible values in a search for optimal solutions. Mathematically, the unfeasible values are rejected on the basis of a predefined set of rules known as fitness-function, also called objective-function. Optimization is a recurrently visited problem of science and engineering ranging from profit maximization, to signal interference minimization, to controllers' optimization in process control engineering, to circuit design optimization in evolutionary electronics.

All social living beings yield useful behavior in response to the cooperative behavior of individuals, where individuals act asynchronously in parallel and individuals communicate with each other using some form of stigmergy (Bonabeau *et al*, 1999). Nature inspires researchers to propose solutions for optimally-solving problems which do not have straight-to-the-point solutions. The proposed solutions adopt multi-agent, task distribution and/or resources allocation phenomena exhibited by such social living beings. This evolves the term bio-inspired global optimization algorithms. Bio-inspired optimization algorithms belong to derivative-free, stochastic and population-based meta-heuristic optimization algorithms.

A survey carried out by Eck *et al.* (2006) has clearly divulged the importance of bio-inspired optimization. The research work has shown that the optimization algorithms have been effectively applied in very diverse fields such as control engineering, data mining, clustering, and optimizing neural networks and fuzzy systems. For instance, El-Zonkoly (2006) and Mostafa *et al.* (2012) have applied Particle Swarm Optimization (PSO) algorithm to optimize power-system stabilizers (PSS) for stability enhancement of power-systems. Ant Colony Optimization (ACO) algorithm has been applied by Karaboga *et al.* (2004) to design an optimal infinite impulse-response (IIR) digital filter. Evolutionary algorithms and PSO have been applied to evolve optimal proportional integral derivative (PID) controller in the works of Jiang *et al.* (2006), Elbayomy *et al.* (2008) and Kim *et al.* (2008). Artificial Bee Colony (ABC) and PSO algorithms have been used to cluster data (Chuang *et al.*, 2011; Karaboga and Ozturk, 2011). Genetic Algorithm (GA) and Differential Evolution (DE) have been applied for image-segmentation by Melkemi *et al.* (2006) and Cuevas *et al.* (2010). Liu *et al.* (2008) have applied DE for microelectronic circuit design where reported results have confirmed enhanced performance of the systems designed using DE in comparison to conventional techniques. The diverse applications of bio-inspired algorithms are increasing with passage of time. This proves the importance and strength of the optimization algorithms in real-world problem solving.

Research carried out in the field of bio-inspired optimization algorithms can be divided into two areas; computing inspired by the natural phenomenon and simulation-and-emulation of the natural phenomenon (Castro, 2006). Computing inspired by natural phenomenon makes use of state-of-the-art natural inspirations to develop techniques for solving problems, which do not have straight-to-the-point solutions. The core idea of this area is to develop algorithms on the basis of natural phenomena as we know it. The second area, simulation-and-emulation of nature synthesizes patterns, adopts the behaviors of organisms which do not necessarily resemble the natural phenomena. Hence, the second area deals with enhancing the performance of the algorithms synthesized in the first area by incorporating many diverse heuristics. Research presented in this thesis is related to the second area of bio-inspired optimization algorithm's research.

Bio-inspired optimization algorithms have been classified into two major classes; evolutionary algorithms (EA) and swarm-intelligence-based algorithms (Karaboga and Basturk, 2007). Evolutionary optimization algorithms evolve optimal solutions on the basis of evolution notion. GA, DE, Evolution Strategy (ES) and Evolutionary Programming (EP) are examples of evolutionary algorithms. On the other hand, swarm-intelligence-based optimization algorithms such as ACO, PSO and ABC have been inspired by the behavior of tiny social-insect societies such as ants, swarm of birds and honeybees. This research work is related to performance enhancement of ABC optimization algorithms.

1.2 Motivation to Artificial Bee Colony (ABC) Algorithm

Artificial bee colony (ABC) optimization algorithm is an element of swarm-intelligence-based bio-inspired optimization algorithms. It has been inspired by honeybees foraging philosophy. ABC optimization algorithm has been proposed in 2005 (Karaboga, 2005). Honeybees optimize time spent on the nectar-amount of foraged food-sources. Although ABC algorithm is a relatively new optimization algorithm than very prominent bio-inspired optimization algorithms, it has captured much attention of the research community since its inception. This is mainly due to its better convergence and fewer control-variables.

Many research works have been carried out to assess the performance of the standard ABC optimization algorithms. Normally, the performance evaluation has been carried out by using two different approaches, i.e., based on benchmark functions and another on applications. The following two subsections present the performance analysis of ABC algorithm based on the two approaches.

1.2.1 Performance of ABC Algorithm on Benchmark-functions

Research carried out by Karaboga and Basturk (2007) has compared ABC algorithm with GA, PSO and Particle Swarm inspired Evolutionary Algorithm (PS-EA) on high-dimensional five benchmark-functions. The results have proven superior convergence of ABC algorithm among the optimization algorithms on all test-functions. Comparative analysis carried out by Karaboga and Basturk (2008) has compared ABC algorithm with PSO, EA and DE on five benchmark-functions. The results validate the best performance of ABC algorithm among the compared optimization algorithms.

Another study carried out by Karaboga and Akay (2009) has evaluated convergence of ABC algorithm in comparison to PSO, GA and DE on fifty benchmark-functions. Moreover, the reference has also compared ABC with a few variants of ES such as Covariance Matrix Adaptation ES (CMA-ES), ES Learned with Automatic Termination (ESLAT), Canonical ES (CES), Self-organizing Maps ES (SOM-ES), Neural Gas ES (NG-ES) and Fast ES (FES) on a few benchmark-functions. ABC has been shown to perform better than PSO, GA and DE on most of the benchmark-functions, specifically multi-modal benchmark-functions. Overall, ES variants have performed better than ABC algorithm. However, it has to be noted that the comparative analysis has used more advanced ES variants which have exhibited better performance but they require more control-variables than the standard ABC algorithm.

Another comparative study carried out by El-Abd (2012) has compared ABC, PSO, DE, ES, ACO, GA, Bee algorithm (BA), Bacterial Foraging Optimization (BFO) and Harmony Search (HS) optimization algorithms. The comparative analysis has been carried out on twenty-five benchmark-functions. PSO and ABC algorithms have stood out as the best algorithms among the compared optimization algorithms with PSO converging faster in comparison to ABC on unimodal functions. Nevertheless, the convergence of ABC has been better than PSO on multi-modal test-functions. Moreover, ABC algorithm has resulted in the best performance among the compared optimization algorithms on hybrid benchmark-functions and on few unimodal functions as well. This demonstrates the capability of ABC algorithm at optimization.

1.2.2 Performance of ABC Algorithm on Applications

ABC optimization algorithm has not only outperformed other bio-inspired optimization algorithms on benchmark-functions but also on a few real-world applications. Taspnar *et al.* (2011) has applied ABC algorithm for performance enhancement of multicarrier code division multiple access (MC-CDMA), a promising wireless communication technique. The performance of ABC has been compared with various conventional techniques and the results have shown that ABC-optimized system has outperformed all other optimized systems in terms of computational complexity and power consumption. Moreover, Yajun *et al.* (2010) have compared ABC, PSO and GA for performance enhancement of orthogonal frequency division multiplexing (OFDM), which is another potential technique for wireless communication. The performance of ABC-optimized OFDM has shown to be better than other optimized OFDM.

Research work carried out by Akay (2012) has extensively evaluated the performance of ABC and PSO algorithms for multilevel threshold segmentation, a technique employed in image processing field. The results have shown better performance of ABC algorithm in comparison to PSO optimization algorithm.

Data clustering technique has been used in various engineering problems to assemblage data into different groups depending upon the associated-attributes. The performance of ABC algorithm for data-clustering has been analyzed by Karaboga and Ozturk (2011). Their work has compared ABC with PSO, Radial Basis Function ANN (RBF) and other techniques such as bagging, multi-boost-AB, ripple down rule (Ridor) and Voting Feature Interval (VFI) on thirteen benchmark data-sets taken from UCI. The reported results have shown that ABC algorithm has performed the best among all the compared techniques on almost all data-sets.

Zhang *et al.* (2010) have evaluated the performance of ABC, ACO, GA, PSO, Simulated Annealing (SA) and Tabu-Search (TS) for data clustering on various benchmark data-sets. The results substantiate the best convergence of ABC algorithm among the compared optimization algorithms. Safarzadeh *et al.* (2011) have compared the performance of ABC and GA algorithms for optimizing pressurized water reactors used in nuclear reactors. It has been concluded that ABC algorithm has been more robust and has better ability to determine the optimal-solutions for the problem.

Unit-commitment is an operation-planning problem of power-systems and it optimizes power-demand allocation to various online power generators. The problem has been optimized using ABC algorithm by Chandrasekaran *et al.* (2012). ABC optimization algorithm has been compared with PSO and GA. The results have testified the best performance of ABC algorithm among the compared optimization.

The performance of ABC and PSO have been extensively evaluated for automatic-generation-control of interconnected power-systems by Gozde *et al.* (2012). ABC optimization algorithm has outperformed PSO algorithm on the optimization problem. Gozde and Taplamacioglu (2011) has optimized PID controller for the performance enhancement of automatic-voltage-regulator (AVR) using ABC, PSO and GA. The reported results have revealed the best performance of ABC optimized PID controller among all other algorithms' optimized PID controllers.

There are numerous real-world application where ABC algorithm has been applied with very promising results (Jeya Mala *et al.,*2010; Sabat *et al.,* 2010; Xu and Duan, 2010; Abu-Mouti and El-Hawary, 2011; Dos-Santos, 2011; Sencan *et al.,* 2011). A review of ABC algorithm applications, modifications and hybridization has been carried out by Karaboga *et al.* (2012). The review has clearly demonstrated an exponential increase of ABC algorithm-based research publications. The literature survey results have been depicted in Figure 1.1. The figure shows that more than half of the total research has been published in 2011. This proves excellent capability of ABC optimization algorithm for determining the optimal-solutions of any problem at hand. Hence, ABC has motivated this research work.

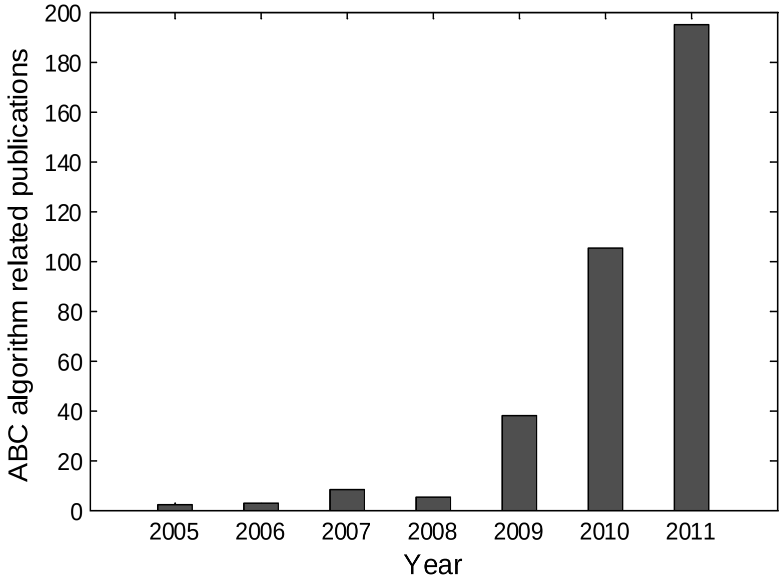

Figure 1.1 Number of ABC optimization algorithm related publications per year (Karaboga *et al.* (2012)).

1.3 Problems in ABC Optimization Algorithm

It is understandable that nothing in this world is perfect. Despite yielding very promising results in the realm of optimization, ABC algorithm suffers from few demerits similar to other bio-inspired optimization algorithms. ABC algorithm has been found to suffer from converge slow (Zhu and Kwong, 2010; Kang *et al*, 2011; Li *et al.* 2012). Figure 1.2 shows the convergence plots of the standard ABC algorithm and few variants of ABC algorithm, i.e. I-ABC, PS-ABC and GABC algorithms (Li *et al.* 2012). The figure clearly shows considerably inferior convergence of ABC algorithm than its variants.

Besides, ABC algorithm has been prone to local optima traps while solving a complex multi-modal test-function (Banharnsakun *et al.*, 2011; Gao and Liu, 2011; Li *et al.* 2012). Figure 1.3 shows the convergence plots of ABC and few variants of ABC algorithm, i.e. I-ABC, PS-ABC and GABC algorithms on a multi-modal test-function (Li *et al.* 2012). The figure shows that ABC and GABC algorithms could not converge on the test-function. On the other hand, I-ABC and PS-ABC algorithms have managed to avert local optima successfully.

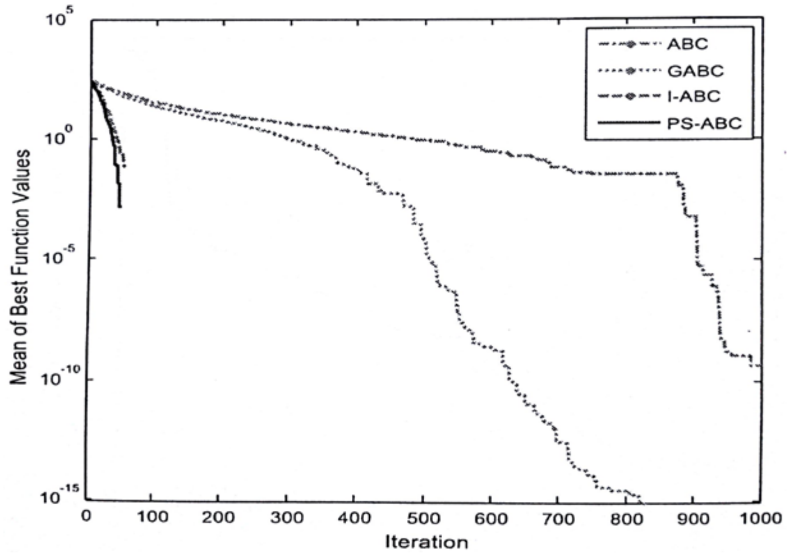

Figure 1.2 Convergence comparisons of ABC algorithm and its variants on a test-function (Li *et al.* 2012).

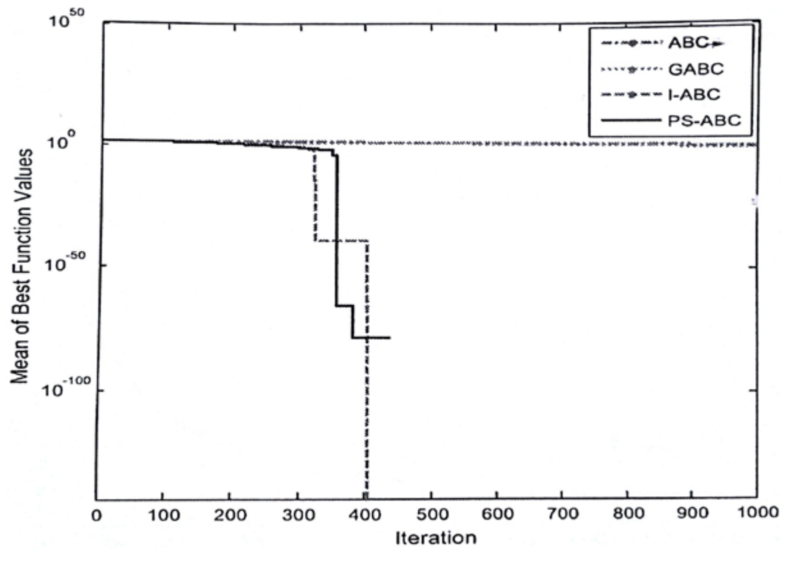

Figure 1.3 Convergence comparisons of ABC algorithm and its variants on a test-function (Li *et al.* 2012)

ABC algorithm has poor capability to replace currently poor-potential solutions. ABC algorithm replaces the poor potential solutions with newly initialized potential solutions. However, the replacement is a randomly initialized potential solution. Due to a random initialization, there are very bleak chances of getting a better (fitter) potential solution as the replacement (Banharnsakunl *et al.*, 2011).

Figure 1.4 portrays possible positions of randomly initialized potential solutions in a search space. If a potential solution is to be randomly initialized from the whole search-space, the chances of placing the solution near to global optimum are very small. Now, consider a potential solution A which is to be replaced because it has been identified as a poor potential solution. As the standard ABC algorithm randomly initializes the replacement of poor potential solution, there are bleak chances of generating a replacement which is fitter than solution A. It would be desirable to have a scheme which narrows the search space only around fitter population space at every generation.

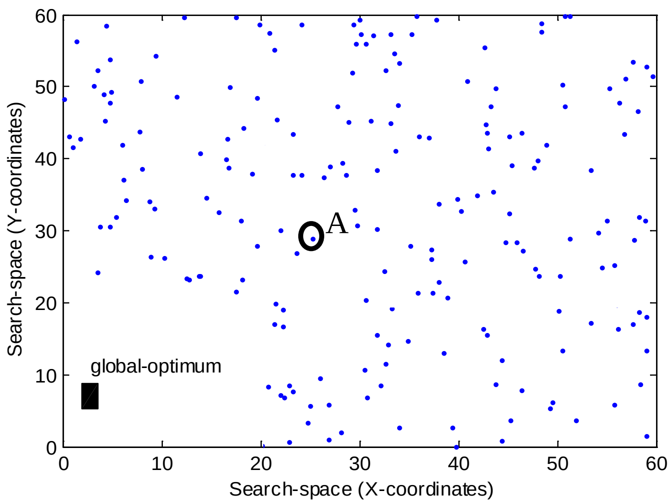

Figure 1.4 Possible positions of randomly initialized potential solutions in a search space

Furthermore, Li *et al.* (2012) have proposed a potential variant of ABC named Probability-Selection ABC (PS-ABC) algorithm. PS-ABC algorithm capitalizes on three different mutation equations for generating optimal solutions. However, all the mutation equations of PS-ABC are excessively self-reinforced and hence, PS-ABC suffers from slow convergence (Castro, 2006). Moreover, all the three mutation equations belong to the same class of mutation equations. Hence, it can be concluded that the equations possess the same merits and demerits that the algorithm may not perform equally well over a wide set of optimization problems. Therefore, it can be concluded that there is scope for enhancing the performance of PS-ABC optimization algorithm.

1.4 Research Objectives

As has been discussed in the previous section, ABC bio-inspired algorithm suffers from few demerits. To overcome the demerits, this research work has proposed few modifications to the standard ABC algorithm and its variants which have essentially produced new ABC variants. The objectives of the research work are:

(i) To develop a new ABC variant, GRABC which employs a modified mutation equation and a proposed scout-bee stage.

(ii) To develop a new ABC variant, MBABC which employs a modified mutation equation, proposed elite-update stage and a proposed scout-bee stage.

(iii) To develop a new ABC variant, EABC which employs a modified mutation equation, proposed elite-update stage and a proposed scout-bee stage.

(iv) To develop enhanced PS-ABC algorithm (EPS-ABC) which employs different mutation equations and a proposed scout-bee stage.

(v) To assess the convergence of the proposed algorithms on numerous benchmark-functions and to evaluate their performance on few optimization applications.

Some intelligence has been integrated into the proposed scout-bee scheme in the sense that it picks a fitter potential solution to replace a poor solution. The proposed scout-bee stage has been named intelligent scout-bee stage. Two different intelligent scout-bee schemes have been proposed. The first proposed scout-bee randomly initializes a potential solution in the vicinity of gbest potential solution. The second proposed scout-bee systematically initializes a potential solution in the vicinity of gbest potential solution. The modifications aim to speed up the convergence of an ABC algorithm. In this research work, a novel stage named elite-update has also been proposed to enhance convergence-rate and to avert local-optima.

Mutation equation of an algorithm governs its performance, as the equation set rules for communication among population elements, i.e. potential solutions. Mutation equation of GRABC algorithm generates candidate-solutions around randomly picked potential solutions. It also incorporates intelligent scout-bee scheme. The mutation equation of MBABC algorithm generates candidate-solutions around multiple gbest potential solutions. The algorithm also capitalizes on the intelligence scout-bee and elite-update stages. During the elite-update stage, MBABC algorithm only updates multiple gbest potential solutions for speeding up convergence and averting local-optima traps.

The proposed EABC algorithm generates candidate-solutions only around the single gbest potential solution. It also employs the intelligent scout-bee and the elite-update stages.

Lastly, the performance of PS-ABC algorithm has been enhanced by replacing its mutation equations in such a way that each mutation equation belongs to a different class. Thus, every mutation equation possesses different merits and suffers from different demerits. This way, EPS-ABC may perform better over a wide-set of optimization problems.

The proposed algorithms have been compared with various existing ABC variants and other bio-inspired optimization algorithms on twenty five benchmark functions. They have also been compared with various existing variants of ABC algorithm on their capability at solving three optimization applications.

1.5 Thesis Outline

This thesis has been organized in the sequence in which the objectives have been stated. The second chapter, Literature Review, discusses various optimization algorithms adapting their principles from various social phenomena of honeybees. The chapter also discusses the standard ABC optimization algorithm in a detailed manner. Additionally, the chapter critically reviews various existing variants of ABC algorithm in good detail.

The third chapter, Intelligent Scout-bee Guided ABC Algorithm, introduces two different suggestions to enhance the performance of ABC algorithm's scout-bee stage. The modifications indoctrinate some intelligence into the scout-bee stage of ABC algorithm. The performance of intelligent scout-bee-based ABC algorithm has been compared with the existing scout-bee schemes, on various benchmark-functions. The best intelligent scout-bee method has been adapted for the proposed ABC variants.

The fourth chapter, Proposed Variants of ABC Algorithm, presents the proposed modifications for enhancing the performance of ABC optimization algorithm. In the four different variants of ABC optimization algorithm have been presented and discussed. All the four-proposed optimization algorithms integrate the proposed intelligent scout-bee scheme rather than the standard scout-bee scheme.

The fifth chapter, Results and Discussion, presents the comparative analysis of the proposed variants of ABC algorithm with a few existing variants of ABC algorithms on high-dimensional benchmark-functions. The results have been statistically analyzed using two different statistical tests. The chapter also presents comparative analysis of the proposed algorithms with nineteen other state-of-the-art optimization algorithms (i.e. PSO and its variants, DE and its variants and, ES and its variants) on a very wide set of benchmark-functions taken from research works published in the reputable journals.

The sixth chapter, Applications of Proposed Optimization Algorithms, of this thesis presents the performance comparison of the proposed optimization algorithms with various existing variants of ABC algorithm on three different applications; parameter estimation of induction motor, economic load dispatch and PID controller optimization. Two different test-cases of each application have been adapted for rigorous performance analysis of the proposed optimization algorithms. The results have also been discussed in the chapter.

The seventh chapter of this thesis presents the conclusions, contribution and scope for possible extension of this work.

CHAPTER 2

LITERATURE REVIEW

2.1 Adapting Honeybee Natural Phenomenon

Honeybee swarm is a very appealing natural-swarm. Honeybees are social insects, which can be conceived as a dynamical society that adjusts its behavior according to the surrounding environment. They gather information, adjust themselves and perform task based on their specializations. Honeybees have photographic memory, excellent navigation and the ability to make a group decision such as queen selection. Besides that, storing, retrieving and distributing honey and pollen, information communication and foraging are the additional capabilities of honeybees which have captured attention of various researchers working in the field of bio-inspired optimization algorithms.

In honeybee society, there are queen bee, forager bees, drone bees, worker bees and others. Queen bee can live for many years and she is the only egg laying female in the colony. The queen fertilizes by consuming sperms stored while mating and produces unfertilized eggs. Then eggs are fertilized and few remain unfertilized also. From the unfertilized eggs male-bees are produced, also called drones and from the fertilized eggs female-bees are produced. The prime role of drones is to fertilize a new queen and they die after mating with the queen. Drones do not live for duration more than six months. On the contrary, the female-bees collect and store food, remove dead-bees, ventilate and guard the hive. On the second-half of their lives, female-bees go outside of the hive for foraging. Jung (2003) has formulated an optimization algorithm based on the queen-bee phenomenon. The queen performs a dance in the hive for attracting the drones and mate with the drones far from the hive during her flights. Hussein (2003), Marinaki *et al.* (2010) and Marinakis *et al.* (2011) have designed optimization algorithm based on honeybees mating phenomenon.

Forager-bees go outside of the hive to forage food-sources. After coming back to the hive, the forager-bees perform a dance. By dancing, the foragers communicate the information about nectar amount, direction and distance of the explored food-sources with the other bees of the colony. This is how a forager recruits other honeybees in search for productive locations. The information exchange among bees is the most important part of the collective knowledge. Various researchers have proposed different optimization algorithms on the basis of honeybees' information sharing approach (Walker, 2003; Wedde *et al.*, 2004).

Honeybee-swarm has excellent capability to accomplish a task by dividing it into smaller units. For example, while selecting a new nest-site, honeybees consider the size of cavity to hold combs, tightness of cavity, weather condition and the construction time. To achieve the task, numerous honeybees work in parallel for exploring the potential sites and share the information with each other using various types of dances to select the best-one. Various optimization algorithms have been proposed in the literature based on task-accomplishing approaches of honeybees swarm (Nakrani and Tovey, 2004; Sadik *et al.*, 2007 and Gutierrez and Huhns, 2008).

Foraging is the process of searching for food-sources and collecting nectar amount for making honey. Various optimization algorithms based on foraging phenomenon have been proposed by Lucic and Teodorovic (2002), Lucic and Teodorovic (2003), Walker (2004), Karaboga and Basturk (2007) and Saleem and Farooq (2007). One among numerous optimization algorithms proposed on the basis of foraging phenomenon of honeybee swarm is Artificial Bee Colony (ABC) optimization algorithm (Karaboga and Basturk, 2008).

A survey carried out by Karaboga *et al.* (2012) has produced a plot of popular honeybee-based optimization algorithms. The results have shown a prominent contribution of ABC optimization algorithm in comparison to the rest of honeybee-based optimization algorithms. The plot clearly highlights the importance and popularity of ABC optimization algorithm among various honeybees-based optimization algorithms. The percentage of contribution is shown in Figure 2.1.

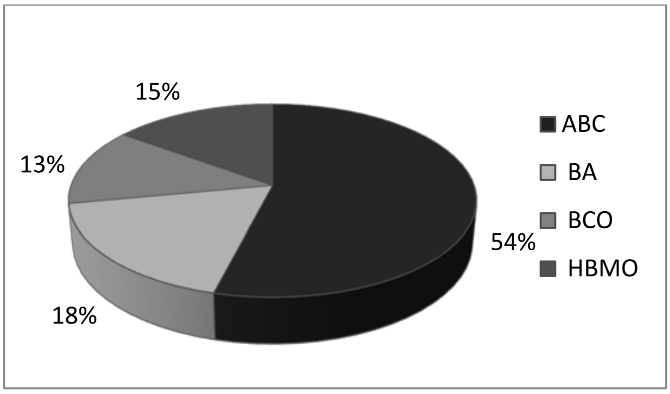

Figure 2.1 Literature contributions of various optimization algorithms based on honeybees (Karaboga *et al.* (2012)).

2.2 Standard Artificial Bee Colony (ABC) Optimization Algorithm

As explained earlier, the optimal-solution generating philosophy of ABC optimization algorithm has been inspired by the foraging phenomenon of honeybee-swarm. ABC optimization algorithm divides the swarm into three types of bees. The first type of bees is called employed-bees, the second is named onlooker-bees and the third is known as scout-bees. One of the advantages of ABC algorithm over various other bio-inspired optimization algorithms is the use of fewer control-variables. ABC algorithm carries only three control-variables, i.e. *colony-size, limit* and *number-of-generations*. *Colony-size* and *number-of-generations* are the common control-variables of all bio-inspired optimization algorithms whereas "*limit*" is the only ABC algorithm-specific control-variable. Algorithm-specific control-variables are only utilized by any specific algorithm such as; *limit* has not been used by any optimization algorithm other than ABC algorithm.

ABC algorithm divides colony of honeybees into three different classes, i.e. employed-bees, onlooker-bees and a scout-bee. Number of onlooker and employed bees is equal to half of the *colony-size* in the standard ABC algorithm and its variants. Larger *colony-size* and higher *number-of-generations* will result in better performance of ABC algorithm (Karaboga and Basturk, 2008).

Figure 2.2 illustrates the flow chart of ABC optimization algorithm. ABC optimization algorithm starts searching for optimal-solutions by randomly initializing the initial food-sources. The food-sources symbolize potential solutions. Every potential solution has number of indices equals to the number of a problem dimensions. Each index of a potential solution represents a dimension of the problem. Therefore, if a problem has one-hundred dimensions then each potential solution is required to have one-hundred indices. Table 2.1 portrays structure of food-sources/potential solutions. In Table 2.1, D represents dimension, m is the last food-source, n_{m1} symbolizes the first index of m_{th} food-source and n is any integer.

After randomly initializing food-sources, ABC algorithm assesses nectar-amount of every food-source. In ABC algorithm, the nectar-amount of a food-source corresponds to the quality of a potential solution or the fitness of a potential solution. Alternatively, after initializing potential solutions ABC algorithm calculates fitness of every potential solution. The fitness of a potential solution has been calculated by the formula presented in equation (2.1) (Karaboga and Basturk, 2007; Karaboga and Akay, 2009).

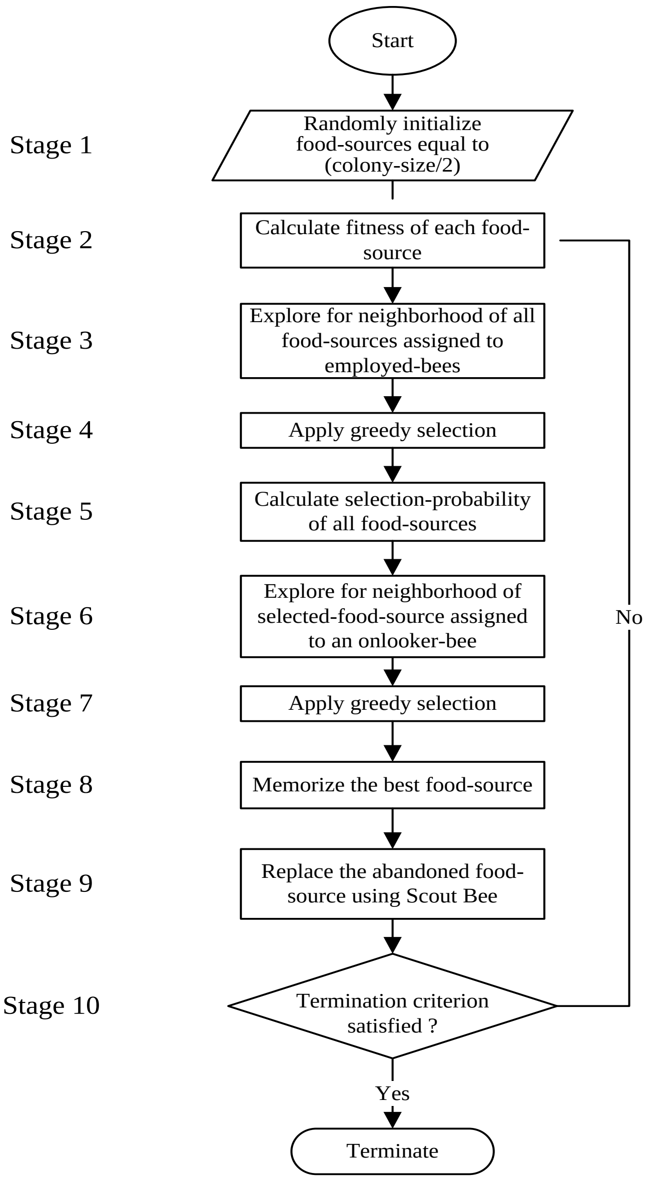

Figure 2.2 Flow chart of the standard ABC optimization algorithm.

Table 2.1 Structure of ABC algorithm food-sources/potential solution

Food-source	**Indices of food-sources**								
	1	**2**	**3**	**4**	**5**	**…………………**	**D-2**	**D-1**	**D**
1^{st} Food-source	n_{11}	n_{12}	n_{13}	n_{14}	n_{15}	…………………	n_{1D-2}	n_{1D-1}	n_{1D}
2^{nd} Food-source	n_{21}	n_{22}	n_{23}	n_{24}	n_{25}	…………………	n_{2D-2}	n_{2D-1}	n_{2D}
3^{rd} Food-source	n_{31}	n_{32}	n_{33}	n_{34}	n_{35}	…………………	n_{3D-2}	n_{3D-1}	n_{3D}
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
m^{th} Food-source	n_{m1}	n_{m2}	n_{m3}	n_{m4}	n_{m5}	…………………	n_{mD-2}	n_{mD-1}	n_{mD}

$$fit_i = \begin{cases} \dfrac{1}{1+f_i}, f_i \geq 0, \\ 1+abs(f_i), f_i < 0, \end{cases} \quad (2.1)$$

where f_i symbolizes objective-function value of i_{th} food-source and fit_i is the corresponding fitness value after calculation.

It is important to mention that the number of food-sources is equal to the number of employed-bees. After fitness calculation of all food-sources, every employed-bee is assigned a food-source for its neighborhood exploration. The neighborhood of food-sources is explored by the following equation (Karaboga and Basturk, 2007; Karaboga and Akay, 2009).

$$z_{ij} = y_{ij} + \phi_{ij}(y_{ij} - y_{kj}) \quad (2.2)$$

where y_{ij} symbolizes j_{th} dimension of i_{th} food-source, y_{kj} represents j_{th} dimension of k_{th} food-source, z_{ij} corresponds to candidate-solution of j_{th} dimension of i_{th} food-source, i and k are the mutually-exclusive food sources, j Є [1,2,…. D], D is the dimension of search space, j and k are randomly chosen numbers, $\emptyset$ is a random number within [-1, 1] and it is called scale factor.

ABC algorithm's scale factor varies from [-1, 1] and hence, creates more diverse population. Diversity among food-sources is the primary condition for better exploration of a search-space. Equation (2.2) is also called mutation equation of the standard ABC optimization algorithm. Mutation equation of an optimization algorithm governs its performance. ABC algorithm explores neighborhood of a food-source using a randomly selected food-source. If the randomly selected food-source is a fitter then, the mutation may produce a fitter neighborhood and vice versa.

ABC algorithm explores the neighborhood of a food-source using vector difference similar to DE algorithm. In fact, ABC algorithm capitalizes on the same mutation equation as that of DE algorithm. However, the results presented in Karaboga and Basturk (2008), Karaboga and Akay (2009) and El-Abd (2012) (Section 1.2) show that ABC algorithm has performed better than DE algorithm. Hence, it can be concluded that the philosophy behind generating optimal-solutions of ABC algorithm is better than DE algorithm. After exploring the neighborhood of a food-source, ABC algorithm calculates fitness of the modified food-source (i.e. candidate food-source) using equation (2.1). Then ABC algorithm compares fitness of the food-source before and after the modification. ABC algorithm selects the food-source which has higher fitness value. This is called greedy-selection.

From the discussion of two previous paragraphs, it can be concluded that there are three different steps involved in updating a food-source. Firstly, ABC algorithm mutates a food-source. Secondly, ABC algorithm evaluates fitness of the mutated food-source using a user-defined fitness-function. This step has also been termed as fitness-function evaluation. Finally, ABC algorithm attempts to update the food-source, if the mutated food-source is fitter than the existing food-source. ABC algorithm attempts to update only one index of every food-source during employed-bee stage of the algorithm and this is also called mutation-rate. Hence, the number of mutations, fitness-function evaluations and attempts to update food-sources are equal in the standard ABC optimization algorithms. Additionally, other bio-inspired optimization algorithms follow the same rule however, there are exceptions and the algorithms shall be duly identified as the thesis progresses.

For unbiased comparison optimization algorithms should update food-sources/potential solutions for the equal number of times. As the number of mutations, fitness-function evaluations and attempts to update food-sources are generally equal. Therefore, it is generally said that for even comparison the total number of fitness-function evaluations (FFEs) should be the same (Suganthan *et al.*, 2005; Karaboga and Basturk, 2008; Zhu and Kwong, 2010). For ABC optimization algorithm, FFEs can be calculated by the following equation;

$$\textit{Number of FFE} = 2 \times \textit{Population size} \times \textit{MCN} \tag{2.3}$$

where *Population size* = *Colony-size*/2 and *MCN* is maximum number of cycles/generations

Once the neighborhood of all food-sources has been explored by employed-bees, the bees then pass the information to onlooker-bees. However, there is a slight difference between neighborhood exploration of food-sources by employed-bees and onlooker-bees although mutation equation is the same during both stages of ABC algorithm. Employed-bees explore the neighborhood of all food-sources whereas, onlooker-bees explore only selected food-sources. Food-sources which have higher nectar-amount have higher probability for being selected by onlooker-bee. Hence, fitter food-sources among the population have been enhanced more-times than less-fitter food-sources. Therefore, the algorithm may converge rapidly.

Onlooker-bees wait in a dancing area of the hive where employed-bees come to recruit the onlooker-bees. Employed-bees communicate all required information of a food-source such as its direction with respect to hive, distance from hive and nectar amount using round or waggle dance. Time-period of the dance-performance corresponds to the nectar-amount of a food-source. Similar to employed-bees, onlooker-bees explore the neighborhood of food-sources based on equation (2.2).

The probability of selecting a food-source for onlooker-bees can be calculated by the following equation (Karaboga and Basturk, 2007; Karaboga and Akay, 2009);

$$p_i = \frac{fit_i}{\sum_{j=i}^{NS} fit_j} \tag{2.4}$$

where NS corresponds to the number of food-sources, fit_i is the fitness of a selected food-source and P_i is the selection-probability of the i_{th} food-source.

ABC algorithm has the ability to induct new food-sources into its population while the algorithm is running. ABC algorithm abandons any food-source, which has been explored over a maximum number of times without any success. The maximum number of times has been controlled by a user-defined control variable named *limit.* At the end of every generation, ABC algorithm looks for any food-source which is to be abandoned. If the food-source exists, then ABC algorithm replaces the current food-source with a newly found food-source. The capability of ABC algorithm limits its dependency on *colony-size*, as it reinitializes exhausted food-sources. The new food-source can be obtained based on the following equation (Karaboga and Basturk, 2007; Karaboga and Akay, 2009);

$$y_{ij} = y_j^{\min} + rand(0,1)(y_j^{\max} - y_j^{\min}) \tag{2.5}$$

where y_{ij} symbolizes j_{th} dimension of i_{th} food-source, $y_j^{\min}$ is the lower limit of search space and $y_j^{\max}$ is the upper bound of search space.

It is clear from the above equation that the food-source has been randomly initialized from the whole search-space. Hence, there are bleak chances of getting a food-source having higher fitness value.

2.3 Variants of ABC Optimization Algorithm

To overcome the flaws of the standard ABC optimization algorithm, as discussed in Section 1.3, various variants of ABC algorithm have been proposed. The standard ABC algorithm optimizes real parameters. To avert the limitation, Tasgetiren *et al.* (2011) and Kashan *et al.* (2012) have proposed ABC algorithm for discrete parameter optimization. The standard ABC algorithm can only optimize unconstrained problems. Singh (2009), and Karaboga and Akay (2011) have proposed ABC algorithm for constrained optimization problems. Karaboga, Ozturk *et al.* (2012) have very recently proposed artificial bee colony algorithm on the foot-steps of genetic-programming for symbolic regression called ABC programming. Manuel and Elias (2012) have modified the initialization step of potential solutions for a filter design.

2.3.1 Hybrid ABC Algorithms

Yildiz (2012 (a)) and Yildiz (2012 (b)) have proposed a hybrid ABC algorithm by incorporating a local search-technique called Taguchi method into ABC algorithm. The proposed variants have been compared with other optimization algorithms on two low-dimensional mechanical engineering problems. The reported results show better performance of the hybrid algorithm.

Similarly, Wu *et al.* (2012) have hybridized ABC and HS algorithms. The results show better performance of the hybrid ABC variant then few variants of HS algorithm. However, the hybridized algorithm has not been compared with the standard-ABC algorithm.

Kang *et al.* (2011) have incorporated a local-search technique named Rosenbrock into ABC algorithm and the hybridized algorithm has been named