

# An Improved Artificial Bee Colony (IABC) Algorithm for Numerical Function Optimization

S.Naveena, S.Malathy, D.Saranya, D.Rajesh Kumar

**Abstract**— This paper proposes an Improved Artificial Bee Colony (IABC) algorithm by introducing the Newtonian Law of Universal Gravitation between the employed bee and onlooker bee. The Universal Gravitation considers the fitness value of the employed bee that is picked by applying the roulette wheel selection as well as the fitness value of the randomly selected employed bees. Since the proposed modification makes the onlooker bee to perform neighborhood search using more than one employed bee it widens the exploration capability of the algorithm. The performance of the proposed IABC is tested using six benchmark functions. From the simulation result it is found the exploration ability of the proposed IABC is not constrained through a narrow zone and produces better results without getting stuck in to the local optima when compared with simple ABC.

**Keywords**— Numerical Optimization, Swarm Intelligence, Artificial Bee Colony, Newtonian Law of Gravitation

## I. INTRODUCTION

Optimization [1] is the most important process faced by every Human being during their life time. The process of optimization is obtaining the ‘best’, from the possible ‘good’ or ‘bad’ things. In general, the word ‘optimum’ is taken to mean ‘maximum’ or ‘minimum’ depending on the circumstances; e.g., one wishes the ‘most’ or ‘maximum’ salary or the ‘least’ or ‘minimum’ expenses. Thus ‘optimum’ is a technical term which implies quantitative measurement and is a stronger word than ‘best’. Likewise, the word ‘optimize’, means to achieve an optimum and is a stronger word than ‘improve’. In its earliest form, optimization consisted of unscientific rituals and prejudices. As the ages advanced, unscientific rituals were replaced by the development in mathematics and mathematical calculations.

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Optimization theory [2] is the branch of mathematics encompassing the quantitative study of optima and methods for finding them. Optimization problems occur in most disciplines like engineering, physics, mathematics, economics, administration, commerce, social sciences, and even politics. Approaches to optimization problems are categorized as analytical, graphical, and numerical. Analytical methods are based on the classical techniques of differential calculus. However, it cannot be applied to highly nonlinear problems or to problems where the number of independent parameters exceeds two or three. A graphical method can be used to plot the function to be maximized or minimized if the number of variables does not exceed two. Unfortunately, the graphical method is of limited usefulness since in most practical applications the function to be optimized depends on several variables, usually in excess of four.

Numerical methods [3] are the most important general approach to optimization in which iterative numerical procedures are used to generate a series of progressively improved solutions to the optimization problem, starting with an initial estimate for the solution. The process is terminated when some convergence criterion is satisfied. During the past 40 years, several branches of mathematical programming have evolved such as Linear Programming, Integer Programming, Quadratic Programming, Nonlinear Programming, and Dynamic Programming. But these branches of mathematical programming are concerned with a specific class of optimization problems.

Several modern heuristic algorithms [4] have been developed for solving optimization problems. Depending on the criteria being considered, these algorithms can be classified into iterative based, stochastic, and population based. Algorithms employing multiple iterations to find the solution are called iterative algorithm where as algorithms employing a probabilistic rule for improving a solution is called probabilistic or stochastic. Algorithms working with a set of solutions and trying to improve them are called population based algorithms. Depending on the nature of phenomenon used, the population based algorithms further classified into Evolutionary Algorithms (EA) and Swarm Intelligence (SI) based algorithms.

The most popular EA is Genetic Algorithm (GA) [5] that attempts to simulate the phenomenon of natural evolution.

Although periodic attempts and improvements have been made in GA since 1975 to produce improved quality solution, still new techniques are emerging as GA takes more processing time and get trapped in local optima for some of the optimization problems. The most popular SI is Particle Swarm Optimization (PSO) [6] which simulates the social behavior of bird flocking or fishes schooling. Even though PSO has received significant interest from researchers, they are computationally inefficient and have slower convergence speed when solving complex multimodal optimization problems. Attempts can also be made to develop a hybrid model [7] of GA and PSO by combining their strengths but that also didn't produce a satisfactory result for several real world problems.

*A. Recently several algorithms have been developed based on the social behavior of honey bees that can be categorized into three groups. First one is the mating behavior that is based on the reproduction phenomenon guaranteed by the queen in the bee colony. Marriage Bee Optimization (MBO) [8], Honey Bees Mating Optimization (HBMO) [9] and Faster Marriage Behavior Optimization (FMBO) [10] are the optimization algorithms falls under this group. Second one is inspired by the queen bee evolution process and is used to enhance the optimization capability of genetic algorithm. Finally third group is inspired by the foraging behavior which is in turn divided into two sub groups. In [11], author proposed an algorithm based on the nest searching behavior of the bee.*

Food source searching behavior of honey bees is studied by most researchers. Bee System (BS) [12], Bee Hive [13], Bee Colony Optimization (BCO) [14], Artificial Bee Colony (ABC) [15], Bee Swarm Optimization (BSO) [16], Virtual Bee Algorithm (VBA) [17], Honey Bee Colony Algorithm (HBCA) [18] and Bee Algorithm (BA) [19] are the algorithms developed during the last decade based on this intelligent behavior of bees. Even though these algorithms seem to be similar but they have significant differentiations in terms of principles, projections, objectives and applications. Among all the above mentioned algorithms, Karaboga [14] and his team reached to the conclusion that ABC gets out of local minimum, more efficient for multivariable and multimodal function optimization function and outperformed GA, PSO and Differential Evolution (DE) [20].

ABC maintains a colony of artificial bees that contains three groups of bees. Bees assigned to the food source are called Employed Bees, Bees waiting on the dance area for making decision to choose a food source are called Onlooker Bees, and a bee carrying out random search is called a Scout Bee. In general, the onlooker bee of the ABC algorithm can move straight to one of the nectar sources discovered by the employed bees. This behavior narrow down the exploration zones of the bees and make the ABC

algorithm perform poor. To overcome this difficulty, this paper proposes an interactive strategy by considering the universal gravitation [21] between the onlooker bee and the selected employee bee. The performance of the proposed Improved ABC (IABC) algorithm is tested using six benchmark function.

The structure of the rest of this paper is described as follows. Section II gives the overview of basic Artificial Bee Colony Algorithm. In Section III, details of the proposed Improved ABC Algorithm are presented. Implementation issues of the proposed IABC algorithm are discussed in Section IV. Details of simulations conducted using six bench mark functions and the results are reported in Section V. Concluding remarks are given in Section VI.

## II. REVIEW OF ABC ALGORITHM

Artificial Bee Colony (ABC) is an optimization algorithm based on intelligent food source searching behavior of swarm of honey bees for solving multidimensional and multimodal optimization problems. In this algorithm, the possible solution for any optimization problem is viewed as position of a food source, the number of possible solution is equal to half of the colony size and the fitness of each possible solution represents the nectar amount of a food source. Figure 1 depicts the flowchart of ABC algorithm.

As shown in figure 1, at first employed bees are sent to the food sources for measuring the nectar amount. Candidate food position from the old one is produced by using the following expression

$$x_{ij}(t+1) = \theta_{ij} + \phi(\theta_{ij}(t) - \theta_{kj}(t)) \quad (1)$$

where '  $x_{ij}$  ' denotes the position of  $i^{\text{th}}$  employed bee of  $j^{\text{th}}$  variable, '  $t$  ' represents the iteration number and '  $\phi$  ' is a real number randomly generated in the range [-1,1]. After that onlooker bee selects the food source from the employed bee by sharing the information in the dance area. Further the onlooker bee produces candidate food position using the equation (1) and from which the best food source position are selected using a greedy algorithm. Also if the food position can't be improved for a predetermined number of cycles, then it is abandoned and replaced by a new randomly generated food source by a scout bee. The whole process is repeated until the termination condition is satisfied.

## III. PROPOSED IABC ALGORITHM

In the standard ABC algorithm, both the employed and the onlooker bee use the same expression for finding out the candidate food source position. This clearly depicts that the movement of onlooker bee is based on nectar amount of food source hold by a single employed bee which is selected randomly using a roulette wheel selection. Since only one employed bee is selected, this will not guarantee maximum

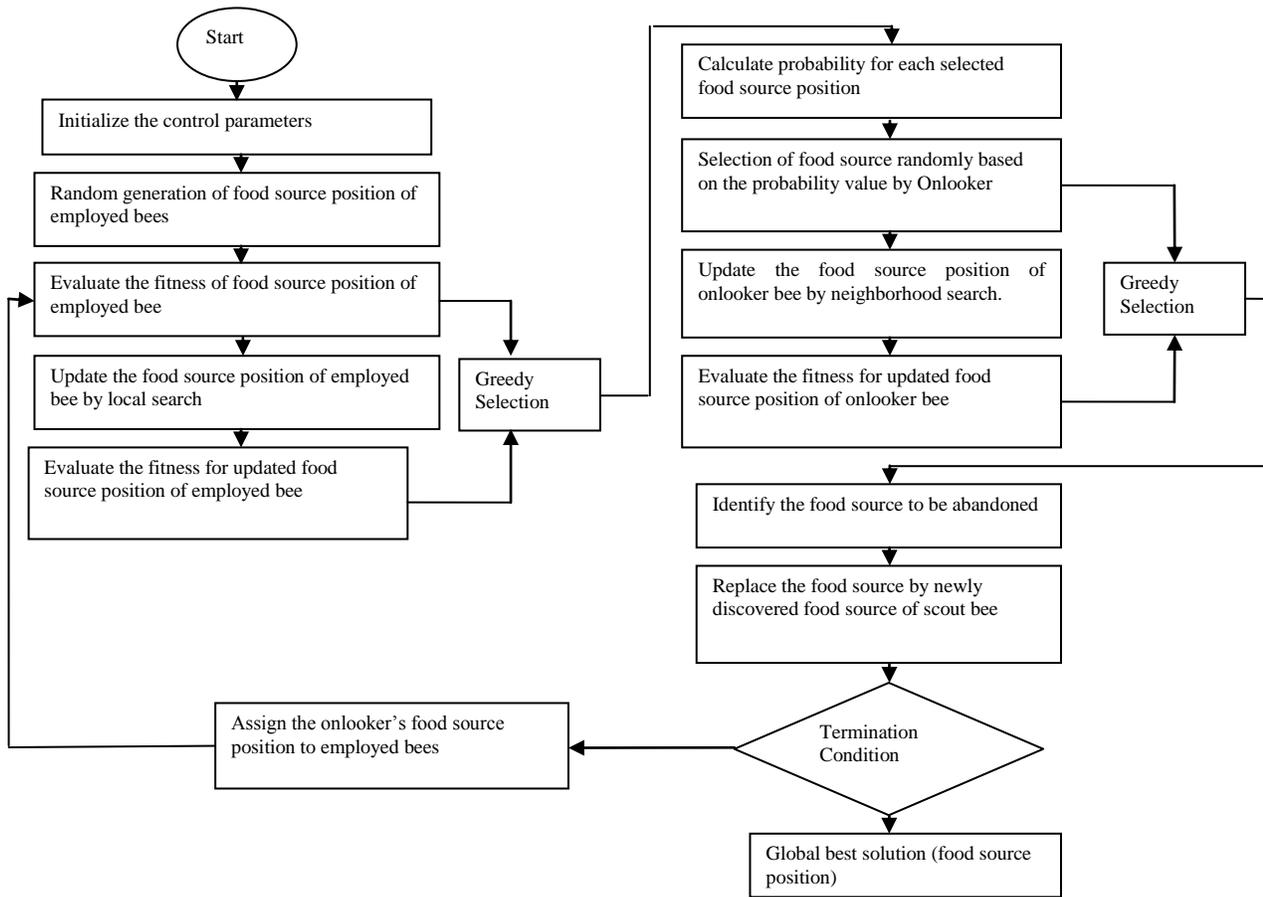


Figure 1 Flow Chart of Simple ABC

exploitation capacity of the solution variables. To address this issue, a modification in the production of candidate food source position is introduced in the onlooker phase by employing the Newtonian law of universal gravitation between the onlooker bee and the selected employed bees. By considering the gravitation between the picked employed bee and 'n' selected employed bees, the equation (1) can be reformed into equation (2) during the onlooker phase.

$$x_{ij}(t+1) = \sum_{k=1}^n \hat{F}_{ik_j} \cdot [\theta_{ij}(t) - \theta_{kj}(t)] \quad (2)$$

where  $\hat{F}_{ik_j}$  is the normalized gravitation and it is calculated using the equation (3)

$$\hat{F}_{ik_j} = \frac{1}{\frac{F(\theta_i) \cdot F(\theta_k)}{(\theta_1 - \theta_i)^2} + \frac{F(\theta_i) \cdot F(\theta_2)}{(\theta_2 - \theta_i)^2}} \left( \frac{F(\theta_i) \cdot F(\theta_k)}{(\theta_{kj} - \theta_{ij})^2} \cdot \frac{\theta_{kj} - \theta_{ij}}{|\theta_{kj} - \theta_{ij}|} \right)_{for k=1,2} \quad (3)$$

where,  $F(\theta_i)$  indicates the fitness of employed bee picked by the roulette wheel selection and  $F(\theta_k)$  indicates the fitness value of the randomly selected employed bees. Equation (2) selects more than one employed bees in addition to a employed bee picked by the onlooker and there by achieves increased exploration ability of the standard

ABC. Further, the gravitation  $F_{ik_j}$  acts as a weight factor controlling the specific weight of  $[\theta_{ij} - \theta_{kj}]$ .

#### IV. IMPLEMENTATION OF PROPOSED IABC ALGORITHM

While applying the proposed IABC algorithm for any function optimization, the following issues are to be addressed

- Initialization
- Employed Bee Phase
- Onlooker Bee Phase
- Scout Bee Phase
- Termination Checking

### A. Initialization

The parameters of the proposed IABC algorithm that are to be initialized first are as follows,

- Colony size (  $C_{size}$  )
- Number of Employed Bee (  $N_E$  ) =  $C_{size} / 2$
- Number of Onlooker Bee (  $N_O$  ) =  $C_{size} / 2$
- Number of Scout Bee (  $N_S$  )
- Dimension (  $D$  )
- Maximum number of Iterations (  $I$  )
- Limit (  $L$  ) = Dimension \* (  $C_{size} / 2$  )
- Number of trials (  $T$  )

The performance of the algorithm depends on the values associated with the parameters. For effective performance of the proposed IABC algorithm, colony size may be varied from 100 to 250, iteration from 2000 to 3000 and T value from 20 to 30.

At first, set of possible food source positions are randomly generated within a given variable range and all the solutions are assigned to employed bees.

### B. Employed bee Phase

Once the randomly generated food sources positions are assigned to employed bee its fitness is evaluated first using the equation (4)

$$fit(i) = \begin{cases} \frac{1}{1 + f_i} & f_i \geq 0 \\ 1 + abs(f_i) & f_i < 0 \end{cases} \quad (4)$$

Then the employed bee performs the neighborhood search for finding new possible food source positions using the equation (1). A greedy selection process is carried out by employed bees to memorize the best food source between old and new fitness of food sources.

### C. Onlooker Bee Phase

The onlooker bee selects the food source of the employed bee based on the probability value associated with the food source position. The probability of each food source is calculated using the equation (5)

$$P_i = \frac{F(\theta_i)}{\sum_{i=1}^s F(\theta_i)} \quad (5)$$

where ' $\theta_i$ ' indicates the fitness value and  $P_i$  is the probability of the  $i^{th}$  employed bee. The probability values are normalized between the range 0 and 1.

Now as a modification to the simple ABC, the onlooker bee performs a neighborhood search by employing the Newtonian law of gravitation using equation (2). The fitness of new food source positions of onlooker bee is evaluated using equation (4).

A greedy selection process is carried out by onlooker bees to memorize the best food source between old and new fitness of food sources.

### D. Scout Bee Phase

If the fitness value of the food source is not improved continuously for a predetermined number of iterations, then the food sources is abandoned and replaced

with food source found by the scout bee. The scout bee searches the food source randomly using the equation (6)

$$\theta_{ij} = \theta_{ij \min} + r \cdot (\theta_{ij \max} - \theta_{ij \min}) \quad (6)$$

where r is a random number between [0, 1],  $\theta_{ij}$  indicates the new food source position,  $\theta_{ij \min}$  specifies the lower limit of the variables of objective function and  $\theta_{ij \max}$  indicates the upper limit of the variables.

### E. Termination Checking

Check if the number of iteration reaches the maximum number of iterations (T). If it reaches, then the termination condition is said to be satisfied. Terminate the algorithm and output the best solution found so far, otherwise go back to the employed bee phase.

## V. SIMULATION RESULT

This section presents the details of simulation carried out using six test functions to demonstrate the effectiveness of the proposed IABC algorithm for numerical function optimization. The details of function used are given in the table 1.

The proposed IABC approach is implemented in MATLAB and executed in a PC with Pentium Dual Core processor with 2.26 GHz speed and 3 GB of RAM. The proposed algorithm is run with different values of ABC control parameters and the optimal results are obtained with the following setting

$C_{size}$  : 250  
 $N_E$  : 125  
 $N_O$  : 125  
 $I$  : 2000  
 $T$  : 30  
 $D$  : 10, 20 and 30  
 $L$  :  $D * 125$

For all the benchmark functions, each of the experiments is repeated 30 times with different random seeds. The mean function values of the best solution found by the algorithms for different dimension have been recorded. The mean and standard deviation of the function values obtained by the simple ABC and the proposed IABC are given in Table 2.

**Table 1 Benchmark Functions**

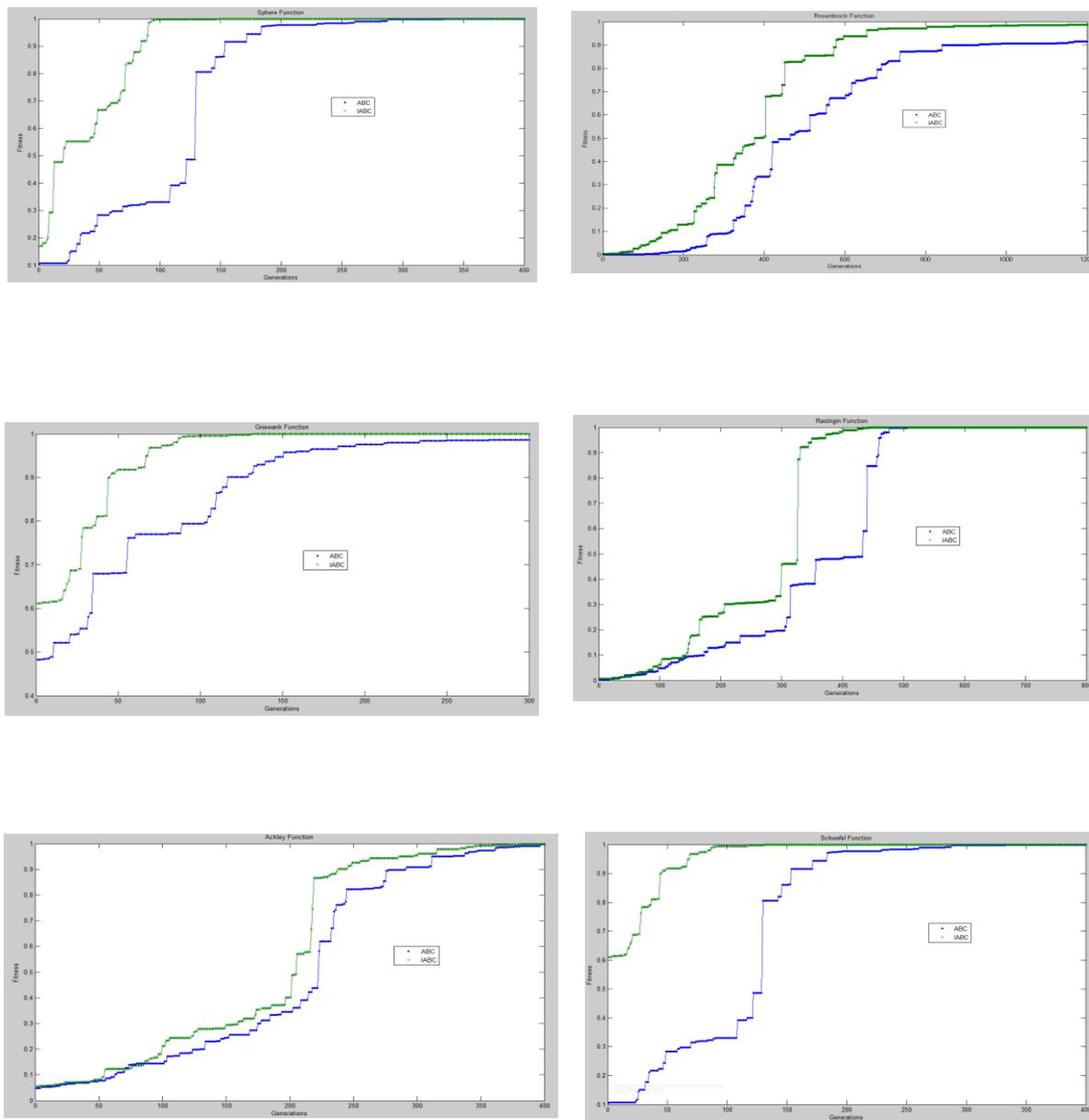
Test Function	Equation	Range
Sphere	$f(x) = \sum_{i=1}^n x_i^2$	[-600, 600]
Rosenbrock	$f(x) = \sum_{i=1}^n (100(x_{i+1} - x_i^2)^2 + (x_i - 1)^2)$	[-15 15]
Rastrigin	$f(x) = \sum_{i=1}^n (x_i^2 - 10 \cos(2\pi x_i) + 10)$	[-15, 15]
Griewank	$f(x) = (1/4000) * \sum_{i=1}^D (x_i)^2 - \prod_{i=1}^D \cos(x_i / \sqrt{i}) + 1$	[-600, 600]
Ackley	$f(x) = -20 \exp\left(-0.2 * \sqrt{\frac{1}{D} \sum_{i=1}^D x_i^2}\right) - \exp\left(\frac{1}{D} \sum_{i=1}^D \cos 2\pi x_i\right) + 20 + e$	[-32.768, 32.768]
Schwefel	$f(x) = D * 418.9829 + \sum_{i=1}^D -x_i * \sin(\sqrt{ x_i })$	[-500, 500]

**Table 2 Performance of the IABC algorithm**

Test Functions	Dimensions	ABC		IABC	
		Mean	Standard Deviation	Mean	Standard Deviation
Sphere	10	0.000537E-12	0.000537E-10	0.000435E-12	0.00435E-11
	20	5.00056E-14	5.00056E-14	4.98751E-15	4.98751E-14
	30	9.034509E-17	9.034509E-16	0.724343E-17	7.24343E-17
Rosenbrock	10	0.0098761	0.0087534	0.098973	0.0028364
	20	0.3967336	0.299921	0.222374	0.123921
	30	0.1874537	0.235134	0.139821	0.119082
Rastrigin	10	0.053663E-17	0.465878E-16	0.084734E-18	0.084653E-17
	20	0.8564363E-6	0.757487E-5	0.475958E-8	0.397754E-7
	30	0.645373	0.446323	0.746373E-1	0.537474
Griewank	10	0.000537	0.004457	0.002356	0.002245
	20	5.003451E-5	4.032561E-4	3.954673E-5	2.67531E-4
	30	6.879541E-6	4.987321E-5	4.998341E-6	3.65784E-5
Ackley	10	7.46352E-10	5.896746E-10	3.758476E-10	4.883744E-10
	20	0.568932E-10	0.493736E-9	0.867463E-10	0.746635E-10
	30	0.984635E-11	0.746323E-10	0.846849E-9	0.537474E-9
Schwefel	10	9.985746E-6	5.847479E-8	8.5435858E-7	5.534535E-8
	20	0.0000987	0.00000965	0.857344E-4	0.8477432E-3
	30	0.874635E-2	0.5748339E-2	0.5948485E-2	0.4398584E-2

From table 2, it is found that the proposed IABC algorithm can converge to the minimum for all the benchmark function compared with simple ABC algorithm.

It shows that the proposed IABC has the ability to getting out of the local minimum while solving benchmark functions.



**Figure 2 Convergences of ABC and IABC for Benchmark Functions**

From figure 2, it is found that the proposed modifications in the neighborhood search of onlooker phase widens the exploration zone and improves the convergence speed when compared with simple ABC. Further the consideration of universal gravitation between the selected employed bees and onlooker bees increases the exploitation ability of the IABC.

## VI. CONCLUSION

In this paper, an Improved Artificial Bee Colony optimization algorithm is proposed. The proposed IABC uses the concept of universal gravitation to the movement of onlooker bees during neighbourhood search. The performance of the proposed IABC has been compared with the original ABC using six well-known numerical benchmark functions. From the simulation result it is found that the proposed IABC performs better than the original ABC which clearly depicts the essence of the universal gravitation and can be efficiently applied to solve the many kind of complex optimization problems.

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