A Novel Approach for Firefly Colony Optimization on Solving Multiobjective Optimization

Prasannajit Dash, Dr.Maya Nayak

Abstract— The objective of this paper is to propose inspired by meta-heuristic ant colony optimization (ACO), the new firefly colony optimization (FCO) is presented here. As per the standard firefly algorithm, the newly proposed method is a distributive, meta-heuristic in nature to construct greedily good solutions. The performance of the newly adopted approach is assessed by bin packing problem (BPP). The bin packing problem(a combinatorial NP-hard problem) checks per the minimum number k of identical bins of capacity C needed to store a finite collection of weights w1, w2, w3,…..,wn so that no bin has weights stored in it whose sum exceed the bin capacity. When the number of bins is restricted to 1 and each item is characterized by both a volume and a value, the problem of maximizing the value of items that can fit in the bin known as knapsack problem.

Index Terms— Firefly Algorithm, Firefly Colony Optimization, Bin Packing Problem, Ant Colony Optimization, Particle Swarm Optimization, Artificial Bee Colony Optimization

1 Introduction

On the nature-inspired meta-heuristic inspired by ant colony optimization a new firefly optimization algorithm as there are many algorithms based on swam intelligence, artificial neural network and genetic algorithms. For example, the Ant Colony Optimization (ACO), Particle Swam Optimization (PSO) and Artificial Bee Colony algorithm (ABC)[1] are based on swam intelligence. There are about two thousand fireflies species out of which most of the fireflies produce short and periodic flashes. Always the flashing light intensity decreases as the distance increases. This phenomenon inspired by Yang to develop the Firefly Algorithm(FA).Of course, the firefly algorithm is one of the best multimodal, multiobjective algorithm but its performance to deal with discrete optimizations i.e. light intensity and distance are not good enough compared to Ant Colony Optimization[2], Particle Swam Optimization(PSO)[3] and Artificial Bee Colony Optimization(ABC)[4] etc.

However the algorithm complexity is much higher than the above algorithms. This paper is to produce the new variant based on the new behavior of the firefly where it has the new impact on the firefly algorithm. The new variant makes the firefly as the new cooperative agents like ants in ant colony optimization. Like in ant colony optimization[5], there is an indirect communication called as stigmergy between fireflies to search for a good solution. The assumption in fireflies group is that they emit phosphorescent materials in their way such that they become more brightened. When they make a decision point, probably they make a choice biased on the intensity of the phosphorescent substance light they see on their way. This effect is called as autocatalytic because when the firefly opts for a good path, it increases the probability of that particular path which becomes the arrival of other fireflies in future. It is assumed that when they return back to the path that they have chosen due to the increase of its brightness. The final graph solution in the firefly colony algorithm looks like the roads in city. Since the firefly colony optimization (FCO)[6] does not make any pairwise comparisons between the fireflies because of the speed significantly increases, the performance of FCO[7] is significantly improved due to the randomization capacity of the basic Firefly Algorithm (FA) [8]which is the standard algorithm. Due to the hybridization between the greediness ability of the constructive algorithms, the exploration and exploitation of the firefly algorithm gives the way to deal with the discrete optimization problem. As the approach is towards the multiobjective algorithm, the FCO got tested successfully on the bin packing problem (BPP)[9] which is np-hard combinatorial problem. Comparing with ant colony optimization, the performance of the newly proposed FCO[10] is significantly better and simultaneously gives best solutions in low computational problem. Generally the social behavior of fireflies is not meant for foraging but more for reproduction. Hence it is observed that there are direct communications between fireflies by means of periodic flushing light. Two basic methods of a firefly flashing light due to attract mating partners and to attract the potential pray. The FA algorithm[11] is based on the potential of flashing light patterns and the behavior of fireflies.

Generally these idealized flashing characteristics are given below:

(a) Fireflies are simply the unisex so that one firefly could attract the other fireflies regardless their sex.

(b) The attractiveness is proportional to the brightness and they gradually decrease as soon their distance increases. Hence for any two flashing fireflies, the less brighter firefly will definitely move towards the more brighter firefly. So in case if there is no brighter one in respect to the particular firefly, it will move randomly.

2 Related Works

In the firefly algorithm, there are two important issues that is the variation in the light intensity and formulation of attractiveness. In case of maximum optimization[12], the brightness factor I of a firefly at a particular location x can be I(x) α f(x). However, the attractiveness factor β is relative in comparison to the brightness factor I. In case of the light intensity I(x), it gradually varies with the distance r monotonically and exponentially in the following equation (1) :

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$$I(r) = I_0\ e^{/-yr^2} \quad . \qquad (1)$$

But for some particular occasions, the light intensity function decreases monotonically at a slower rate approximately in the following equation (2) :

$$I(r) = \frac{I_0}{yr^2} \qquad (2)$$

It has been observed that a firefly attractiveness is proportional to the light intensity seen by adjacent fireflies. The variation between the attractiveness factor ß with the distance r in the following equation (3) :

$$\beta = \beta_0\ e^{-yr^2} \qquad (3)$$

where β_0 is the attractiveness coefficient at r = 0.

The exponent yr^2 in the above equation (3) will be replaced by the exponent yr^m where m > 0.

The Cartesian distance[13] r between any two fireflies i and j at x_i location and x_j location is given in the following equation :

$$r_{ij} = \| x_i - x_j \| = \sqrt{\sum_{k=1}^{d} (x_{i,j} - x_{j,k})} \qquad (4)$$

In course of time, the firefly i movement attracted to another more attractive firefly that means the more brighter one i.e. j is determined by the following given equation(5) :

$$\mathbf{x}_i^{t+1} = \mathbf{x}_i^t + \beta \exp[-\gamma r_{ij}^2](\mathbf{x}_j^t - \mathbf{x}_i^t) + \alpha_t \boldsymbol{\epsilon}_t \qquad (5)$$

where the equation(5) is having the second term i.e.

$$\beta_0\ e^{-yr_{i,j}^2} (x_j^t - x_i^t)$$

is the particular firefly attraction parameter in location i and the third term i.e. α_t is the coefficient which is nothing but the randomization parameter of the particular firefly at location i and the time variant t where $\in_i^t$ is the vector due to the gaussian distribution which is the uniform distribution at time t.

If β_0 is the coefficient compared to the value zero, then the second term is non-gaussian[14] in uniform distribution which is basically a random walk. If the exponent y is equal to zero, the second term becomes a variant to particle swarm optimization. The firefly algorithm (FA)[15] is a metaheuristic algorithm, inspired by the flashing behavior of fireflies. The primary purpose for a firefly's flash is to act as a signal system to attract other fireflies. Xin-She Yang formulated this firefly algorithm by assuming all fireflies are unisexual, so that any individual firefly will be attracted to all other fireflies. Attractiveness is proportional to their brightness, and for any two fireflies[16], the less bright one will be attracted by (and thus move towards) the brighter one; however, the intensity (apparent brightness) decrease as their mutual distance increases. If there are no fireflies brighter than a given firefly, it will move randomly. The brightness[17] should be associated with the objective function. Firefly algorithm is a nature-inspired metaheuristic optimization algorithm.

The pseudo code can be summarized as:

Begin

1) Prepare the objective function: f(x), $X=(X_1, X_2, X_3, \ldots, X_d)$;
2) Formulate an initial population of fireflies i.e. X_i (i = 1,2,…..,n);
3) Calckate the light intensity I so that it is associated with f(x). For example, for maximization problems, I α f(x) or simply I = f(x)
4) Let us define the absorption coefficient γ

```
while ( t <  maximum generation)
 for i = 1 : n (for all of the  n fireflies)
     for j = 1 : n (for all of the  n fireflies)
       if ( Ij > Ii),
              do the movement of firefly i towards j;
       end if
Generally the  attractiveness varies with distance r
exp (-γr);
Formulate  new solutions and update light intensity;
 end for j
end for i
Rank the fireflies and check  the current best;
end while
Post-processing the results and visualization;
End
```

The main update formula for any pair of two fireflies $\mathbf{x}_i$ and $\mathbf{x}_j$ is given in Equation(6) below:

$$\mathbf{x}_i^{t+1} = \mathbf{x}_i^t + \beta \exp[-\gamma r_{ij}^2](\mathbf{x}_j^t - \mathbf{x}_i^t) + \alpha_t \boldsymbol{\epsilon}_t \qquad (6)$$

Where $\gamma \to 0$ corresponds to the standard Particle Swarm Optimization (PSO). In fact, if the inner loop (for j) is removed and the brightness I_j is replaced by the current global best g^*, then FA essentially becomes the standard PSO.

2.1 Firefly Algorithm(FA) Implementation

The γ should be related to the scales of design variables. Ideally, the β term should be order one, which requires that γ should be linked with scales. For example, one possible choice is to use $\gamma = 1/\sqrt{L}$ where L is the average scale of the problem. In case of scales vary significantly, γ can be considered as a vector to suit different scales in different dimensions. Similarly, α_t should also be linked with scales. Forexample, $\alpha_t \leftarrow 0.01 L \alpha_t$. It is worth pointing out the above description does not include the randomness reduction. In fact, in actual implementation by most researchers, the motion of the fireflies is gradually reduced by an annealing-likerandomnessreductionvia $\alpha = \alpha_0 \delta^t$ where $0 < \delta < 1 (e.g. \delta = 0.97)$.

In some difficult problem, it may be helpful if by increasing α_t at some stages, then reduce it when necessary. This nonmonotonic[18] variation of α_t will enable the algorithm to escape any local optima when in the unlikely case it might get stuck if randomness is reduced too quickly.

Parametric studies show that n (number of fireflies) should be about 15 to 40 for most problems. Recent studies shows that the firefly algorithm is very efficient, and could outperform other metaheuristic algorithms including particle swarm optimization(PSO). Most metaheuristic algorithms may have difficulty in dealing with stochastic test functions, and it seems that firefly algorithm can deal with stochastic test functions very efficiently. In addition, FA is also better for dealing with noisy optimization problems with ease of implementation.

It has been shown in many instances that the firefly algorithm can be superior to particle swarm optimization in their applications, the effectiveness of the firefly algorithm was further tested in later studies. In addition, firefly algorithm can efficiently solve non-convex problems with complex nonlinear constraints. Further improvement on the performance is also possible with promising results.

2.2 Variants of Firefly Algorithm(FA)

A recent, comprehensive review showed that the firefly algorithm and its variants have been used in almost all areas of science. There are more than twenty variants

2.2.1 Discrete Firefly Algorithm(DFA)

A discrete version of Firefly Algorithm, namely, Discrete Firefly Algorithm (DFA)[19] proposed recently by M. K. Sayadi, R. Ramezanian and N. Ghaffari-Nasab can efficiently solves NP-hard scheduling problems. DFA outperforms existing algorithms such as the ant colony algorithm. For image segmentation, the FA-based method is far more efficient to Otsu's method and recursive Otsu. Meanwhile, a good implementation of a discrete firefly algorithm for QAP problems has been carried out by Durkota.

2.2.2 Multiobjective Firefly Algorithm

An important study of FA was carried out by Apostolopoulos and Vlachos[20], which provides a detailed background and analysis over a wide range of test problems including multobjective load dispatch problem.

2.2.3.Lagrangian Firefly Algorithm

An interesting, Lagrangian[21] firefly algorithm is proposed to solve power system optimization unit commitment problems.

2.2.4.Chaotic Firefly Algorithm

A chaotic firefly algorithm (CFA)[22] was developed and found to outperform the previously best-known solutions available.

2.2.5.Firefly Algorithm Based Memetic Algorithm

A firefly algorithm (FA) based memetic algorithm (FA-MA)[23] is proposed to appropriately determine the parameters of SVR forecasting model for electricity load forecasting. In the proposed FA-MA algorithm, the FA algorithm is applied to explore the solution space, and the pattern search is used to conduct individual learning and thus enhance the exploitation of FA

2.2.6.Parallel Firefly Algorithm with Predation (pFAP)

In implementation for shared memory environments with the addition of a predation mechanism that helps the method to escape local optimum.

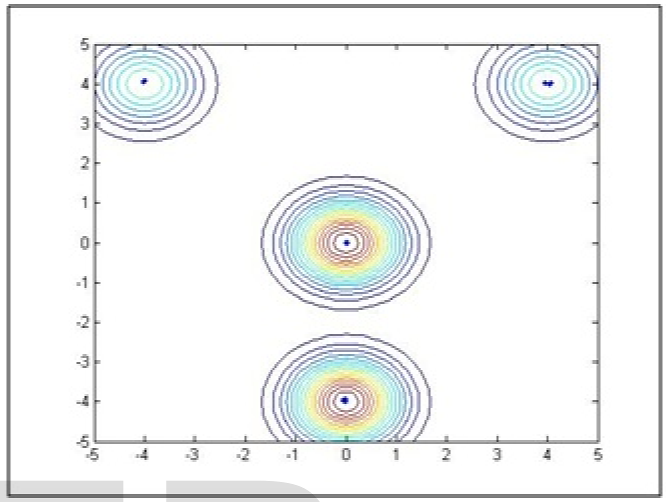

Fig 1 Simple Firefly Algorithm

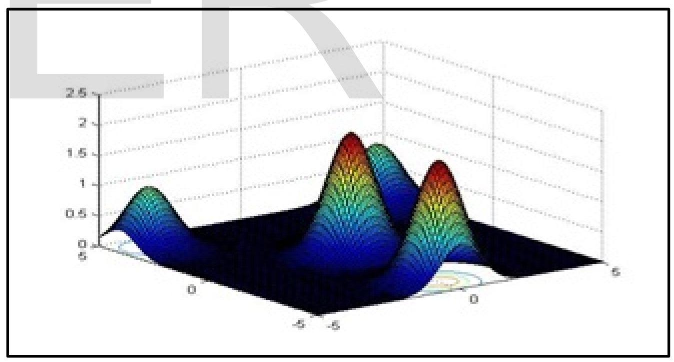

Fig 2. Shape of multiobjective function

Xin-She Yang, Nature-Inspired Metaheuristic Algorithms from Dataset1

Table 1

0.9998	1.0002	0.9998	1.0000	0.9999
0.9999	1.0001	1.0000	1.0001	0.9999
1.0001	1.0002	1.0001	0.9999	1.0000

- *Dr.Maya Nayak is currently working as Head of the Depatment of Computer Science and Engineering , Orissa Engineering College, Bhubaneswar, Odisha. E-mail: mayanayak_3299@yahoo.com*
- *Prasannajit Dash is currently working as Asst.Professor,Dept. of Information Technology ,Orissa Engineering College,Bhubaneswar, Odisha .
E-mail: prasannajitdash11@gmail.com*

Bestsolution = 0.9998
Bestobjective = 2.7210e-07
total_number_of_function_evaluations = 10000

Xin-She Yang, Nature-Inspired Metaheuristic Algorithms from Dataset2

Table 2

0.999977698063855	0.999996593145523
0.999952180009702	0.999940022654231
1.000069552683028	0.999924118783051
0.999973288865707	0.999970022374775
0.999999758679134	0.999940909932101
0.999980638817090	1.000032401241844
0.999927096047113	1.000009874232563

Bestsolution = 0.999855945391779
Bestobjective = 4.968130120408029e-08
total_number_of_function_evaluations = 10000

4 PROPOSED FIRE COLONY OPTIMIZATION (FCO)

In case of overcoming the limitations of firefly algorithm for discrete and combinatorial optimization, we have developed the new constructive version on top of the basic firefly algorithm called Firefly Colony Optimization (FCO)[24]. The proposed one is covering both the behaviors of ant colony optimization and firefly algorithm. The Firefly Colony Optimization Algorithm FCO was originally inspired by the ability of the real fireflies to attract each other, and to be attracted by the brightest ones and by sources of light. However, the proposed firefly colony optimization (FCO)[25] is a distributed, and constructive greedy metaheuristic. More formally, given a fully connected graph *(n,E)* with *n* nodes and *E* edges, representing all the potential trajectory solutions, the FCO[26] is able to find the best (optimal) combination of these nodes encoding a feasible solution for a given combinatorial optimization problem. In this metaheuristic, we suppose that the fireflies are able to release phosphorescent substance while flying.

The paths can absorb this substance and, in turn, they become luminous. We assume also that, the quantity of the phosphorescent substance emitted by the fireflies, at.Eevery iteration, is fixed. Consequently, shorter is the path, higher is its brightness. It is clear, that the shortest path become brighter and more attractive than the others, influencing other fireflies to follow it. After few time, the entire colony will follow this shortest path(figure. 3).

In addition to the above characteristics, fireflies are considered as simple agents that cooperate between themselves to construct good solutions. The proposed FCO is guided by the following assumptions (Algorithm 2):

1. The fireflies communicate indirectly using stigmergy by means of the phosphorescent substance.
2. They build a solution by moving on the graph's nodes.
3. They will have some memory for memorizing their paths.
4. They put a phosphorescent substance on each node visited at the end of the complete tour.
5. The attractiveness between nodes depends to the distance between them and the quantity of the phosphorescent substance.

Algorithm2: Firefly Colony Optimization (FCO) Algorithm

1. Objective Function f (X), $X = (X_1, X_2, \ldots, X_n)^T$
2. Place all fireflies on their start points {Initialization}
3. Initialize the attractiveness matrix
4. Define light absorption coefficient γ

   while t < MaxGeneration **do**
   for k = 1: n **do** {Solution Construction}
   s = constructSolution (k,t);
   L = f(s);
   end for

5. Evaluate new solutions {evaluation}
6. Update the attractiveness matrix and reset the fireflies' memory {global update}
   end while
7. Let S^+ be the shortest path, L^+ is the corresponding length

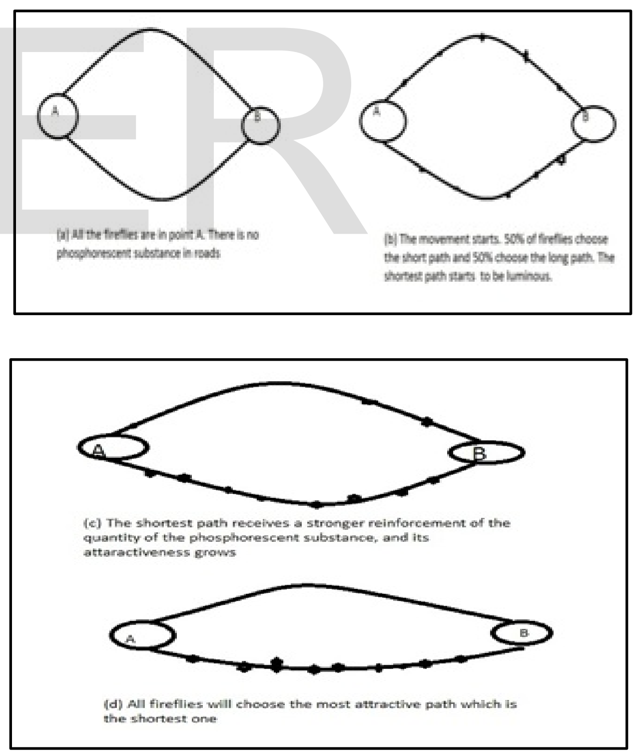

Fig 3 Shortest and most attractive path finding capability of fireflies in FA

5 Conclusion

In this paper, we have proposed a new constructive and distributed version of the firefly algorithm which we have called the Firefly Colony Optimization (FCO)[27]. FCO combines between the phenomenon of bioluminescent communication of fireflies and foraging behavior of ants. The FCO is very efficient for solving the combinatorial and discrete optimization problems. In order to validate our new algorithm, we have applied it for solving the one-dimensional bin packing problem (BPP)[28]. The results are very encouraging and clearly show the effectiveness of our approach. FCO obtains near optimal results with significant faster convergence ability. Therefore, we can say that FCO was found to be more effective compared to standards FA for the discrete optimization problem studied in this paper. As perspective, we want to test the effectiveness of the use of local search methods and difference update brightness rules.

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