I. J. Computer Network and Information Security, **2017, 3, 1-10**
Published Online March 2017 in MECS (http://www.mecs-press.org/)
DOI: 10.5815/ijcnis.2017.03.01

Efficient Dynamic Resource Allocation in OFDMA Systems by Firefly Pack Algorithm

Haider M. AlSabbagh
Department of Electrical Engineering, College of Engineering, University of Basra, Basra, Iraq
E-mail: haidermaw@ieee.org

Mohammed Khalid Ibrahim
Department of Electrical Engineering, College of Engineering, University of Babylon, Babylon, Iraq
E-mail: mohammedkhalidibraheem@gmail.com

Abstract—The resource allocation of Orthogonal Frequency Division Multiple Access (OFDMA) is one of the core issues in the next generation mobile systems. The improvement in the performance and quality of service (QoS) of communication systems is relying upon the efficient utilization of the available communication resources. The resource allocation of the OFDMA systems is mainly depends on both power and subcarrier allocations of each user for different operation scenarios and channel conditions. This paper proposes and applies Firefly Pack Algorithm (FPA) to find the optimal or near optimal power and subcarrier allocations for OFDMA systems. It takes into consideration the power and subcarrier allocations constrains, channel and noise distributions, distance between users equipments and base station, user priority weight to approximate the most of the variables, constrains, and parameters that encounter in the OFDMA systems. Four important cases for the number of subcarriers and users are addressed, simulated, and analyzed with employing the FPA algorithm under specific operation scenarios to meet the standard specifications. The results demonstrate that FPA is an effective algorithm in finding the optimal or near optimal for both subcarrier and power allocation.

Index Terms—Communication systems, Firefly Algorithm, Firefly Pack Algorithm, OFDMA, optimization, resource allocation.

I. INTRODUCTION

Optimization techniques deal with a wide range of problems aim to find a certain or a suitable optimality. Subsequently, there are diverse ways for identifying and classifying optimization problems. The optimization techniques may also significantly vary depending on the nature of the problem in the hand. Since the complexity of an optimization problem highly depends on the form of its objective functions and constraints, therefore, unified approaches are not always possible [1].

Many efficient biology-inspired metaheuristic algorithms have used to deal with various combinatorial optimization problems and non-linear optimization constrained problems in general [2]. Recently, Firefly Algorithm (FA) has been introduced as a powerful and promising approach for solving optimization problems. It can deal with multimodal functions naturally and efficiently and it is considered to be superior to both particle swarm optimization (PSO) and standard genetic algorithm (GA) in terms of both success rate in obtaining the global optima and efficiency [3]. In general, FA has two major advantages over other algorithms: the ability of dealing with multimodality and the ability of automatic subdivision [4].

Literatures of Firefly algorithm have considerably expanded with diverse purposes and applications. Many conscious studies were conducted with using original and modified versions of FA to solve optimization problems in their fields of study successfully and efficiently. For example, it has been used to: solve the path planning problem [5], optimize the back-propagation neural network training [6], optimize Job Shop Scheduling [7], detection of complete, as well as, for partial faulty elements position [8], Economic Emissions Load Dispatch Problem [2], optimization of queuing systems [9], train the radial basis function network for data classification and disease diagnosis[10], create multiple solution alternatives for satisfy required system performance criteria [11]. Also, multi-objective optimization firefly algorithm was used to design bio-chemical engineering system [12].

The most important issue in OFDM and OFDMA is to find suitable or optimal subcarrier (or subchannel) allocation and power allocation, which known as resource allocation problem. Solving of such issue has drawn a great attention and concentration of many researchers. For instance, Wonjong Rhee and John M. Cioffi [13] have proposed an analytic algorithm to solve suboptimal multiuser subchannel allocation in the downlink of OFDM systems. Jiho Jang and Kwang Bok Lee [14] have suggested an analytic transmit power adaptation method to maximize the total data rate of multiuser OFDM systems in a downlink transmission. Yenumula B. Reddy and Nandigam Gajendar [15] have proposed a genetic algorithm approach for subcarrier and bit allocation to minimize the overall transmit power in downlink transmission for OFDM. Atta-ur-Rahman, Ijaz Mansoor

Qureshi and Aqdas Naveed Malik [16] have introduced and investigated adaptive resource allocation schemes for OFDM systems: The first one is based on using the standard Genetic Algorithm and Fuzzy Rule while the other is depending on utilizing Water-Filling and Fuzzy Rule. Hai-Lin Liu and Qiang Wang [17] have studied a hybrid algorithm for the OFDM resource allocation by combining evolutionary algorithm (EA) with Karush-Kuhn-Tucker conditions.

This work utilizing Firefly Pack Algorithm (FPA) to find the optimal or near optimal solution for the OFDMA resource allocation. Four important cases are considered to analyze the effectiveness of the FPA under specific operation scenarios that meet the next generation mobile systems requirements: In the first case, relatively a small equal number of users and subcarriers (6 for each) are chosen to find the best subcarrier and power allocation through multi runs (10 runs). Doubling the number of users and subcarriers which is considered in the first case (12 for each) are selected in case four to explore the strength of the algorithm as the number of users and subcarriers are increased. Both second and third cases represented special yet important and more practical scenarios: In the second case, the number of users (6 users) is half the available number of subcarriers (12 subcarriers) as an example of situation when users are less than the available subcarriers. While case three represents the contrary situation, where the subcarriers are less than number of users (12 users and 6 subcarriers). Case three is an example of resource sharing of limited resource in which a time-frequency sharing plan is needed to provide a reasonable data rate for each user with respect to the channel conditions. The obtained results demonstrate that FPA is an effective algorithm in finding optimal or near optimal solution for both subcarrier and power allocation for OFDMA resource allocation.

The rest of the paper is organized as follows: section II presents a theoretical background for the resource allocation and the algorithms used in this work. Section III illustrates the achieved simulation results. Then, section IV concludes the main achieved results.

II. Theory

Consider a single cell uplink OFDMA system with K users and N subcarriers to be allocated. Also, consider VBR (Variable Bit Rate) for all users with error-free data throughput and a proper coding for the given assignment of subcarriers to the user, then, the channel gain-to-noise ratio (CNR) is given by [13-19]:

$$g_{k,i} = \frac{H_{k,i}}{\sigma_{k,i}^2}\ , \ \text{for } k = 1, \dots K, i = 1, \dots, \mathrm{N} \qquad (1)$$

where $H_{k,i}$ is the channel gain and $\sigma_{k,i}^2$ is the total noise power for each user k and subcarrier i. Now, if $\alpha_{k,i}$ denotes the binary decision variable of subcarrier allocation, then:

$$\alpha_{k,i} = \begin{cases} 1, & subcarrier\ i\ is\ assign\ to\ user\ k \\ 0, & subcarrier\ i\ is\ not\ assign\ to\ user\ k \end{cases} \qquad (2)$$

Given that each subcarrier is only assigned to a single user. This turn to:

$$\sum_{k=1}^{K} \alpha_{k,i} \leq 1\ , \quad for\ i\ 1, \dots, \qquad (3)$$

$\alpha_{k,i}$ may take either 1 or 0. The 0 value indicates that the subcarrier is not assigned to any user. Also, let **A** is a $(K \times N)$ matrix of the channel allocation indices $(\alpha_{k,i})$ which is given as:

$$\boldsymbol{A} = \begin{bmatrix} \alpha_{11} & \cdots & \alpha_{1N} \\ \vdots & \ddots & \vdots \\ \alpha_{K1} & \cdots & \alpha_{KN} \end{bmatrix} \qquad (4)$$

The power spent by a specific user over all its allocated subcarriers should not exceeded allowable maximum transmission power $P_{k,max}$ for that specific user; this can be stated as:

$$\sum_{i=1}^{N} P_{k,i} \leq P_{k,max}\ , \quad for\ k = 1, \dots, \qquad (5)$$

where $P_{k,i}$ is the power allocated to subcarrier *i* by user *k* which should satisfying:

$$P_{k,i} \geq 0, \quad for\ k = 1, \dots, \mathrm{K} \qquad (6)$$

Likewise, **P** is a $(K \times N)$ matrix of allocated powers $P_{k,i}$ and given as:

$$\boldsymbol{P} = \begin{bmatrix} P_{11} & \cdots & P_{1N} \\ \vdots & \ddots & \vdots \\ P_{K1} & \cdots & P_{KN} \end{bmatrix} \qquad (7)$$

as a consequence, the total rate of user *k* may be defined as:

$$\mathrm{R}_k = \sum_{i=1}^{N} \alpha_{k,i}\ \log_2(1 + P_{k,i} g_{k,i}) \qquad (8)$$

and the total system rate is:

$$\mathrm{R}(\boldsymbol{A}, \boldsymbol{P}) = \sum_{k=1}^{K} \sum_{i=1}^{N} \alpha_{k,i}\ \log_2(1 + P_{k,i} g_{k,i}) \qquad (9)$$

The OFDMA resource allocation problem of the maximization of the weighted sum-rate can be formulated as follows:

$$\max \mathrm{E}\left\{\sum_{k=1}^{K} \pi_k \sum_{i=1}^{N} \alpha_{k,i}\ \log_2(1 + P_{k,i} g_{k,i})\right\} \qquad (10)$$

which is subject to

$$\mathrm{E}\left\{\sum_{i=1}^{N} P_{k,i} \leq P_{k,max}\ \right\},\ for\ k\ user \qquad (11)$$

and the user rate must be greater or at least equal to its allowable (or desired) minimum data rate $R_{k,min}$, for user *k*:

$$\mathrm{E}\left\{\sum_{i=1}^{N} \alpha_{k,i} \ \log_2(1 + P_{k,i} g_{k,i})\right\} \geq R_{k,min} \qquad (12)$$

where E{ ·} is the expectation operator, π_k is the weight set to the rate of specific user k. The weights given to the users' rates are chosen to be:

$$\sum_{k=1}^{K} \pi_k \ = 1 \qquad (13)$$

The resource allocation problem, due to the discrete set of values of $\alpha_{k,i}$, in (10) is non-convex. It may become convex once relaxing the condition of $\alpha_{k,i}$ by permits them to take any value in the interval [0, 1]. This is equivalent to allowing the time-sharing of a single subcarrier between different users. In this way during a given scheduling interval, a number of users can transmit on a given subcarrier with each user transmitting alone for a portion of the interval. Moreover, assuming that $f_{k,i} = \alpha_{k,i} P_{k,i}$ then the resource allocation problem can be rewritten to be:

$$\max \mathrm{E}\left\{\sum_{k=1}^{K} \pi_k \ \sum_{i=1}^{N} \alpha_{k,i} \ \ \log_2(1 + \frac{f_{k,i}}{\alpha_{k,i}} g_{k,i})\right\} \qquad (14)$$

which is subject to:

$$\mathrm{E}\left\{\sum_{i=1}^{N} f_{k,i} \leq P_{k,max} \ \right\}, \ \ for\ k\ user \qquad (15)$$

or,

$$\mathrm{E}\left\{\sum_{k=1}^{K} \ \sum_{i=1}^{N} \alpha_{k,i} P_{k,i} \ \leq P_{total} \ \right\}, \ \ for\ all\ users \qquad (16)$$

and for user k:

$$\mathrm{E}\left\{\sum_{i=1}^{N} \alpha_{k,i} \ \log_2(1 + \frac{f_{k,i}}{\alpha_{k,i}} g_{k,i})\right\} \geq R_{k,min} \ , \qquad (17)$$

where (14) is convex since expectation conserve convexity and $\log_2 (1 + b/a)$ is recognized as a concave function form. By such way the problem may be solved reliably and efficiently [18,20]. It should be noted that the resource allocation problem is subject to constraints of. (3), (5), (6) and (13) in addition to that in (15)-(17).

A. The Original Firefly Algorithm (FA)

The original Firefly Algorithm (FA) is a metaheuristic optimization algorithm, developed by Xin-She Yang at Cambridge University in 2007 [1]. This algorithm was inspired by the flashing light behavior of fireflies. FA can be reduced to either random search or particle swarm optimization (PSO) under special cases. FA can find the global optima in addition to the local optima simultaneously and effectively. A further advantage of FA is that different fireflies can work almost independently. It is considered even better than standard genetic algorithm (GA) and PSO because fireflies aggregate more closely around each optimum. The FA established on the following three idealized rules [21-23]:

- All fireflies are unisex so that one firefly will be attracted to other fireflies regardless of their sex.
- Attractiveness is proportional to their brightness, therefore for any two flashing fireflies, the less bright one will move towards the brighter one. The attractiveness is proportional to the brightness and they both decrease as their distance increases. A particular firefly will move randomly if there is no brighter one than it.
- The brightness of a firefly is affected or determined by the landscape of the objective function.

For a maximization problem, the brightness can simply be proportional or related to the value of the objective function. Other forms of brightness can be defined in a similar way to the fitness function used in genetic algorithms [21] and [24]. In the firefly algorithm, there are two important aspects: the variation of light intensity and attractiveness formulation. For simplicity, it can be assume that the firefly's attractiveness is determined by its brightness which in turn is related with the encoded objective function.

In the simplest case for maximum optimization problems, the brightness I of a firefly at a specific location x can be chosen as:

$$I(x) \propto \mathrm{f(x)} \qquad (18)$$

or,

$$I(x) = \mathrm{C} * \mathrm{f(x)} \qquad (19)$$

where f(x) is the objective function and C is a constant. However, the attractiveness β is relative as it depends on what have been seen by the eyes of the beholder or judged by the other fireflies. Hence, attractiveness will vary with the distance r_{ij} between firefly i and firefly j. In addition, light intensity decreases due to fact that light is also absorbed by the media, so the attractiveness will vary with the degree of absorption.

In the simplest form, the light intensity $I(r)$ varies according to the inverse square law

$$I(r) = \frac{I_s}{r^2} \qquad (20)$$

where I_s is the intensity at the source. For a given medium with a fixed light absorption coefficient γ, the light intensity I vary with the distance r as:

$$I = I_o e^{-\gamma r} \qquad (21)$$

where I_o is the initial light intensity. The combined effect of both the inverse square law and absorption can be approximated, to avoid the singularity at $r = 0$ in the expression I_s/r^2, as the following Gaussian form [21]:

$$I(r) = I_o e^{-\gamma r^2} \qquad (22)$$

Since a firefly's attractiveness β is proportional to the light intensity seen by adjacent fireflies, the attractiveness of a firefly can be defined as:

$$\beta = \beta_o e^{-\gamma r^2} \tag{23}$$

where β_o is the attractiveness at r = 0 (usually $\beta_o = 1$, $\gamma = 1$). Another more general attractiveness expression is [25]:

$$\beta = (\beta_o - \beta_{\min}) e^{-\gamma r^2} + \beta_{\min} \tag{24}$$

It is clear that if $\beta_{\min} = 0$ then (24) is reduced to (23). In the actual implementation, the attractiveness function $\beta(r)$ can be any monotonically decreasing functions such as the following form

$$\beta(r) = \beta_o e^{-\gamma r^m}, \quad (m \geq 1) \tag{25}$$

so, this leads to more general form as:

$$\beta(r) = (\beta_o - \beta_{min}) e^{-\gamma r^m} + \beta_{min}, \quad (m \geq 1) \tag{26}$$

The distance between any two fireflies i and j at x_i and x_j, respectively, is the Cartesian distance given as:

$$r_{ij} = \left\|x_i - x_j\right\| = \sqrt{\sum_{d=1}^{D} \left(x_{i,d} - x_{j,d}\right)^2} \tag{27}$$

where $x_{i,d}$ is the d^{th} component of the spatial coordinate x_i of i^{th} firefly. The distance r is not restricted to the Euclidean distance. The definition of other distance r in the n-dimensional hyperspace is depending on the specific problem of interest; any measure of interest quantities in the optimization problem can be used as the distance r. In scheduling problem for example the distance can be time delay or any other suitable forms [1], [21] and [24]. The movement of a firefly i is attracted to another more attractive firefly j is given as:

$$x_i = x_i + \beta_o e^{-\gamma r_{ij}^2} \left(x_j - x_i\right) + \alpha \varepsilon_i \tag{28}$$

the first term represents the initial location. The second term is due to the attraction. The third term is randomization effect with α being the parameter of randomization movement ($\alpha \in [0, 1]$), and ε_i, is a random vector of numbers drawn from a Gaussian distribution or uniform distribution.

To be in simple way the ε_i may be replaced by (*rand* - 1/2), where *rand* is a random number generator uniformly distributed (*rand* $\in$ [0, 1]). Furthermore, the randomization term can easily be extended to other distributions such as Levy flights as explained in [24].

In addition, if the scales vary significantly in different dimensions, it is a good idea to replace α by (α S_D) where the scaling parameters S_D (d = 1 ..., D) in the D dimensions should be determined by the actual scales of the problem of interest [24]. Also, it's possible to add a reduction coefficient δ which will reduce α gradually (i.e. reduces randomness effect) to increase the convergence [21],

$$\alpha = \delta * \alpha \tag{29}$$

B. Firefly pack algorithm

The proposed firefly pack algorithm (FPA) is a multi-groups, multi-elements algorithm that designed to deal with complex multi-dimensions, multi-elements, multi-constrained optimization problems. This may be achieved by using several fireflies' packs (solutions) to explore the entire search space. Each Fireflies' pack is a combination of several different but related groups which also can be divided into related multi-subgroups. On the other hand, using of original FA is not suitable for such complex optimization problems because it will not fully address the individuality (groups and sub-groups). Therefore, this work presents pack principles along with some assumptions and modifications on firefly algorithm to allow dealing with such optimization problems and provids efficiency and robustness in structure and search mechanisms. The term pack is used to express the multi fireflies' groups (can be divided further into multi-subgroups). Also, the term is used to focus on nature inspiration of the algorithm itself. The proposed principles of pack (of fireflies) can be summarized as follows:

1. Each pack (of fireflies) contains several groups that follow or obey single or multi constrains.
2. The movement of any pack depends on its neighbor packs (not on a single firefly). This may be extended to groups (and sub groups) within the pack to those within neighbor packs.
3. The groups within each pack can be divided into subgroups which can further be subdivided into smaller subgroups (to deal with different local and global constrains).

In addition, it's obvious that packs should be similar in structure to avoid further complexity. These principles allow several approaches to solve optimization problems.

In case of firefly algorithm, it gives several possibilities to find distances in multi level approach. The multi level distance may be one of the following:

1. Pack distance which can be in its simplest form as average of all distances of the fireflies F within specific pack Z to those in pack W, which can be simply stated in similar to (27) as:

   $$r_{ZW} = \frac{\sum_{f=1}^{F} r_{ij}^{(f)}}{F} \tag{30}$$

   or any other suitable form such as nearest, dominant (most frequent), or constrain favorite, … etc.
2. Group (or subgroup) distances in similar way to that explained before.
3. Element (firefly in this case) distance which is similar to original FA form.

This in turn offers several possibilities to find attractiveness in multi level or multi-group approach.

Also, the FPA parameters and scale coefficients allow having several values depending on multi level selected in implementation and the nature of problem (which can be set to fixed values for simplicity). It is worth to point out that the proposed Firefly Pack Algorithm can be considered as the generalization form. It can be reduced to a form similar to original FA under special conditions (assuming that each pack has single group, contain a single firefly, with no further subgroups). The pseudo code of the FPA may be summarized as:

```
% Firefly Pack Algorithm
Define Problem related information and objective function.
Define Firefly pack algorithm parameters and coefficients.
Initialize a population of fireflies' packs (solutions)
Evaluate Light intensity of packs I_FP (determined by objective function).
While Counter < Generation_Max
   For z = 1: FP % all FP fireflies' packs
      For w = 1: FP % all FP fireflies' packs
        If (z ≠ w) % optional to increase computation speed
           If (I_FPw > I_FPz)
              Move fireflies' pack z towards fireflies' pack
              w in all dimensions (depending on level selected).
           End If
        End If
        Attractiveness varies with respect to multi level distance employed.
        Evaluate new fireflies' packs and update light intensities.
      End For w
   End For z
   Rank the fireflies' packs and find the current best pack
End While
Output results and required visualization
```

III. Implementation and Simulation Results

In this work MATLAB m-file is used to express and simulate the resource allocation problem model and the implementation of the Firefly Pack Algorithm to find the optimal or near optimal subcarrier and power allocation matrixes to maximize the weighted sum-rate of OFDMA system (measured in bit/sec/Hz). Assuming a single cell uplink OFDMA system with centralized scheduling which has subcarriers that subject to Rayleigh fading distribution (1000 channel realizations are used) and mean equals to the path gain which representing the propagation loss. The path loss is used to descript the propagation loss as:

$$L_P = cD_k^{-u} \quad (31)$$

where c is the path loss constant, set to be −128.1 dB, D_k is the distance in Km from the user k to the base station (BS), and u is the path loss exponent (= 3.76 for urban environments) [18] and [26]. All users are assumed to be equally distanced away from the base station. It should not be confused with firefly distances used in (27 or that in fireflies' Pack distance in (30). The minimum rate allowed is selected to be equal to zero for all users. The noise level assumed to be -16.9 dBm. The weights are assumed to be equal i.e., weight of any user is equal to reciprocal of the number of users to satisfy condition of (13). Also, the maximum allowed transmitted power for each user $P_{k,max}$ set to be equal for each simulated case. It must be noticed that these assumptions are made to simplify the simulation while the m-file program is designed to allow different distances, minimum data rates, and/or weights for each user. The simulation is done for several cases as summarized in Table 1.

Table 1. Summarization for the Considered Cases

Case No.	Users (K)	Subcarriers(N)	$P_{k,max}$ (inwatt)	Distance in meter)	Generations	Fireflies pack(FP)
1st	6	6	0.6	500	200	50
2nd	6	12	0.6	500	200	50
3rd	12	6	0.6	500	200	50
4th	12	12	0.6	500	200	50

Other parameters value used for FPA simulation are: $\beta_{o(multi\text{-}level)} = 1$, $\beta_{min(multi\text{-}level)} = 0$, $\gamma_{(multi\text{-}level)} = 1$, $\alpha_{(multi\text{-}level)} = 0.2$, $S_{D(multi\text{-}level)}=1$, $\delta_{(multi\text{-}level)} = 0.999$.

The packs of FPA's represent the legal solutions of the subcarrier and power allocation. Each pack have a pair of groups: the first group is the subcarrier allocation matrix **A** $(K \times N)$ and the second one is the power allocation matrix **P** $(K \times N)$, where K is the number of users and N is the number of subcarriers. The subcarrier allocation group is in turn subdivided to N subgroups. Also, the power allocation group is in turn subdivided into K subgroups. This FPA representation of resource allocation problem is shown in Fig. (1).

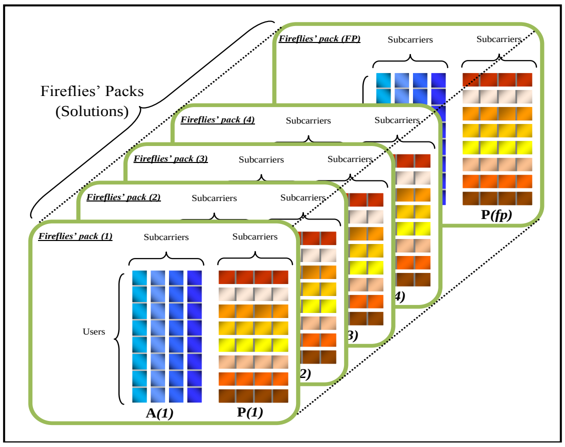


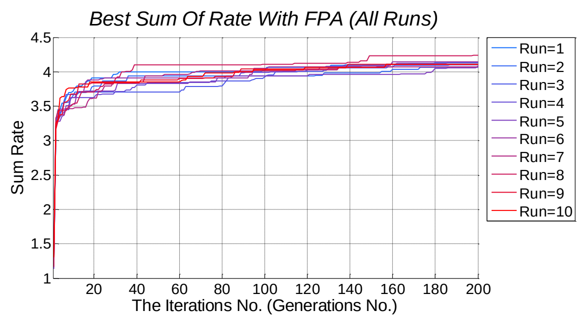
Fig.1. FPA Representation of Resource Allocation Problem.

The values of **A** elements lies between [0,1] while **P** elements may take any value between 0 to the max power value of a specific user. This representation is done in a way that ensures the subcarrier and power allocation constrains are both satisfied and to ensure that all the solutions are within the legal area of the search space.

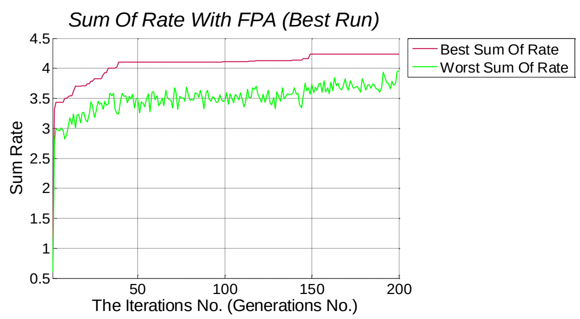
The termination condition is selected to be depending on the number of generation to explore the power of the Firefly Pack Algorithm and to avoid premature-termination. The following results are detailed for each of the cases listed in table (1) with the best result was selected over 10 runs (each run has 200 generations). Each run is used the same channel conditions and resource allocation operation scenario assumptions. The best run is selected depending on final iteration results (best sum of rates which related to best solution (fireflies' pack) that contain best A and P).

A. Case 1

The best sum of rates for 10 runs (200 iterations for each run) with 6 users over 6 subcarriers is shown in Fig. 2(a). It's clear that all FPA runs are rapidly convergent toward the targeted best sum of rates, especially in the early iterations. Afterward, the obtained best sum of rates improving is tending to slow down with obvious (but relatively small) differences in values between runs as the iteration number increases. This is due to the nature of fireflies' movement within their pack as they will try to move from their current locations to better possible locations (A and P) due combined effect of multi level attractiveness and random walk. Both best and worst sum of rates, for each iteration, the obtained in the best resulted run (run 8) is shown in Fig. 2 (b). It's noticeable that the gap between them is decreased especially at last iterations which is a result of fireflies' packs convergence behavior toward their best value.



(a)



(b)

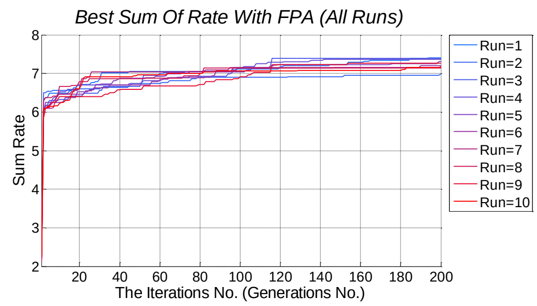
Fig.2. (a) Best sum of rates of 10 runs using FPA (users = 6, subcarriers = 6), (b) Best and worst sum of rates of 8th run.

Figure 6 (a) shows the subcarrier and power allocation of the best fireflies' pack (solution) of run 8. In despite of scale difference, both subcarrier and power allocation distributions of the best solution are similar but not identical. For run 8, the users' rates are shown in Fig. 7(a), which is depending on the subcarrier and power allocation of the best fireflies' pack (solution) and the channel condition. It's clear that all the users have a data rate greater than the minimum data rate which is set to zero.

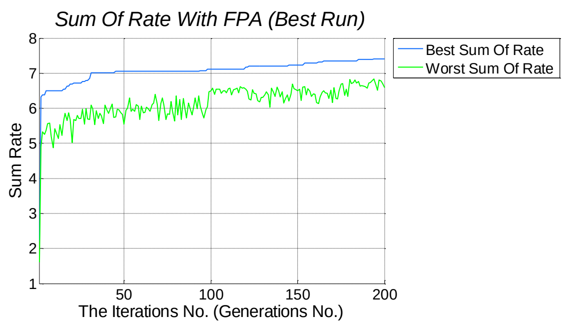
B. Case 2

The best sum of rates for 10 runs (200 iterations each) with 6 users over 12 subcarriers is shown in Fig. 3 (a). All FPA runs share the response of rapid convergence toward the targeted best sum of rates especially in the first few iterations. As the iteration number increases the obtained best sum of rates improvement is proceed in slower manner with obvious (yet comparatively small) differences in values between runs. This is because the nature of fireflies' movement within their pack due the combined effect of multi level attractiveness mechanism between fireflies' packs and random walk. Both best and worst sum of rates obtained in the best resulted run (run 1) is shown in Fig. 3 (b). It's clear that the gap between them is reduced as iteration number increases. This is due to the fireflies' packs convergence behavior toward their best.

Figure 6 (b) shows the subcarrier and power allocation of the best fireflies' pack (solution) of run 1. Keeping in mind that the scale difference between them both the subcarrier and power allocation distributions of the best solution is sharing some similarity. The users' rates of run 1 are shown in Fig. 7 (b), which is depending on the subcarrier and power allocation of the best fireflies' pack (solution) and the channel condition. Data rate of each users is greater than the minimum data rate (minimum data rate is set to zero).



(a)

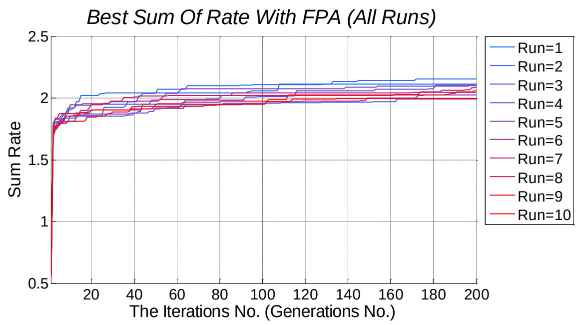


(b)

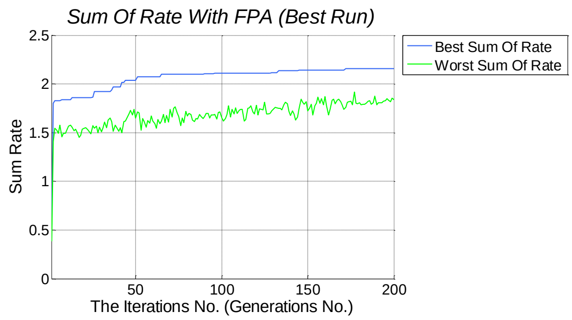
Fig.3. (a) Best sum of rates of 10 runs using FPA (users = 6, subcarriers = 12), (b) Best and worst sum of rates of 1st run.

C. Case3

The best sum of rates for 10 runs (200 iterations for each run) with 12 users over 6 subcarriers is shown in Fig. 4 (a). The property of rapid convergence toward the targeted best sum of rates is noticed for all runs especially in the first few iterations. The increasing of the obtained best sum of rates is tending to slow down with observable and moderately small differences in values between runs as the iteration number increases. This is due to the nature of fireflies' movement within their pack and the combined effect of multi level attractiveness and random walk. Both best and worst sum of rates of each iteration of best resulted run (run 2) is shown in Fig. 4 (b). It's noteworthy that the gap between them is decreased very slowly as iteration number increases due to the fireflies' packs movement toward their best.



(a)



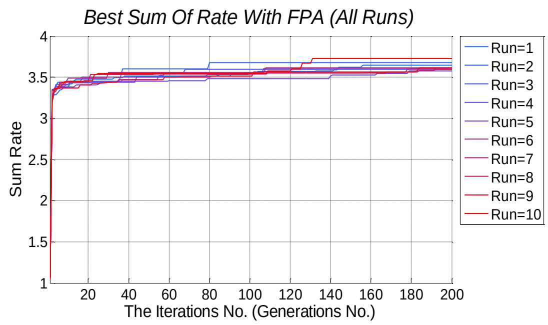
(b)

Fig.4. (a) Best sum of rates of 10 runs using FPA (users = 12, subcarriers = 6), (b) Best and worst sum of rates of 2nd run.

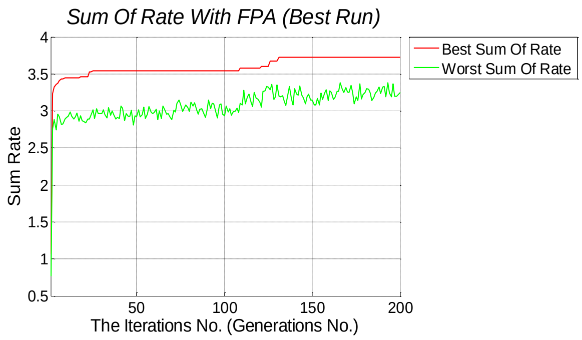
Figure 6 (c) shows the subcarrier and power allocation of the best fireflies' pack (solution) of run 2. In both subcarrier and power allocation distributions of the best solution are having some similarity with obvious differences. For run 2, the users' rates are shown in Fig. 7 (c), which is depending on the subcarrier and power allocation of the best fireflies' pack (solution) and the channel condition. All users have a data rate greater than the minimum data rate (which is set to zero).

D. Case4

The best sum of rates for 10 runs (200 iterations each) with 12 users over 12 subcarriers is depicted in Fig. 5 (a). The best sum of rates that found by all FPA runs is rapidly increased toward the targeted best sum of rates (solution) especially in the first few iterations. As the iteration number increases this improvement decelerates with obvious (yet still comparatively small) differences in values between runs. This can be explained by the nature of fireflies' movement within their pack due to the combined effect of multi level attractiveness mechanism between fireflies' packs and random walk. Both best and worst sum of rates of best resulted run (run 10) is shown in Fig. 5 (b). It's obvious that the gap between them is slightly reduced as iteration number increases which can be explained by the fireflies' packs convergence behavior toward their best.



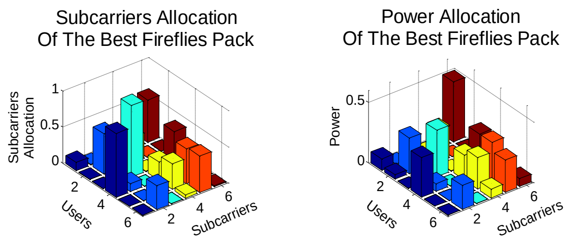
(a)



(b)

Fig.5. (a) Best sum of rates of 10 runs using FPA (users = 12, subcarriers = 12) (b) Best and worst sum of rates of 10th run.

Figure 6 (d) shows the subcarrier and power allocation of the best fireflies' pack (solution) of run 10. Keeping in mind the scale difference between both distributions of the best solution, similarity between them is clear even with presence of some differences. The users' rates of run 10 are shown in Fig. 7 (d), which is depending on the subcarrier and power allocation of the best fireflies' pack (solution) and the channel condition. The rate of each user is greater than the minimum data rate (minimum data rate is set to zero).



(a)

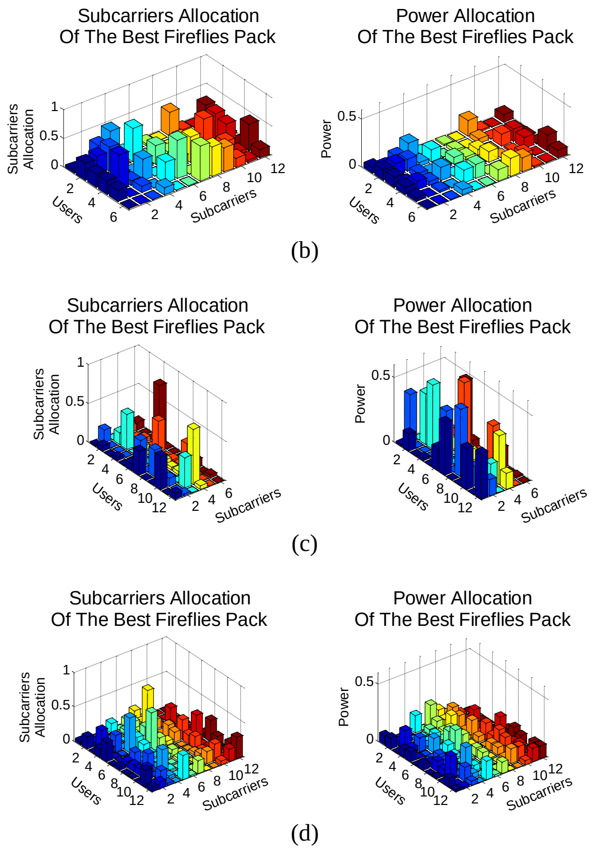
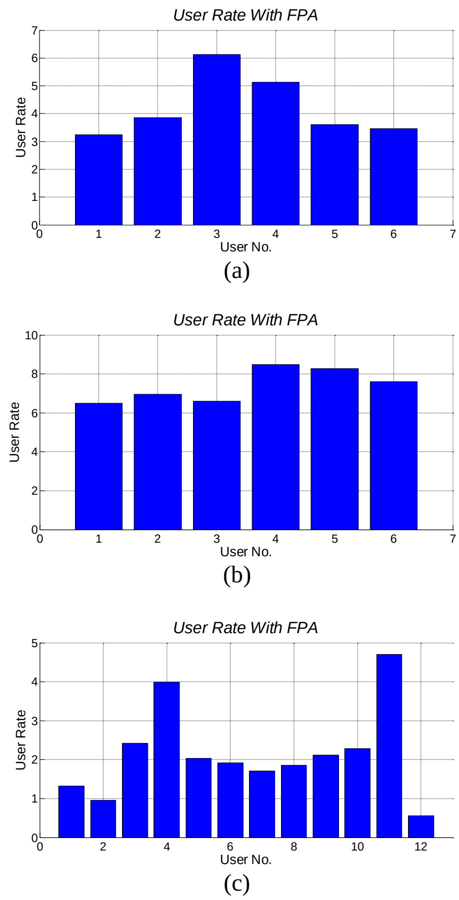


Fig.6. Subcarrier and power allocation of best solution (a) 8th run of case 1, (b) 1st run of case 2, (c) 2nd run of case 3, (d) 10th run of case 4.



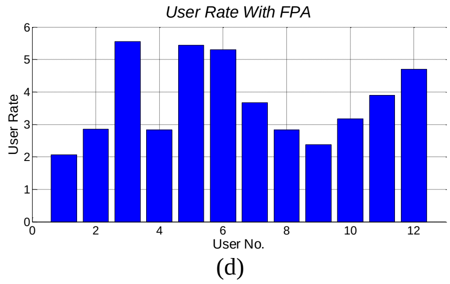


Fig.7. Users' rates. (a) 8th run of case 1, (b) 1st run of case 2, (c) 2nd run of case 3, (d) 10th run of case 4.

IV. Conclusions

This work introduces the Firefly Pack Algorithm (FPA) as an intelligent method for solving the resource allocation problem in OFDMA efficiently, in addition to the ability to extend its implementation to solve other complex communication problems. The obtained results demonstrate that FPA is an effective algorithm in finding the optimal or near optimal solution for both subcarrier and power allocation. It is inherit the advantages of standard FA automatic subdivision and the ability of dealing with multimodality with the present of improved multi-level, multi-group distances and attractiveness mechanism. The improved multi-group mechanism gives an effective and fast approach for local and global search with a high converging speed.

In all the analyzed cases, the results show that FPA reaching suitable solutions with ability for adaptively adjust the solutions with respect to constrains and problem variables and parameters. Also, using multi runs (10 runs) for each case show that there are notice but still small differences between the different runs and they tend to become more visible as the number of iterations increases especially after the first few ones. These results depended on other FPA parameters values, such as number of packs, number of groups in each pack, number of fireflies within each pack, maximum attractiveness, light absorption coefficients, random movement coefficients, scaling parameters and reduction coefficients. It is also depending on the targeted problem in hand to provide a balance between level of best result required in one side and the processing cost and time on the other side.

References

[1] X. S. Yang, *Engineering Optimization: An Introduction with Metaheuristic Applications*, John Wiley & Sons Inc., New York City, United States, July, 2010, pp. 15 – 18.

[2] T. Apostolopoulos, and A. Vlachos, "Application of the Firefly Algorithm for Solving the Economic Emissions Load Dispatch Problem," *International Journal of Combinatorics*, vol. 2011, pp. 1-23, Nov., 2011.

[3] X. S. Yang, "Firefly Algorithms for Multimodal Optimization," Stochastic Algorithms: Foundations and Applications, 5th International Symposium, SAGA 2009 Sapporo, Japan, October 26-28, vol. 5792, pp. 169-178, 2009.

[4] X. S. Yang, Xingshi He, "Firefly Algorithm: Recent

Advances and Applications," *Int. J. of Swarm Intelligence*, vol.1, no.1, Aug. 2013, pp. 36-50.
[5] G. Wang et al., "A Modified Firefly Algorithm for UCAV Path Planning", *International Journal of Hybrid Information Technology*, vol. 5, no. 3, pp. 123–143, July 2012.
[6] S. Nandy, P. P. Sarkar, and A. Das, "Analysis of a Nature Inspired Firefly Algorithm based Back-propagation Neural Network Training", *International Journal of Computer Applications*, vol. 43, no. 22, pp. 8–16, Apr. 2012.
[7] A. Khadwilard, S. Chansombat, and T. Thepphakorn, "Application of Firefly Algorithm and Its Parameter Setting for Job Shop Scheduling", *The Journal of Industrial Technology*, vol. 8, no. 1, pp. 1798–1807, Jan. 2012.
[8] S.U. Khan et al., "Application of Firefly Algorithm to Fault Finding in Linear Arrays Antenna", *World Applied Sciences Journal*, vol. 26, no. 2, pp. 232-238, Nov. 2013.
[9] J. Kwiecien and B. Filipowicz, "Firefly algorithm in Optimization of Queuing Systems", *Bulletin Of the Polish Academy of Sciences: Technical Sciences*, vol. 60, no. 2, pp. 363-368, 2012.
[10] M. H. Horng et al., *Firefly Meta-Heuristic Algorithm for Training the Radial Basis Function Network for Data Classification and Disease Diagnosis*, in: *Theory and New Applications of Swarm Intelligence*, Edited by Rafael Parpinelli and Heitor S. Lopes, Croatia – European Union, InTech, 2012, pp. 115-132.
[11] R. Imanirad, X. S. Yang and J. S. Yeomans, "Modelling-to-generate-alternatives via the Firefly Algorithm", *Journal of Applied Operational Research*, vol. 5, no. 1, pp. 14–21, 2013.
[12] F. S. Lobato, and Jr V. Steffen, "Multi-Objective Optimization Firefly Algorithm Applied to (Bio) Chemical Engineering System Design", *American Journal of Applied Mathematics and Statistics*, vol. 1, no. 6, pp. 110-116, 2013.
[13] W. Rhee, and J. M. Cioffi, "Increase in Capacity of Multiuser OFDM System Using Dynamic Subchannel Allocation", 51st IEEE Vehicular Technology Conf. (VTC2000), Tokyo, pp. 1085–1089, 2000.
[14] J. Jang, and K. B. Lee, "Transmit Power Adaptation for Multiuser OFDM Systems," *IEEE Journal on Selected Areas in Communications*, vol. 21, no. 2, pp. 171 - 178, Feb. 2003.
[15] Y. B. Reddy, and N. Gajendar, "Evolutionary Approach for Efficient Resource Allocation in Multi-User OFDM Systems", *Journal of Communications*, vol. 2, no. 5, pp. 42–48, Aug. 2007.
[16] A. Rahman, I. M. Qureshi, and A. N. Malik, "Adaptive Resource Allocation in OFDM Systems Using GA and Fuzzy Rule Base System," *World Applied Sciences Journal*, vol. 18, no. 6, pp. 836-844, 2012.
[17] H. L. Liu, and Q. Wang, "A Resource Allocation Evolutionary Algorithm for OFDM Based on Karush-Kuhn-Tucker Conditions," *Mathematical Problems in Engineering*, vol. 2013, pp. 1–8, 2013.
[18] E. Yaacoub, and Z. Dawy, *Resource Allocation in Uplink OFDMA Wireless Systems: Optimal Solutions and Practical Implementations*, Wiley-IEEE Press, New York City, United States, 2012.
[19] H. Ajra, Md. Z. Hasan, and Md. S. Islam, "BER Analysis of Various Channel Equalization Schemes of a QO-STBC Encoded OFDM based MIMO CDMA System", *International Journal of Computer Network and Information Security(IJCNIS)*, Vol. 6, No. 3, February 2014, PP.30-36.
[20] S. Boyd, and L. Vandenberghe, *Convex Optimization*, Cambridge university press, Cambridge, England, 2009.
[21] X. S. Yang, *Nature-Inspired Metaheuristic Algorithms*, Luniver Press, United Kingdom, 2nd ed., 2010.
[22] X. S. Yang, "Firefly Algorithm, Stochastic Test Functions and Design Optimization," *Int. J. Bio-Inspired Computation*, vol. 2, no. 2, pp.78–84, 2010.
[23] X. S. Yang, "Efficiency Analysis of Swarm Intelligence and Randomization Techniques", *Journal of Computational and Theoretical Nanoscience*, vol. 9, no. 2, pp. 189–198, 2012.
[24] X. S. Yang, "Firefly algorithm, Levy flights and global optimization", in: Research and Development in Intelligent Systems XXVI, Springer, pp. 209-218, 2010.
[25] E. J. Inclana, G. Dulikravicha, and X. S. Yang, "Modern Optimization Algorithms and Particle Swarm Variations", *4th Inverse Problems Design and Optimization Symposium (IPDO-2013)*, pp. 26-28, 2013.
[26] ETSI TR 136 931 v9.0.0, "LTE; Evolved Universal Terrestrial Radio Access (E-UTRA); Radio Frequency (RF) requirements for LTE Pico Node B", (3GPP TR 36.931 version 9.0.0 Release 9), 2011. Online at: http://www.etsi.org/deliver/etsi_ts/136100_136199/136104/09.04.00_60/ts_136104v090400p.pdf

Authors' Profiles

Haider M. AlSabbagh (haidermaw@ieee.org) was born in 1970, received his Ph.D. degree from school of electronic information and electrical engineering (SEIEE), Shanghai JiaoTong University in 2008, and his M.S. degree in communications and electronics engineering from Basra University in 1996. From 1996 to 2002, he worked in Basra University as a lecturer. Currently, he is an associate professor and director of Avicenna E-learning center at Basra University. His research interests include wireless communication systems, mobile and wireless networks, data communications, information networks, optical communications, body area networks, and antennas design. Dr. Haider is a member of editorial board and referee for several international prestigious journals and occupies TPC committee member and referee for many international conferences. He is scholar of Council of Assisting Refugee Academics (CARA) organization, London, UK, for two years. Dr. Haider is a publicity chairman for the first international conference on Electrical Engineering and applications (MIC – Electrical 2014), Greece, Athena. He was academic visitor to Loughborough University, UK, from mid Sept. to mid Oct. 2012. Dr Haider is a member of academic staff of 5G research center (5GRC), Loughborough, UK, Dr. Haider is senior member of IEEE.

Mohammed Khalid Ibraheem was born in 1982, received his PhD degree in communications and electronics engineering from Basra University in 2014, and his M.Sc. degree in electronics engineering from University of Technology in 2007. Since 2007, he worked in Babylon University as a lecturer. His research interests include wireless communication, artificial intelligence and evolutionary algorithms, automated electronic circuit design, mobile and wireless networks, information networks, and antenna designs.

How to cite this paper: Haider M. AlSabbagh, Mohammed Khalid Ibrahim,"Efficient Dynamic Resource Allocation in OFDMA Systems by Firefly Pack Algorithm", International Journal of Computer Network and Information Security(IJCNIS), Vol.9, No.3, pp.1-10, 2017.DOI: 10.5815/ijcnis.2017.03.01

