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Enhanced Bundle-based Particle Collision Algorithm for Adaptive Resource Optimization Allocation in OFDMA Systems

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Abstract
The necessity for an efficient algorithm for resource allocation is highly urgent because of increased demand for utilizing the available spectrum of the wireless communication systems. This paper proposes an Enhanced Bundle-based Particle Collision Algorithm (EB-PCA) to get the optimal or near optimal values. It applied to the Orthogonal Frequency Division Multiple Access (OFDMA) to evaluate allocations for the power and subcarrier. The analyses take into consideration the power, subcarrier allocations constrain, channel and noise distributions, as well as the distance between user's equipment and the base station. Four main cases are simulated and analyzed under specific operation scenarios to meet the standard specifications of different advanced communication systems. The sum rate results are compared to that achieved with employing another exist algorithm, Bat Pack Algorithm (BPA). The achieved results show that the proposed EB-PAC for OFDMA system is an efficient algorithm in terms of estimating the optimal or near optimal values for both subcarrier and power allocation.

KEYWORDS: OFDMA, Enhanced Bundle-based Particle Collision Algorithm, Resource Allocation, Particle Collision Algorithm, optimization, communication systems, Adaptive Resource Allocation, power allocation algorithm, multi-objective optimization.

I. INTRODUCTION

In recent years, global demand for higher data transmission rates with quality of services in wireless communication systems have been growing enormously. However, the available communication resources are too limited to satisfy such huge demand [1] – [3]. There are many resource allocation protocols and algorithms were proposed to manage the case. Orthogonal frequency–division multiple access (OFDMA) has been adapted as one of the efficient schemes of resource allocation [4], [5]. In OFDMA systems, Radio Resource Management (RRM) algorithms are the key elements. It crucially affects the current and overall future communication performance largely by providing different QoS experienced by each of the end users [6]–[8]. The key issue in OFDM/OFDMA is solving the resource allocation problem which means finding the optimal or suboptimal resource allocation - for the subcarrier (subchannel) and the power.

Four key cases are analyzed under some specific optimization scenarios with employing the EB-PCA. In the first case, a relatively small equal number of users and subcarriers (7 each) are considered to estimate the best subcarrier and power allocation. The second case is conducted to discuss when the number of users is less than the available subcarriers (half number of available subcarriers is taken), While in the third case the contrary situation is discussed (the available subcarriers are less than the number of users). It mimics the scenario for sharing a limited subcarrier to provide a reasonable data rate to each user with respect to the channel conditions. Finally, case four discussed the case when both number of users and subcarriers are doubled.

The achieved results show that the proposed EB-PAC for OFDMA system is an efficient algorithm in terms of estimating the optimal or near optimal values for both subcarrier and power allocation.

Section 2 investigates some related work and Section 3 of this paper presents a theoretical background for the resource allocation and the algorithms used in this work whereas Section 4 reports the main simulation results. A comparison with that achieved by employing Bat Pack

Algorithm (BPA) is given in Sections 5 and finally Section 6 synthesizes research main conclusions.

II. Related Research

Several calculation-based approaches have been presented by researchers. Condoluci, M., et al. [9] and JuYeop Kim et al. [10] discussed minimizing power consumption with employing a heuristic algorithm for allocating resources suboptimal with low complexity in OFDM While [11] applied it to the resource allocation in the OFDMA. Junzhi Yu et al. [12] utilizing the Stachelberg game algorithm to handle the complex robust joint allocation problem. It is applied to the OFDM system to achieve power allocation in the downlink.

Importance to finding a powerful and efficient algorithm is taking priority to deal with complex optimization problems. Several algorithms were inspired by mimicking some of nature or physical phenomena. A stochastic optimization algorithm that was loosely inspired by the physics of nuclear particle collision reactions was introduced. This algorithm is called Particle Collision Algorithm (PCA) [13].

The original and modified versions of PCA are used with different optimization problems. For instance, Sacco, Filho et al., [14] applied original PCA for cost-based formulation of a reactor core design optimization problem and Domiciano et al. [15] used it to automatically estimate the digital elevation models in a specific area for the unmanned aerial vehicles. Knupp, Neto et al., [16] implemented a PCA with the deterministic Levenberg-Marquardt method to evaluate the inverse radiative transfer problem. An optimum architecture design for a supervised artificial neural network (ANN) is applied to atmospheric temperature profile identification. It was performed by employing the multi-particle collision algorithm (M-PCA) [17] and the authors in [18] used the M-PCA to generate a set of candidate solutions that correspond to an ANN architecture to retrieve atmospheric temperature profile from satellite data under cloud covering. However, neither the original PCA nor its variants algorithm is used to solve the resource allocation problem yet. The PCA algorithm in its original form is not suitable to deal with such multi elements, multi dimensions, and multi constrained problems. Therefore, this paper proposes Enhanced Bundle-based Particle Collision Algorithm (EB-PCA). Then, the algorithm is applied to find the optimal or near optimal value for the power and subcarrier allocations in an OFDMA system.

III. Theory

A. OFDMA Resource Allocation

Consider a single cell uplink OFDMA system with K users and N subcarriers to be allocated. Also, if all the users with Variable Bit Rate (VBR) and error-free data throughput. So, the channel gain-to-noise ratio (CNR) may be given by [19], [20]:

$$g_{k,i} = \frac{H_{k,i}}{\sigma_{k,i}^2}\ , \quad \text{for } k = 1, \ldots K, i = 1, \ldots, N \tag{1}$$

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.

Let $\alpha_{k,i}$ is the binary decision variable of the subcarrier allocation, then:

$$\alpha_{k,i} = \begin{cases} 1, & \text{if subcarrier } i \text{ is assigned to user } k \\ 0, & \text{if subcarrier } i \text{ is not assigned to user } k \end{cases} \tag{2}$$

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

$$\sum_{k=1}^{K} \alpha_{k,i} \leq 1\ , \quad \text{for } i = 1, \ldots, N \tag{3}$$

$\alpha_{k,i}$ takes either 1 or 0, "0" indicates that the subcarrier is not assigned to any user.

Let the matrix of the channel allocation indices **A** ($K \times N$) is:

$$\mathbf{A} = \begin{bmatrix} \alpha_{11} & \cdots & \alpha_{1N} \\ \vdots & \ddots & \vdots \\ \alpha_{K1} & \cdots & \alpha_{KN} \end{bmatrix} \tag{4}$$

If $P_{k,i}$ is the power allocated to subcarrier i by user k. The power consumed by a specific user over all its allocated subcarriers must not exceeded the allowable maximum transmission power, $P_{k,max}$:

$$\sum_{i=1}^{N} P_{k,i} \leq P_{k,max}\ , \quad \text{for } k = 1, \ldots, K \tag{5}$$

where,

$$P_{k,i} \geq 0, \quad \text{for } k = 1, \ldots, K \tag{6}$$

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

$$\mathbf{P} = \begin{bmatrix} P_{11} & \cdots & P_{1N} \\ \vdots & \ddots & \vdots \\ P_{K1} & \cdots & P_{KN} \end{bmatrix} \tag{7}$$

Therefore, the total rate of user k is:

$$R_k = \sum_{i=1}^{N} \alpha_{k,i}\ \ log_2(1 + P_{k,i} g_{k,i}) \tag{8}$$

and the total system rate is:

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

Therefore, the resource allocation problem for the OFDMA can be formulated for maximizing the weighted sum-rate as:

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

which is subject to:

$$E_g\left\{\sum_{i=1}^{N} P_{k,i} \leq P_{k,max}\ \right\}, \quad \text{for } k \text{ } users \tag{11}$$

The user rate must be greater than or equal to its allowable (or desired) minimum data rate, $R_{k,min}$:

$$E_g\left\{\sum_{i=1}^{N} \alpha_{k,i}\ \ log_2(1 + P_{k,i} g_{k,i})\ \right\} \geq R_{k,min}\ , \quad \text{for k users} \tag{12}$$

where, $E\{\cdot\}$ is an expectation operator and π_k is the weight given to the rate of specific user *k*. The weights given to the users' rates are chosen from:

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

The resource allocation problem is non-convex because the set of values for $\alpha_{k,i}$, given in Eq. (10). It can be converted to a convex when the condition of $\alpha_{k,i}$ is relaxing by allowing them to take any values from the interval [0, 1]. This corresponds to the case when time-sharing is allowed to a single subcarrier between different users.

Assume that $f_{k,i} = \alpha_{k,i} P_{k,i}$ then the resource allocation problem can be rewritten as:

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

which is subject to

$$E_g\{\sum_{i=1}^{N} f_{k,i} \le P_{k,max}\ \},\ \text{for k user} \qquad (15)$$

or,

$$E_g\{\sum_{k=1}^{K}\ \sum_{i=1}^{N} \alpha_{k,i} P_{k,i}\ \le P_{total}\ \},\ \text{for all users} \qquad (16)$$

and,

$$E_g \left\{ \sum_{i=1}^{N} \alpha_{k,i}\ \ log_2(1 + \frac{f_{k,i}}{\alpha_{k,i}} g_{k,i})\ \right\} \ge R_{k,min}\ ,$$

for k users (17)

Equation (14) is convex since expectation conserves convexity and log2 (1 + b/a) is recognized as a concave function form. Therefore, the problem can be solved reliably and efficiently [21]. It should be noted that the resource allocation problem is subject to constraints Eqs. (3), (5), (6) and (13) in addition to Eqs. (15-17). Principles of the PCA and the Enhance Bundle-based Particle Collision Algorithm (EB-PCA) are detailed in the following sections:

B. Particle Collision Algorithm

Wagner F. Sacco and Cassiano R.E. de Oliveira [13] proposed the original version of the Particle Collision Algorithm (PCA). This algorithm is loosely based on the physics of nuclear particle collision reactions, mainly scattering and absorption. In scattering, the incident neutron is scattered by the impact of its collision with a target nucleus. While in absorption, the incident neutron is absorbed by that nucleus. So, depending on the quality or fitness of the target nucleus, the hitting particle either absorbs and explores the boundaries if nucleus quality is high; or scattered to another region if nucleus quality is low. Through these repeated scattering and absorption collision operations, the exploration and exploitation of the search space for better areas is performed. In its structure, the original PCA bears a resemblance to simulated annealing with the basic difference that it does not require the user to define parameters except the number of iterations [13], [14].

The general structure of the PCA is as follows: after selecting the initial (old) configuration, new configuration is generated by modifying the old configuration. Then, evaluation and comparison of both of them are performed to determine their quality and decide whether to accept the new configuration to replace the old one for the next step, or reject it and proceed with a new change of the old configuration. The key pseudo code of the PCA can be formulated as [13], [14], [16], [22], see Appendix – A.

The stochastic perturbation pointed out in the loop of pseudo code represents varying of the variable's values. They are random within their range's boundaries. Stochastic perturbation pseudo code, as Ref.[22], is given in Appendix – B.

An exploration of the boundaries for a better solution is performed upon the particle absorption (the new configuration quality is better than that of the old one). The local search is carried out by exploration as it will generate a small stochastic perturbation. It is similar to the previous stochastic perturbation but the new value of each variable is reserved within the boundaries of the original value. Exploration pseudo code is given as Ref. [13], [14], [16], see Appendix – C. The small stochastic perturbation pseudo code, illustrated in Appendix – D, given as Ref. [22].

The particle, on the other hand, is scattered if the new configuration quality is not better or even worse than the old configuration. The scattering probability, P, is inversely proportional to the quality. This means that as the quality of particles is lowered there is a greater chance to be scattered [13], [14], [16], [22], see Appendix – E.

In PCA, a solution trial acceptance is carried out with a certain probability. Therefore, PCA may be considered as a Metropolis algorithm and this acceptance chance may lead to avoid convergences to local optima [13], [14]. The Multi-Particle Algorithm (M-PCA) is based on the original or canonical PCA, introducing a new characteristic of using several particles (each particle represents a solution) not only a single particle. Particle's coordination was achieved by a blackboard strategy (Best Fitness rank is public for all the particles during the search progression [16]. M-PCA needs multi-processing capability to perform such operations.

C. Enhanced Bundle-based Particle Collision Algorithm (EB-PCA)

Structure of the pseudo code of the PCA and MPCA are matched up with the basic idea that these algorithms are based on. However, a more intensive analysis will reveal that an unintentional but misleading equation in stochastic perturbation is part of the algorithm. This unintentional deceived equation can be explained by simply starting from the basic equation used to generate perturbation as follow:

New_Config [i]= Old_Config [i] + ((Upper - Old_Config [i]) Rand) - ((Old_Config [i] - Lower)*(1- Rand))*

= *Old_Config [i] + (Upper * Rand) – (Old_Config [i] * Rand) - (Old_Config [i] * (1- Rand)) + (Lower * (1- Rand))*

= *Old_Config [i] + (Upper * Rand) – (Old_Config [i] * Rand)- (Old_Config [i]) +(Old_Config [i] * Rand) + Lower – (Lower * Rand)*

= *(Upper * Rand) + Lower – (Lower * Rand)*

or can be rewritten as:

*New_Config [i] = Lower+ (Upper – Lower) * Rand* (18)

where here Rand = random (0,1). The resulting Eq. (18) states that a simple random search. This means that the resulting New_Config is generated randomly and does not even depend on Old_Config (since Old_Config does not appear in Eq.(18)) and only depends on the boundary (Upper and Lower) which is fixed. This explains the weak improvement in New_Config since it does not make use of its previous configuration Old_Config. The small stochastic perturbation in the exploration part applies the same basic equation to generate small perturbation but with the difference that the boundary depends on Old_Config (though this is done indirectly since Upper and Lower are the ones that depend on it). Therefore, this work proposes an efficient approach to avoid this unnecessary complexity and low-efficiency search mechanism and at the same time try to keep it simple to prevent over computation.

First of all, the New_Bundle (Bundle term is used in this work instead Config term as will be explained next) is generated using the principle of random walk to provide an adaptive search mechanism that will utilize Old_Bundle efficiently as follow:

$$New\_Bundle = \begin{cases} Old_{Bundle} + (Upper - Old_{Bundle}) * Rand_W \ , & \text{for } Rand_W \geq 0 \\ Old_{Bundle} - (Old_{Bundle} - Lower) * |Rand_W|, & \text{for } Rand_W < 0 \end{cases}$$

where RandW ∈ [-1, 1] is random walk decision variable, this also can be rewritten as:

```
RandW =2*random (0,1) - 1;
if RandW >= 0
New_Bundle = Old_Bundle * (1- RandW)+ Upper * RandW;
Else
New_Bundle = Old_Bundle * (1-abs(RandW))+Lower *abs(RandW);
End
```

This work presents a Bundle-based approach to solve multi elements, multi dimensions, multi constrained problems combined with the proposed enhanced search mechanism. This new approach is called Enhanced Bundle-based Particle Collision Algorithm (EB-PCA). Then EB-PCA will be applied to solve the resource allocation problem of the OFDMA system to find the optimal or near optimal power and subcarrier allocations.

In this approach a group of particles may be used to search the solution space. The Bundle term is used here to avoid confusion with Multi-Particle Algorithm (M-PCA) which also uses several particles to act over the search space. The main difference is that each particle in M-PCA is represents a solution. On the other hand, in addition to the improved random walk part, Enhanced Bundle-based Particle Collision Algorithm (EB-PCA) proposed here is using a bundle (main group) of particles as a single solution to solve multi elements, multi dimensions, and multi constraint problems. This bundle can be further subdivided into sub-bundles and these can be also subdivided and so on. This dividing approach provides a way that bundle, sub-bundle and so on can obey one or several constraints or conditions in multi-level manner (i.e. global constraints will be applied to bundle, besides that local constraints will also be applied to sub-bundle and so on). Appendix – F shows the main pseudo code of the EB-PCA.

The (stochastic enhanced perturbation) pseudo code is given in Appendix – G, while the (Enhanced Exploration) pseudo code presented in Appendix – H. Therefore, the (small stochastic enhanced perturbation) pseudo code is given in Appendix – I, And, the (Enhanced Scattering) pseudo code is given in Appendix – J.

IV. Implementation and Simulation

In this work, the resource allocation and the power allocation matrices are formulated and simulated with applying the EB-PCA for different scenarios.

If a single cell OFDMA system is used with subcarriers subject to Rayleigh fading distribution noise (1000 channel realizations are utilized). The mean is equal to the path gain representing propagation loss. The propagation loss is modeled using the path loss model as [23], [24]:

$$L_P = cD_k^{-u} \tag{19}$$

where, c is the path loss constant (= −128.1 dB), u is the path loss which is set to 3.76 for urban environments, and D_k is the distance from the user k to the base station (BS).

All the parameters' values use in the simulation are listed in Table I. The minimum allowed rate is chosen to be zero for all the users with noise level -16.9 dBm and equal weights, according to Eq. 13. All the users are allowed to transmit power, $P_{k,max}$ set to 1 watt, distance = 400 meters, and the atterations = 250. These assumptions are made to simplify the simulated cases in terms of distances, data rate, and the weights.

Table I
Summarization for the considered cases.

Case No.	Users (K)	Subcarriers (N)
1st	7	7
2nd	7	14
3rd	14	7
4th	14	14

The bundle (solution) has a pair of sub-bundles, first sub-bundle 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 number of users and N is the subcarriers number.

Elements of **A** lie in the range [0,1] while **P** elements may take any values between 0 to the max power of a specific user. This representation is done in a way that ensures the subcarrier and power allocation constraints are both satisfied as well as ensuring that all the solutions are within the legal area of the search space. The termination condition is selected to depend on the number of iterations to avoid premature-termination and to explore capability of the suggested EB-PCA.

The cases listed in Table I are illustrated in the following subsections. The best results are selected over 10 runs. Each run has 250 iterations. All runs are performed for the same channel conditions and the resource allocation operation scenario. The best run is selected depending on final iteration results (best sum of rates which relate to best solution (bundle) that contain best **A** and **P**).

A. Case 1

In this case 7 users over 7 subcarriers is shown in Figure 1. It is clear that all EB-PCA runs experience a very fast convergence toward the targeted best sum of rates at the first iterations. Afterward, the obtained best sum of rates tends to increase in a slower manner. Even so, small differences in values between runs as the iteration number increases are still observable. The rising behavior of each run is related to the principles of EB-PCA operators (exploration, perturbation, and scattering) that try to search for better solutions in the search space (locally and globally). Also, the difference between runs can be explained by remembering that the EB-PCA algorithm trial solution can be accepted or rejected with a certain probability which is depending on the random factors that might lead to differences between the EB-PCA runs.

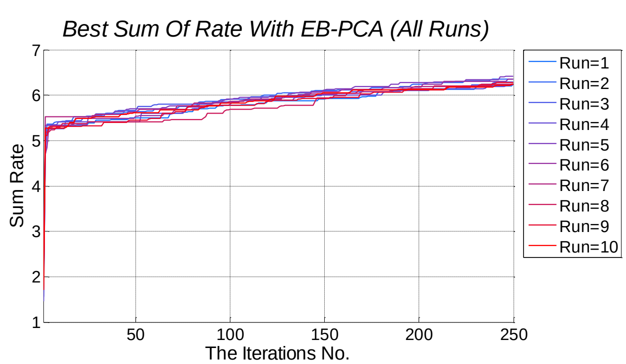


Figure 1. Best sum of rates of 10 runs using EB-PCA (users = 7, subcarriers = 7).

Figure 2 shows both the best and worst sum of rates for each iteration in the run 5. It is notable that the large gap between them is decreased after 24 iterations. After that, the gap keeps increasing slowly to reach the final iteration with more obvious fluctuated differences (due to the worst sum of rate fluctuations caused by EB-PCA operators).

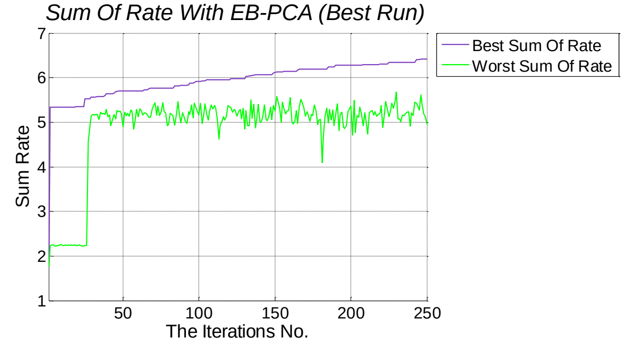


Figure 2. Best and worst sum of rates of 5th run.

In Fig. 3 the subcarrier and power allocation of the best sum of rates (solution) of run 5. The subcarrier and power allocation distributions of the best solution have high similarity even with the presence of some minor differences.

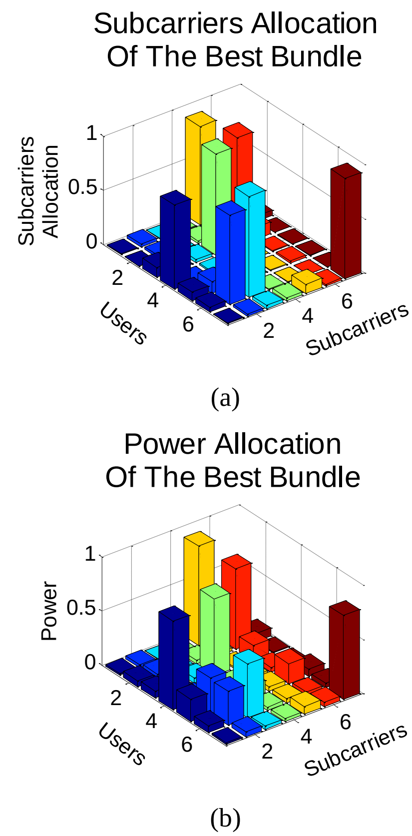


Figure 3. Best solution of 5th run, (a) subcarrier allocation, (b) power allocation.

Figure 4 depicts the case for run 5 with the users' rates which are depending on the subcarrier and power allocation of the best solution and the channel condition. It's clear that all the users have a data rate greater than the minimum data rate (which was set to zero).

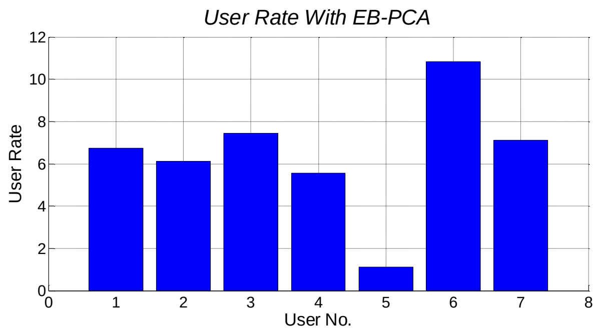


Figure 4. Users' rates of 5th run.

B. *Case 2*

The best sum of rates for 10 runs (250 iterations for each run) with 7 users over 14 subcarriers is shown in Figure 5. At the first iterations, all EB-PCA runs experience a very fast convergence toward the targeted best sum of rates. Afterward, the obtained best sum of rates tends to increase in slow manner with small observable differences in values between runs as the iteration number increases. The rising behavior of each run is related to the principles of EB-PCA operators (exploration, perturbation, and scattering) that will try to search for better solutions in search space. To explain the difference between runs, it must be remembered that the EB-PCA algorithm trial solution can be accepted or rejected with a certain probability which depends on random factors that in turn might lead to differences between EB-PCA runs.

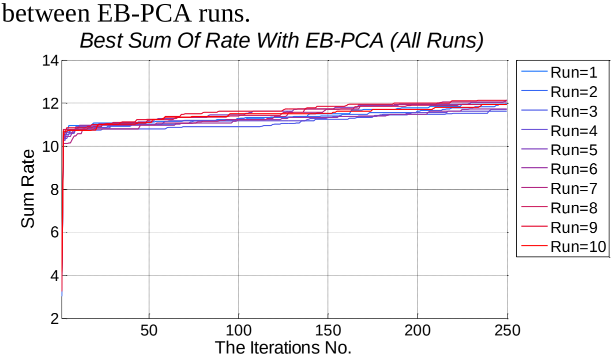


Figure 5. Best sum of rates of 10 runs using EB-PCA (users = 7, subcarriers = 14).

In Figure 6 both best and worst sum of rates of run 5 are given. It is obvious that after iteration 33, the gap between them decreases. Then, the gap returns will slowly be increased until its final iteration with a fluctuated difference due to the worst sum of rate fluctuations caused by EB-PCA operators.

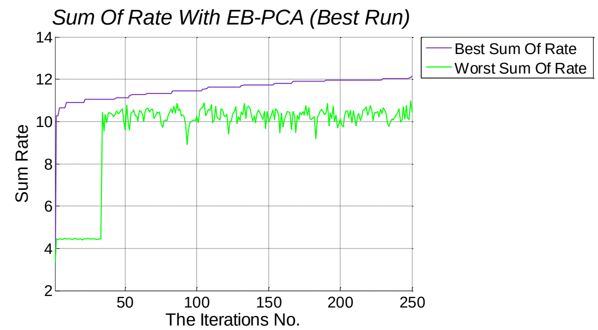
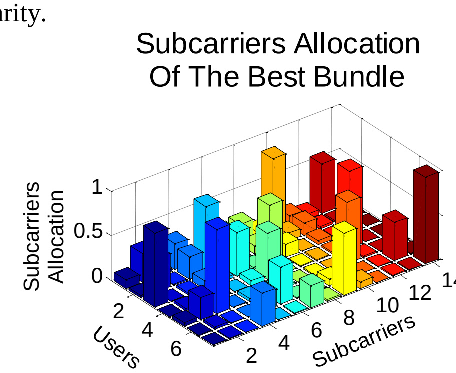
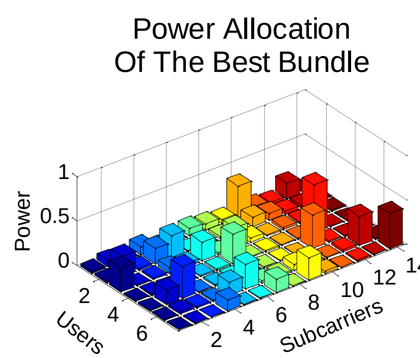


Figure 6. Best and worst sum of rates of 5^{th} run.

The best sum of rates (solution) of run 5 for the subcarrier and power allocation is given in Fig. 7. It is clear that even with some difference between both subcarrier and power allocation of the best solution there is some similarity.



(a)



(b)

Figure 7. Best solution of 5^{th} run, (a) subcarrier allocation, (b) power allocation.

Figure 8 illustrates the users' rates of run 5. It depends on the subcarrier and power allocation of the best solution and the channel condition. Data rates of all users are greater than the minimum data rate (minimum data rate set to zero).

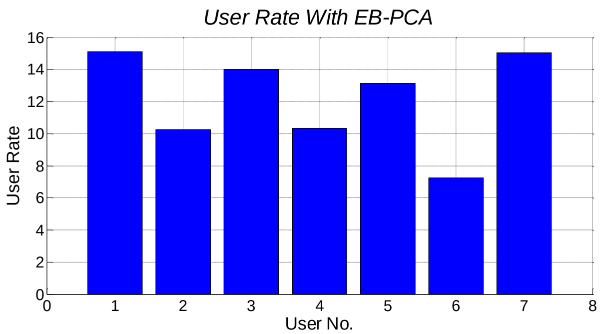


Figure 8. Users' rates of 5th run.

C. Case 3

In this case, the best sum of rates for 10 runs (250 iterations for each run) with 14 users over 7 available subcarriers is presented in Figure 9. During the first iteration, all the EB-PCA runs are going through a very fast convergence toward the targeted best sum of rates.

Then, the obtained best sum of rates is slowly increasing. Also, the small differences in values between runs become more recognizable as the iteration number increases. The rising behavior of each run is related to the principles of the EB-PCA operators (exploration, perturbation, and scattering) that targets searching for the better solution in the search space. In addition, the difference between runs can be plainly explained by remembering that EB-PCA algorithm trial solution can be accepted or rejected with a specific probability that is dependent on the random factors, which might lead to differences between the EB-PCA runs.

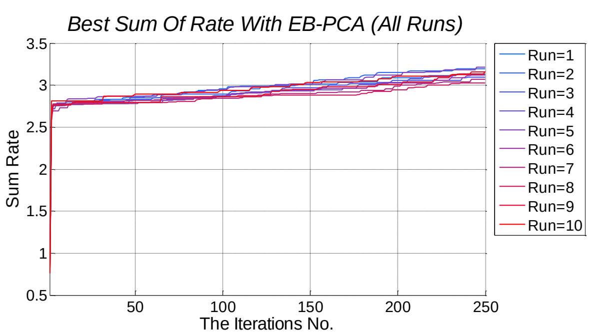


Figure 9. Best sum of rates of 10 runs using EB-PCA (users = 14, subcarriers = 7).

Figure 10 depicts the best and worst sum of rates of run 5. It is clear that the gap between them decreases after iteration 9 and keep increasing in slower manner until the final iteration with more obvious fluctuated difference as the iteration number increases (presented by the worst sum of rate fluctuations that are caused by EB-PCA operators).

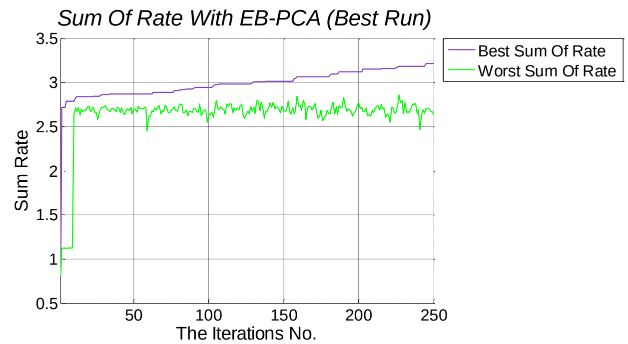
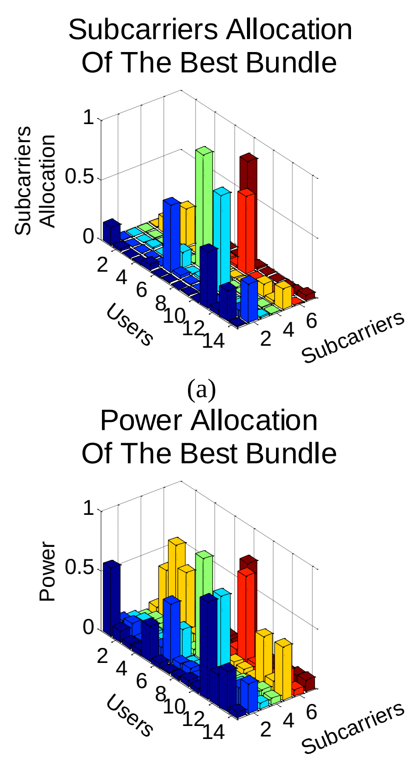


Figure 10. Best and worst sum of rates of 5th run.

Figure 11 illustrates the best sum of rates (solution) of run 5. It shows some similarity even with the presence of obvious differences. Figure 12 gives the users' rate for run 5, which is depending on the subcarrier and power allocation of the best solution and the channel condition. It is clear that all the users have a data rate greater than the minimum data rate value (minimum data rate is set to zero for all users).



(a)

(b)

Figure 11. Best solution of 5th run: (a) subcarrier allocation, (b) power allocation.

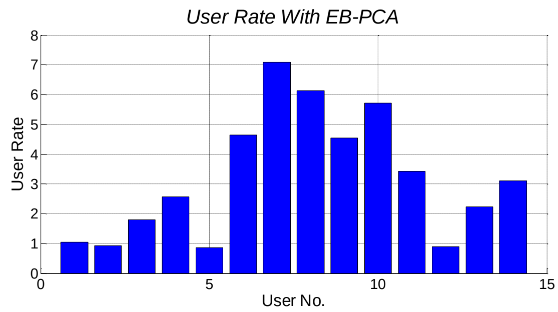


Figure 12. Users' rates of 5th run.

D. Case 4

This case considers 14 users over 14 subcarriers. The beat sum of rates for 10 runs with 250 iterations for each is shown in Fig. 13. EB-PCA runs experience a very fast convergence toward the targeted best sum of rates at the first iteration. Later, the obtained best sum of rates is decelerated with diminutive differences, yet recognizable, in values between runs as the iteration number increases. The improving behavior of each run is related to the principles of EB-PCA operators (exploration, perturbation, and scattering) that will try to explore the search space for better solutions. The difference between runs can be explained simply by recalling that acceptance or rejection of EB-PCA algorithm trial solutions is made with a distinct probability that depends on random factors which may in turn lead to differences between EB-PCA runs.

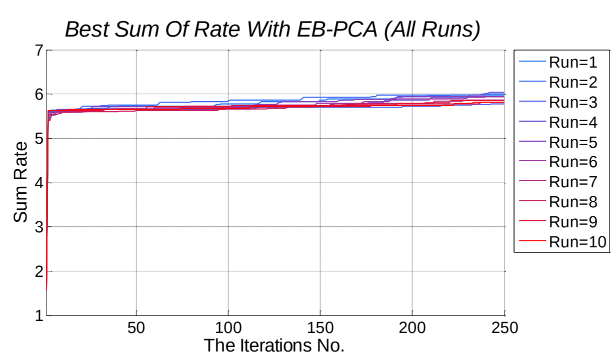


Figure 13. Best sum of rates of 10 runs using EB-PCA (users = 14, subcarriers = 14).

Both best and worst sum of rates of run 4 is shown in Figure 14. It is obvious that the large difference between them is decreased after iteration 88 and then keep increasing slightly to the rest of iterations with much smaller differences with slight fluctuations (caused by fluctuations of the worst sum of rates that in turn is caused by EB-PCA operators).

For run 4, the subcarriers and power allocation of the best sum of rates (solution) are explained in Figure 15. Both subcarrier and power allocation of the best solution show modest similarity with the presence of differences.

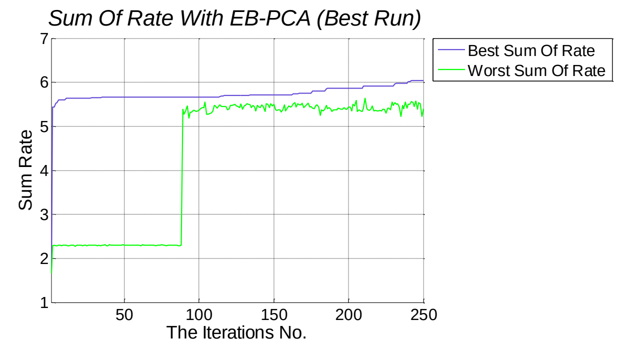
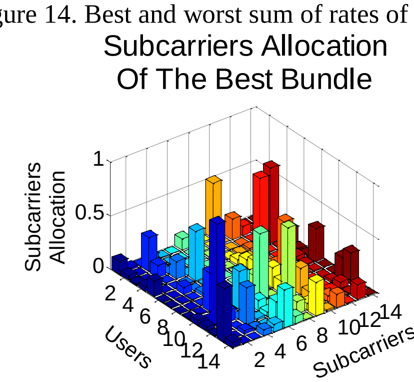
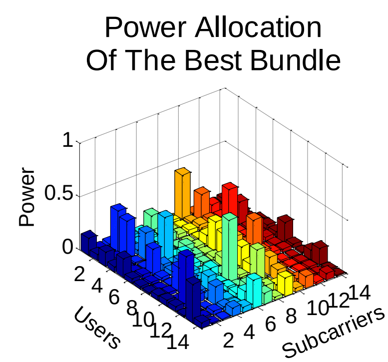


Figure 14. Best and worst sum of rates of 4th run.



(a)



(b)

Figure 15. Best solution of 4th run, (a) subcarrier allocation, (b) power allocation.

Depending on the subcarrier and power allocation and the channel condition, the users' rates of the best solution for run 4 is given in Figure 16. It is clear that all the users have a data rate greater than the minimum data rate value (which was set to zero).

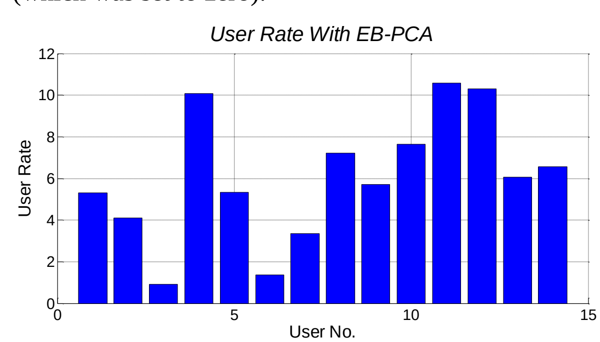


Figure 16. Users' rates of 4th run.

V. Comparison Study

In this section, we present a comparison for the performance versus employing our work with another algorithm called Bat Pack Algorithm (BPA) [24]. The comparison is based on evaluating the sum rate for the considered main four scenarios, as follows: the results in Fig. 1 is compared to that with using the BPA, Fig. 17, when the number of users and available subcarriers are relatively small and equal. After 50th iterations the best sum of 10 runs will hold about 5 with applying BPA, but with EB-PCA the sum rate keeps growing to be about 6.

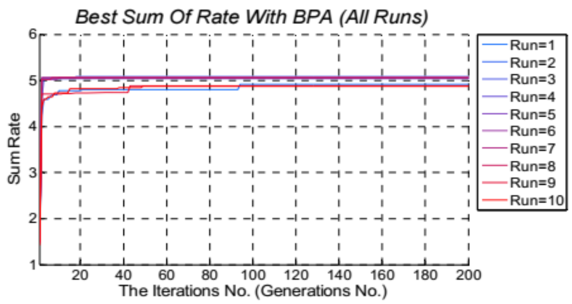


Figure 17. Best sum of rate using BPA [25], when number of users equal to the available subcarriers.

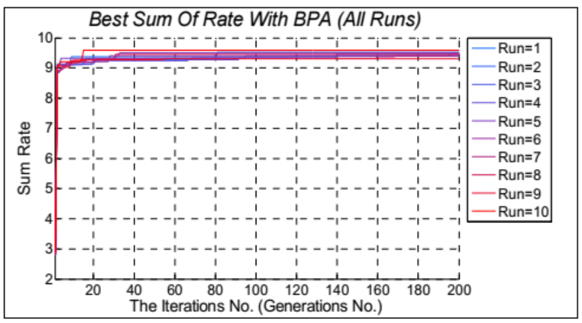


Figure 18. Best sum of ratesusing BPA [25], when number of users is half the subcarriers.

When the number of subcarriers is doubled the number of users, the sum rate approaches 9.3 with employing the BPA, see Fig. 18 (Fig. 6 in [25]), and about 12 with applying the EB-PCA, Fig. 5.

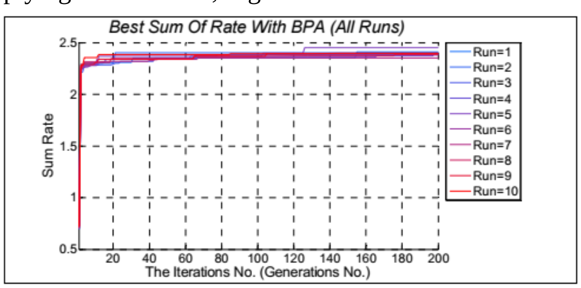


Figure 19. Best sum of rate of 10 runs using BPA [25], when number of users = 14 doubled the subcarriers.

In the third scenario, when number of users is doubled the available subcarriers, amount of sum rate with employing the BPA is about 2.4, as presented in Fig. 19 (Fig. 10 in [25]), but is approximate to 3 with applying the EB-PCA, see Fig. 9.

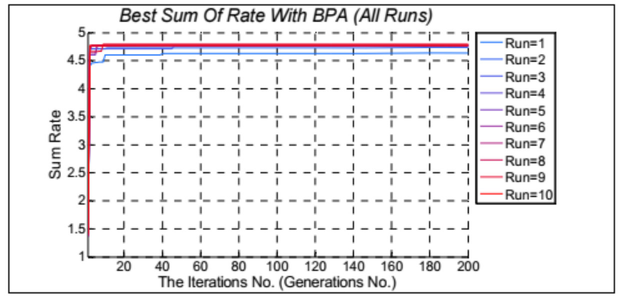


Figure 20. Best sum of rates of 10 run using BPA [25], when number of users equal to the subcarriers.

In the last case, when the number of users equals to the subcarriers, the sum rate is about 4.7, and 5.8 using the BPA, Fig. 20, and EB-PCA, Fig. 13, respectively.

VI. Conclusions

This work proposes and applies Enhanced Bundle-based Particle Collision Algorithm (EB-PCA) to find the optimal or near optimal power and subcarrier allocations for OFDMA system. The results demonstrate that EB-PCA is adaptive and efficient in finding the optimal or near optimal solution for both subcarrier and power allocation. It inherits the structural advantages of the original PCA with the presence of enhanced adaptive perturbation mechanisms (dependent on random walk principles) that give an effective and fast approach for local and global search with a highly converging speed. In addition, this approach provides a better basis for other variants of the PCA or in hybrid forms with other algorithms.

In all the analyzed cases, the results show the ability of the EB-PCA for searching and reaching suitable and acceptable solutions in both efficient and adaptive manner. Also, using multi run (10 runs) for each case shows that there is notable but yet small differences between the different runs. The best obtained run of the first three cases were the fifth runs which are depending on MATLAB internal random seed generator. Also, depending on the nature of the targeted problem in hand, to provide a balance between the level of the required best result on one hand and the processing cost and time on the other hand.

Appendices

Appendix – A

```
Generate an initial solution Old_Config
For n = 0 to # of iterations
    Generate a stochastic perturbation of the solution
    If Fitness (New_Config) > Fitness (Old_Config)
        Old_Config = New_Config
        Exploration ( )
    Else
        Scattering ( )
    End If
End For
```

Appendix – B

```
Perturbation ( )
For i=0 to # (Dimensions-1)
    Upper=Superior_Limit[i]
    Lower=Inferior_Limit[i]
    Rand=random (0,1)
    New_Config [i] = Old_Config [i] + ((Upper -
                              Old_Config [i]) * Rand )
           - ((Old_Config [i] - Lower) * (1-Rand))
    If New_Config [i]> Upper
        New_Config [i]= Superior_Limit[i]
    Else
         if New_Config [i] < Lower
              New_Config [i] = Inferior_Limit[i]
        End IF
     End IF
End For
Return
```

Appendix – C

```
Exploration ( )
For n = 0 to # of iterations
Generate a small stochastic perturbation of the
solution
    If Fitness (New_Config) > Fitness (Old_Config)
        Old_Config = New_Config
    End If
End For
Return
```

Appendix – D

```
Small Perturbation ( )
For i=0 to # (Dimensions-1)
    Upper =Random (1, 1.2)* Old_Config [i]
    If Upper > Superior_Limit[i]
        Upper = Superior_Limit[i]
    End IF
    Lower =Random (0.8, 1)* Old_Config [i]
    If Lower < Inferior_Limit[i]
        Lower = Inferior_Limit[i]
    End IF
    Rand=random (0,1)
    New_Config [i]= Old_Config [i] + ((Upper-
     Old_Config [i])* Rand) - ((Old_Config [i]-
     Lower)*(1- Rand))
End For
Return
```

Appendix – E

Scattering ( )

$$Pscattering = 1 - \frac{\text{Fitness (New\_Config)}}{\text{Best Fitness}}$$

```
If Pscattering > random (0, 1)
    Old_Config = random solution
Else
    Exploration ( );
End if
Return
```

Appendix – F

```
% Enhanced Bundle-based Particle Collision
Algorithm (EB-PCA)
Generate an initial Old_ Bundle (multi-elements
solution)
For n = 0 to Iterations_max
    Generate a stochastic enhanced perturbation of the
solution
    If Fitness (New_ Bundle) > Fitness (Old_ Bundle)
        Old_ Bundle = New_ Bundle
        Enhanced Exploration
    Else
        Enhanced Scattering
    End If
End For
```

Appendix – G

```
% Generate a stochastic enhanced perturbation of the
solution
For i=0 to Iterations_max
    Upper=Superior_Limit
    Lower=Inferior_Limit

    Rand_W =2*Random (0, 1) - 1;
    If Rand_W > = 0
            New_ Bundle = Old_ Bundle *(1- Rand_W)+
Upper * Rand_W;
    Else
            New_ Bundle = Old_ Bundle * (1-
abs(Rand_W))+Lower *abs(Rand_W);
    End if
    If New_ Bundle > Upper
        New_ Bundle = Upper
    Else if New_ Bundle < Lower
        New_ Bundle = Lower
    End If
 End For
```

Appendix – H

```
% Enhanced Exploration
For n = 0 to Iterations_max
    Generate a small stochastic enhanced perturbation of the solution
    If Fitness (New_ Bundle) > Fitness (Old_ Bundle)
        Old_ Bundle = New_ Bundle
    End If
End For
```

Appendix – I

```
% Generate a small stochastic enhanced perturbation of the solution
For i=0 to Iterations_max
    Upper =Random (1, 1.2)* Old_ Bundle
    If Upper > Superior_Limit
        Upper = Superior_Limit
    End If
    Lower =Random (0.8, 1)* Old_ Bundle
    If Lower < Inferior_Limit
        Lower = Inferior_Limit
    End If
    Rand_W =2*Random (0, 1) - 1;
    If Rand_W > = 0
            New_ Bundle = Old_ Bundle *(1- Rand_W)+ Upper * Rand_W;
    Else
            New_ Bundle = Old_ Bundle * (1-abs(Rand_W))+Lower *abs(Rand_W);
    End if
End For
```

Appendix – J

% Enhanced Scattering

$$\text{Pscattering} = 1 - \frac{\text{Fitness }(New\_Bundle\ )}{\text{Best Fitness}}$$

If Pscattering > random (0, 1)

    Old_ Bundle = random Bundle (multi-elements solution)

Else

    Enhanced Exploration

End if

CONFLICT OF INTEREST

The authors have no conflict of relevant interest to this article.

REFERENCES

[1] J. Y. Wu, K. Wu, and M. Wang, "Power-Constrained Quality Optimization for Mobile Video Chatting with Coding-Transmission Adaptation," *IEEE Transactions on Mobile Computing*, vol. 20, no. 9, pp. 2862–2876, Sep. 2021.

[2] S. Nosheen and J. Y. Khan, "Quality of Service-and Fairness-Aware Resource Allocation Techniques for IEEE802.11ac WLAN," *IEEE Access*, vol. 9, pp. 25579–25593, 2021.

[3] N. Samarji and M. Salamah, "ERQTM: Energy-Efficient Routing and QoS-Supported Traffic Management Scheme for SDWBANs," *IEEE Sensors Journal*, vol. 21, no. 14, pp. 16328–16339, Jul. 2021.

[4] Y. Guo, Z. Qin, Y. Liu, and N. Al-Dhahir, "Intelligent Reflecting Surface Aided Multiple Access over Fading Channels," *IEEE Transactions on Communications*, vol. 69, no. 3, pp. 2015–2027, Mar. 2021.

[5] B. Zhai, A. Tang, C. Peng, and X. Wang, "SS-OFDMA: Spatial-Spread Orthogonal Frequency Division Multiple Access for Terahertz Networks," *IEEE Journal on Selected Areas in Communications*, vol. 39, no. 6, pp. 1678–1692, Jun. 2021.

[6] N. T. Le, L. N. Tran, Q. D. Vu, and D. Jayalath, "Energy-Efficient Resource Allocation for OFDMA Heterogeneous Networks," *IEEE Transactions on Communications*, vol. 67, no. 10, pp. 7043–7057, Oct. 2019.

[7] L. Jiao, H. Yin, and Y. Wu, "Dynamic Resource Allocation for Scalable Video Streaming in OFDMA Wireless Networks," *IEEE Access*, vol. 8, pp. 33489–33499, 2020.

[8] I. Basturk and Y. Chen, "Energy Efficiency for MISO-OFDMA-Based User-Relay Assisted Cellular Networks," *IEEE Systems Journal*, vol. 14, no. 4, pp. 5274–5283, Dec. 2020.

[9] M. Condoluci, G. Araniti, A. Molinaro, and A. Iera, "Multicast Resource Allocation Enhanced by Channel State Feedbacks for Multiple Scalable Video Coding Streams in LTE Networks," *IEEE Transactions on Vehicular Technology*, vol. 65, no. 5, pp. 2907–2921, May 2016.

[10] J. Y. Kim, T. Kwon, and D. H. Cho, "Resource allocation scheme for minimizing power consumption in OFDM multicast systems," *IEEE Communications Letters*, vol. 11, no. 6, pp. 486–488, Jun. 2007.

[11] M. Ibrahim and H. AlSabbagh, "Adaptive OFDMA Resource Allocation using Modified Multi-Dimension Genetic Algorithm," *Iraqi Journal for Electrical and Electronic Engineering*, vol. 12, no. 1, pp. 103–113, 2016.

[12] J. Yu, S. Han, and X. Li, "A Robust Game-Based Algorithm for Downlink Joint Resource Allocation in Hierarchical OFDMA Femtocell Network System," *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, vol. 50, no. 7, pp. 2445–2455, Jul. 2020.

[13] W. F. Sacco and C. R. E. de Oliveira, "A New Stochastic Optimization Algorithm based on a Particle Collision Metaheuristic." 6th World Congresses of Structural and Multidisciplinary Optimization, Rio de Janeiro, 30 May - 03 June 2005, Brazil.

[14] H. Alves Filho, P. Claudio, W. F. Sacco, and C. M. NA Pereira, *Cost-Based Optimization Of A Nuclear Reactor Core Design: a preliminary mode*. 2007. [Online]. Available: https://www.researchgate.net/publication/238621160

[15] M. A. Pizani Domiciano, E. H. Shiguemori, L. A. Vieira Dias, and A. M. da Cunha, "Particle collision

algorithm applied to automatic estimation of digital elevation model from images captured by UAV," *IEEE Geoscience and Remote Sensing Letters*, vol. 15, no. 10, pp. 1630–1634, Oct. 2018.

[16] D. Campos Knupp, A. J. Silva Neto, N. Friburgo, and W. Figueiredo Sacco, "Estimation of Radiative Properties with the Particle Collision Algorithm," 2007.

[17] S. Bergoch *et al.*, "Automatic configuration for neural network applied to atmospheric temperature profile identification." EngOpt 2012-International Conference on Engineering Optimization, Rio de Janeiro, Brazil, 1-5 July 2012.

[18] P. O. Soares, J. Da, S. Neto, and H. Fraga De Campos Velho, "Atmospheric Temperature Profile Estimation under Clouds by Self configuring Neural Network." Atmospheric Temperature Profile Estimation under Clouds by Self configuring Neural Network, *Albi, France, June 26-28, 2013*

[19] T. M. Wu and S. L. Wang, "Dynamic and fair resource allocation algorithm for OFDM systems," *IEEE Communications Letters*, vol. 11, no. 12, pp. 931–933, Dec. 2007.

[20] D. Kim, T. Fujii, and K. Lee, "A resource allocation algorithm for OFDM-based cellular system serving unicast and multicast services," *Eurasip Journal on Wireless Communications and Networking*, vol. 2013, no. 1, 2013.

[21] Stephen Boyd and Lieven Vandenberghe, *Convex Optimization*. Cambridge university press, 2009.

[22] E. Fávero Pacheco Da Luz, C. Becceneri, and H. Fraga De Campos Velho, "A new multi-particle collision algorithm for optimization in a high-performance environment 4 a new multi-particle collision algorithm for optimization in a high-performance environment," *Journal of Computational Interdisciplinary Sciences*, vol. 18, no. 1, pp. 3–10, 2008, [Online]. Available: http://epacis.org

[23] Li, Sheng, Wang, and Sun, "Interference and Resource Management in Heterogeneous Wireless Networks."

[24] TSGR, "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]. Available: http://portal.etsi.org/chaircor/ETSI_support.asp

[25] M. K. Ibrahim, H. M. AlSabbagh, A. Al-Omary, and H. Al-Rizzo, "Bat pack algorithm for dynamic resource allocation in OFDMA systems," *International Journal of Mobile Network Design and Innovation*, vol. 9, no. 1, 2019.