Composite Differential Evolution Aided Channel Allocation in OFDMA Systems with Proportional Rate Constraints

Nitin Sharma and Alagan Anpalagan

Abstract: **Orthogonal frequency division multiple access (OFDMA) is a promising technique, which can provide high downlink capacity for the future wireless systems. The total capacity of OFDMA can be maximized by adaptively assigning subchannels to the user with the best gain for that subchannel, with power subsequently distributed by water-filling. In this paper, we propose the use of composite differential evolution (CoDE) algorithm to allocate the subchannels. The CoDE algorithm is population-based where a set of potential solutions evolves to approach a near-optimal solution for the problem under study. CoDE uses three trial vector generation strategies and three control parameter settings. It randomly combines them to generate trial vectors. In CoDE, three trial vectors are generated for each target vector unlike other differential evolution (DE) techniques where only a single trial vector is generated. Then the best one enters the next generation if it is better than its target vector. It is shown that the proposed method obtains higher sum capacities as compared to that obtained by previous works, with comparable computational complexity.**

Index Terms: **Computational complexity, differential evolution (DE), orthogonal frequency division multiple access (OFDMA), resource allocation, sum capacity.**

I. INTRODUCTION

The advent of new generation of communication technologies has ushered in an era of high data rates, better quality and improved reliability. In order to meet the need of high data rates and reliable data services, orthogonal frequency division multiple access (OFDMA) has been selected as the multiple access scheme for state-of-the-art wireless systems such as LTE and WiMAX. Orthogonal frequency division multiplexing (OFDM) is a promising modulation technique which mitigates the effect of frequency selective fading, inherent in high data rate environment. It can be considered as a type of multicarrier modulation scheme, based on the idea of dividing a given high-bit-rate data stream into several parallel lower bit-rate streams and modulating each stream on separate carriers often called subchannels or tones. Multicarrier modulation schemes eliminate or minimize inter-symbol interference by making the symbol time large enough so that the channel-induced delays are an insignificant fraction of the symbol duration. Therefore, in high data rate systems in which the symbol duration is small, being inversely proportional to the data rate, splitting the data stream into many parallel streams increases the symbol duration of each stream such that the delay spread is only a small fraction of the symbol duration. The number of subchannels should be selected in such a way that each subchannel has a bandwidth less than the coherence bandwidth of the channel, thus each subchannel experiences relatively flat fading. OFDMA adds multiple access to OFDM [1], [2] by allowing a number of users to share an OFDM symbol. OFDMA can also take advantage of channel diversity among users in different locations by adaptively assigning subchannels depending on channel characteristics. This approach allows efficient use of all the subchannels.

Resource allocation in OFDMA [3]–[13] includes subchannel allocation, power allocation, and bit loading. Developing efficient resource management techniques have drawn enormous attention in recent years. Solutions to the resource allocation problem in OFDMA have been broadly divided into two categories: Margin adaptive (MA) and rate adaptive (RA) [8]. Resource allocation was tackled in [11] using MA scheme, wherein an iterative subchannel and power allocation algorithm was proposed to minimize the total transmit power given a set of fixed user data rates and the bit error rate (BER) requirements. In [4], RA method was used, wherein the objective was to maximize the total data rates over all users subject to power and BER constraints. It was shown in [4] that in order to maximize the total capacity each subchannel should be assigned to the user with best gain on it. However, there was no consideration given for the fairness of allocation among the users, which can leave some users with low channel gains, without any channel being allocated to them. In [8], [9], and [12] proportional fairness was incorporated by imposing a set of nonlinear constraints into the optimization problem. The cost of better proportional fairness is higher computational cost. Most of the existing literature assume the availability of perfect channel state information at transmitter and receiver. This restricts the practical systems to use algorithms with lower computational cost. However, there are instances [14]–[16] where the effect of imperfect or partial channel state information at transmitter on the capacity of the OFDMA systems was considered. In [14], throughput performance analysis of the chunk-based subcarrier allocation was presented by considering the average BER constraint over a chunk in downlink OFDMA transmission. The outage probabilities per subcarrier were compared between the average BER-constraint based chunk allocation and the average signal-to-noise-ratio (SNR) based chunk allocation. The effects of system parameters, such as the number of users, the number of

Manuscript received April 26, 2013; approved for publication by Huang, Kaibin, Division II Editor, April 11, 2014.

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Digital object identifier 10.1109/JCN.2014.000091

subcarriers per chunk, and the coherence bandwidth, were also evaluated. It was shown through numerical results that, when the chunk bandwidth is smaller than the coherence bandwidth, the average downlink throughput of the chunk-based subcarrier allocation is very close to that of the single-subcarrier-based allocation.

Authors in [15] developed an analytical framework in order to investigate heterogeneous partial feedback in a general OFDMA-based heterogeneous multicell employing the best-M partial feedback strategy. Exact sum rate analysis was first carried out and closed form expressions were obtained by decomposition of the probability density function of the selected user's signal-to-interference-plus-noise ratio. Further, asymptotic analysis using extreme value theory to examine the effect of partial feedback on the randomness of multiuser diversity was performed. Through this analysis it was shown that the best-1 feedback is asymptotically optimal. The asymptotic approximation for the sum rate in order to determine the minimum required partial feedback was also derived in [15]. In [16], the throughput of an adaptive frequency division duplex OFDMA system with channel state information digitized over a feedback channel to the transmitter was investigated. Therein, the instantaneous SNR of the different subcarriers was used as channel state information to exploit multi-user diversity using adaptive subcarrier allocation. A closed form expression of the average throughput of an adaptive multi-user OFDMA system using imperfect channel state information and uncoded M-QAM modulation was derived. Furthermore, a closed form expression of the average throughput of an OFDMA system exploiting frequency diversity, which does not require channel state information at the transmitter, was presented. Both the throughput performances were compared with the aim to identify the optimal transmission strategy depending on the grade of channel state information imperfectness.

Genetic algorithms (GAs), which are a class of evolutionary algorithms [3], were used in [6], [7], [10], and [13] for resource allocation. In this paper, the use of the composite differential evolution (CoDE) [17] algorithm, which is an adaptive differential evolution (DE) [18] variant, is proposed for subchannel allocation among the users. DE is simple, straight forward to implement and has few number of control parameters, thus the space complexity of DE is low. The gross performance of DE in terms of accuracy, convergence, speed and robustness makes it attractive choice for resource allocation in OFDMA. Being computationally less expensive than GA and particle swarm optimization (PSO) [3], CoDE is better placed to quickly arrive at an optimal allocation. Evolutionary algorithms basically are unconstrained optimization methods and require additional mechanisms to deal with constraints. Furthermore, in practical applications, the choice of stopping criteria can significantly influence the duration of an optimization process. Therefore, in this paper, we propose the use of dynamic-objective based constraint handling along with standard deviation based stopping criterion.

This paper is organized as follows: Section II gives the OFDMA system model. Section III provides a brief overview of related work and compares CoDE algorithm with GAs and other traditional algorithms. Section IV briefly describes CoDE algorithms and its various subcomponents. In Section V the use of CoDE algorithm for channel allocation in downlink OFDMA systems is presented. Simulation results are illustrated in Section VI and conclusions and future scope are presented in Section VII.

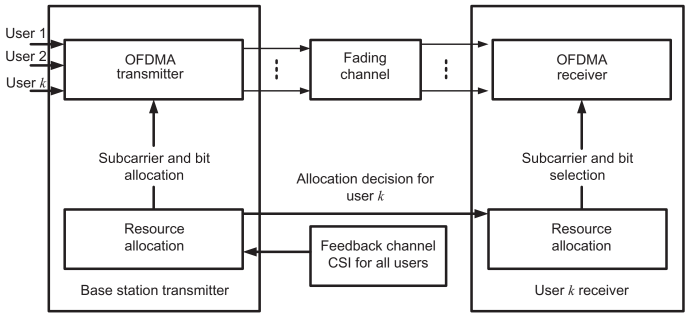

Fig. 1. System model.

II. SYSTEM MODEL

Consider an OFDMA system with K users and N subchannels, as shown in Fig. 1. The serial data from all the users are fed into the resource allocation block at the transmitter, which then allocates bits from different users to different subchannels. It is assumed that each subchannel has a bandwidth that is much smaller than the coherence bandwidth of the channel and that the instantaneous channel gains on all the subchannels of all the users are known to the transmitter. Using this channel information, the transmitter applies the subchannel, bit, and power allocation algorithm to assign different subchannels to different users and the number of bits/OFDM symbol to be transmitted on each subchannel. Depending on the number of bits assigned to a subchannel, the adaptive modulator will use a corresponding modulation scheme, and the transmit power level will be adjusted according to the subchannel, bit, and power allocation algorithm. The basic idea behind adaptive modulation is quite simple: transmit as high a data rate as possible when the channel is good, and transmit at a lower rate when the channel is poor, in order to avoid excessive dropped packets.

Each user's data is distributed across the set of subchannels assigned to the user. The assumption is that, each subchannel is uniquely assigned to a single user and two or more users never share the same subchannel. The throughput optimization problem is formulated on the same lines as in [8]. We desire to allocate the subchannels and power in such a way that the total error free capacity is maximized while the total power constraint is met. As compared to method in [8], where optimal power allocation was proposed to maximize the total error free capacity, we propose the use of CoDE algorithm for subchannel allocation assuming equal power allocation on each subchannel. The optimization problem can hence be postulated as follows:

$$\max_{\rho_{k,n},p_{k,n}} \sum_{k=1}^{K}\sum_{n=1}^{N} \frac{\rho_{k,n}}{N}\log_2\left(1+\frac{p_{k,n}h_{k,n}^2}{N_o\frac{B}{N}}\right). \tag{1}$$

Subject to constraints:

$$\begin{aligned}
&\text{C1: } \sum_{k=1}^{K}\sum_{n=1}^{N} p_{k,n} \leq P_{\text{total}},\\
&\text{C2: } p_{k,n} \geq 0 \ \forall k,n,\\
&\text{C3: } \rho_{k,n} \in \{0,1\} \ \forall k,n,\\
&\text{C4: } \sum_{k=1}^{K} \rho_{k,n} = 1 \ \forall n,\\
&\text{C5: } R_1 : R_2 : R_3 : ... : R_k = \gamma_1 : \gamma_2 : \gamma_3 : \cdots : \gamma_k.
\end{aligned}$$

In (1), N_o is the power spectral density of additive white Gaussian noise (AWGN), *B* is the total available bandwidth and $h_{k,n}$ is the channel gain for user *k* in subchannel *n*. In C1, P_{total} is the total available power and $p_{k,n}$ is the power allocated for user *k* in subchannel *n*. According to C3, $\rho_{k,n}$ can only be either 1 or 0, indicating whether subchannel *n* is allocated to the user *k* or not. C4 restricts allocation of one subchannel to one user only and C5 is the proportional rate constraint. The capacity for user *k*, denoted as R_k, is defined as:

$$R_k = \sum_{n=1}^{N} \frac{\rho_{k,n}}{N} \log_2 \left(1 + \frac{p_{k,n} h_{k,n}^2}{N_o \frac{B}{N}}\right). \qquad (2)$$

Note here that the rates defined in (1) and (2) are rates per Hertz of bandwidth in units of bits/sec/Hz.

III. RELATED WORK

The resource allocation problem in (1) is an NP-hard combinatorial optimization [8] problem with non-linear constraints. Hence, it is highly improbable to solve the problem optimally using polynomial time algorithms. An optimal solution will require joint allocation of power and subchannels to the users. There are few instances where subchannel and power were jointly allocated using multi-objective GAs such as NSGA-II [7]. Because of high computational complexity involved, such multi-objective algorithms may not be suitable for real time applications. Furthermore, the base station has to rapidly compute the optimal subchannel and power allocation if the wireless channel changes rapidly. Hence, suboptimal algorithms with lower complexity are preferred for cost-effective implementations. Separating the subchannel and power allocation is a way to reduce the complexity since the number of variables in the objective function is almost reduced by half.

In this paper, we propose the use of CoDE [17] algorithm, which is an adaptive variant of DE [18]. To justify the use of CoDE as compared to other optimization algorithms for the resource allocation problem under consideration, we shall briefly introduce and compare them on the basis of their working principle.

DE [18] is a population-based stochastic global optimization algorithm which optimizes a problem by iteratively trying to improve a candidate solution with respect to a given measure of quality. The basic principle of DE is to create new candidate solutions by combining the parent individual and several other individuals of the same population, and a candidate replaces the parent only if it has better fitness. Recently, DE has drawn enormous attention from researchers for its use in multi-objective, constrained, large scale and uncertain optimization problems. The main feature of DE is its simplicity and is straight forward to implement, and has fewer number of control parameters. The space complexity of DE is low. The gross performance of DE in terms of accuracy, convergence, speed and robustness makes it attractive for application to various real world optimization problems [19]–[25].

The control parameters involved in DE are highly dependent on the optimization problem. Moreover, the selection of the appropriate strategy for trial vector generation requires additional computational time using a trial-and-error search procedure. Due to the above drawbacks, there has been an increasing interest among researchers in designing new adaptive and self adaptive DE variants. CoDE [17] is a recently presented adaptive DE variant, which combines three different trial vector generation strategies with three preset control parameter settings. The above combination is performed in a random way in order to generate trial vectors. The main advantage of CoDE is that it has a simple structure and thus it is very easy to be implemented in any programming language. Wireless channels are highly dynamic resulting in the channel characteristics changing in short intervals of time. Thus, the channel gains of users for various subchannels change frequently. This demands a new allocation pattern of subchannels in order to maximize the sum capacity. Thus quick allocation of the subchannels is a highly desired characteristic of the allocation algorithm. Being computationally less expensive than GA and PSO, CoDE is better placed to quickly arrive at an optimal allocation. Moreover, the experimental results presented in [17] suggest that the CoDE is better in overall performance as compared to the other algorithms used for comparison.

Reddy in [6] proposed a simple GA with the aim to minimize the overall transmitted power while satisfying the constraint of minimum data rate for each user. The bits were finally allocated using the water-filling algorithm. Unfortunately, the GA in [6] failed to guarantee a minimum data rate for each user. The PSO algorithm was used to solve the resource allocation problem in [26] through MA allocation. However, no fairness among the users was considered. In the case of large path loss differences among users, it is possible that the users with higher average channel gains will be allocated most of the resources, i.e., subchannels and power, for a significant portion of time. Hence, the users with lower average channel gains may not be able to transmit any data due to non allocation of subchannels to them. In this paper, the use of CoDE is proposed for RA resource allocation. The proportional fairness among the users is also enforced by providing subchannels to each user according to their requirements. With the proportional rate constraints, the data rate fairness among users can be flexibly controlled by a set of parameters. Further, the total system throughput is also adjustable by varying the proportional fairness parameters.

IV. PRELIMINARIES ON COMPOSITE DIFFERENTIAL EVOLUTION (CODE)

A. Differential Evolution (DE)

DE [18], is a class of simple yet efficient evolutionary algorithms for continuous optimization problems. DE is similar to other EAs where a population of individuals is used to search for an optimal solution [27]. The main difference between traditional EAs and DE is that in traditional EAs, mutation results in small perturbations to the genes of an individual, while in DE the mutation is an arithmetic combination of individuals [27]. At the beginning of the evolution process, the DE mutation operator favors exploration; however, as evolution progresses, the mutation operator favors exploitation [28]. Hence, DE automatically adapts the mutation increments (i.e., search step) to the best value based on the stage of the evolutionary process and not based on a predefined probability density function. DE uses the difference between randomly selected vectors (individuals) as the source of variation for a third vector referred to as the target vector. Trial solutions are generated by adding a weighted difference vector to the target vector. This process is referred to as the mutation operator where the target vector is mutated. A recombination or crossover step is then applied to produce an offspring which is only accepted if it improves the fitness of the parent individual.

Due to its simple structure, ease of implementation, and fast convergence speed, DE has been successfully applied to solve a wide range of optimization problems such as clustering [29], unsupervised image classification [30], digital filter design [31], and other non-linear function/process optimization [32]–[35]. In short, DE is generally considered as a reliable, accurate, robust, and fast optimization technique used in many practical optimization problems. The basic DE algorithm is described in more detail in following paragraphs:

During the evolution, DE maintains a population of M individual members, where M is the population size, and each member is a point in the solution space S. DE improves its population generation by generation. It extracts distance and direction information from the current population for generating new solutions for the next generation. Almost all the DE variants adopt the following algorithmic framework:

- Step 1) Set the current generation number $G = 0$.
- Step 2) Sample M points $\vec{x}_{i,G}, \cdots, \vec{x}_{M,G}$ from S to form an initial population.
- Step 3) For i =1,$\cdots$,M , do
  - Step 3.1) Mutation: Generate a mutant vector $\vec{v}_{i,G}$ by using a DE mutation operator;
  - Step 3.2) Repair: If $\vec{v}_{i,G}$ is not feasible (i.e., not in S), use a repair operator to make $\vec{v}_{i,G}$ feasible;
  - Step 3.3) Crossover: Mix $\vec{x}_{i,G}$ and $\vec{v}_{i,G}$ to generate a trial vector $\vec{u}_{i,G}$ by using a DE crossover operator;
  - Step 3.4) Replacement: If $f(\vec{u}_{i,G}) \leq f(\vec{x}_{i,G})$, set $\vec{x}_{i,G+1} = \vec{u}_{i,G}$ otherwise, set $\vec{x}_{i,G+1} = \vec{x}_{i,G}$
- Step 4) If a preset stopping condition is not met, set G=G+1 and go to Step 3.

In the ith pass of the loop in Step 3, $\vec{x}_{i,G}$ is called a target vector, $\vec{v}_{i,G}$ is its mutant vector, and $\vec{u}_{i,G}$ is its trial vector. $\vec{u}_{i,G}$ inherits some parameter values from $\vec{x}_{i,G}$ in Step 3.3 and enters the next generation if its objective function value is better than or equal to the objective function value of $\vec{x}_{i,G}$.

The characteristic feature of DE is its mutation operators. Five commonly used mutation operators are:

DE/rand/1:

$$\vec{v}_{i,G} = \vec{x}_{r1,G} + F(\vec{x}_{r2,G} - \vec{x}_{r3,G}) \tag{3}$$

DE/rand/2:

$$\vec{v}_{i,G} = \vec{x}_{r1,G} + F(\vec{x}_{r2,G} - \vec{x}_{r3,G}) + F(\vec{x}_{r4,G} - \vec{x}_{r5,G}) \tag{4}$$

DE/best/1:

$$\vec{v}_{i,G} = \vec{x}_{best,G} + F(\vec{x}_{r1,G} - \vec{x}_{r2,G}) \tag{5}$$

DE/best/2:

$$\vec{v}_{i,G} = \vec{x}_{best,G} + F(\vec{x}_{r1,G} - \vec{x}_{r2,G}) + F(\vec{x}_{r3,G} - \vec{x}_{r4,G}) \tag{6}$$

DE/current-to-best/1:

$$\vec{v}_{i,G} = \vec{x}_{i,G} + F(\vec{x}_{best,G} - \vec{x}_{i,G}) + F(\vec{x}_{r1,G} - \vec{x}_{r2,G}) \tag{7}$$

where $r1, r2, r3, r4$, and $r5$ are different indexes uniformly randomly selected from $\{1, \cdots, M\}$ and are also different from i. F is a control parameter, often called the scaling factor and $\vec{x}_{best,G}$ is the best individual in the current population.

DE performs a crossover operator on $\vec{x}_{i,G}$ and $\vec{v}_{i,G}$ to generate the trial vector $\vec{u}_{i,G}$. The following two crossover operators are widely used in the DE implementations.

Binomial crossover:

The trial vector $\vec{u}_{i,G} = (u_{i,1,G}, u_{i,2,G}, \cdots, u_{i,D,G})$ is generated in the following way:

$$u_{i,j,G} = \begin{cases} v_{i,j,G}, & \text{if } \beta_j(0,1) \leq C_r \text{ or } j = j_{\text{rand}}; \\ x_{i,j,G}, & \text{otherwise} \end{cases} \tag{8}$$

where index j_{rand} is a randomly chosen integer in the range [1,D], where D is the dimension of the problem defined by the number of variables, β_j(0,1) is a uniform random number in (0,1), and $C_r \in (0, 1]$ is the user-defined crossover control parameter. Due to the use of j_{rand}, $\vec{u}_{i,G}$ is always different from $\vec{x}_{i,G}$.

Exponential crossover:

The trial vector $\vec{u}_{i,G} = (u_{i,1,G}, u_{i,2,G}, \cdots, u_{i,D,G})$ is created as follows [36]:

$$u_{i,j,G} = \begin{cases} v_{i,j,G}, & \text{for } j = \langle l \rangle_D, \langle l+1 \rangle_D, \cdots, \langle l+L-1 \rangle_D; \\ x_{i,j,G}, & \text{otherwise} \end{cases} \tag{9}$$

where $i = 1, 2, \cdots, M, j = 1, 2, \cdots, D$, and $\langle\rangle_D$ denotes the modulo function with modulus D. The starting index l is a randomly chosen integer in the range of [1,D]. The integer L is also drawn from the range [1,D] with the probability $P_r(L \geq v) = C_r^{v-1}, v > 0$. The parameters l and L are re-generated for each trial vector. If the jth element $u_{i,j,G}$ of the trail vector $\vec{u}_{i,G}$ is infeasible (i.e., out of boundary), then it is reset using repair operator, described below.

Repair operator:

A simple and popular repair operator works as follows:

if the jth element $u_{i,j,G}$ of the trail vector $\vec{u}_{i,G} = (u_{i,1,G}, u_{i,2,G}, \cdots, u_{i,D,G})$ is out of the search region $[L_j, U_j]$, then $u_{i,j,G}$ is reset as follows:

$$u_{i,j,G} = \begin{cases} \min\{U_j, 2L_j - u_{i,j,G}\}, \text{ if } u_{i,j,G} < L_j; \\ \max\{U_j, 2L_j - u_{i,j,G}\}, \text{ if } u_{i,j,G} > U_j. \end{cases} \quad (10)$$

Finally, the selection operator is used to select the better one from the target vector $\vec{x}_{i,G}$ and the trail vector $\vec{u}_{i,G}$ to enter next generation. The selection operator is defined as follows:

$$\vec{x}_{i,G+1} = \begin{cases} \vec{u}_{i,G}, \text{ if } f(\vec{u}_{i,j}) \le f(\vec{x}_{i,j}); \\ \vec{x}_{i,G}, \text{ otherwise.} \end{cases} \quad (11)$$

Different DE variants can be obtained by combining different mutation operators with different crossover operators. For example, DE/rand/1/bin can be obtained by combining DE/rand/1 with the binomial crossover, and DE/rand/1/exp can be obtained by combining DE/rand/1 with the exponential crossover. In general, DE/rand/1/bin is the most classic variant of DE.

B. Composite Differential Evolution (CoDE)

Trial vector generation strategies and control parameters have a significant influence on the performance of DE. DE exhibits remarkable performance in a wide variety of problems from diverse fields. It uses mutation, crossover, and selection operators at each generation to move its population towards the global optimum. The DE performance mainly depends on two components. One is its trial vector generation strategy (i.e., mutation and crossover operators), and the other is its control parameters (i.e., population size M, scaling factor F, and crossover control parameter C_r).

There are numerous forms of DE depending upon the trial vector generation strategy and the choice of control parameters such as DE algorithm with strategy adaptation, adaptive DE with optional external archive, self-adapting control parameters in DE and DE algorithm with ensemble of parameters and mutation and crossover strategies [17] among the others apart from CoDE. In summary, CoDE is the best in overall performance among the five methods in comparison on basic multimodal functions, expanded multimodal functions, and hybrid composition functions.

Each trial vector generation strategy i.e., rand/1/bin, rand/2/bin or current-to-rand/1 in CoDE randomly selects a control parameter setting from the three pre-determined parameter groups for generating a trial vector. CoDE uses random control settings in the search. Therefore, CoDE is more effective. This is because random selection of the control parameter settings increases the search diversity.

The three vector generation strategies used:

rand/1/bin:

$$u_{i,j,G} = \begin{cases} x_{r1,j,G} + F(x_{r2,j,G} - x_{r3,j,G}), \text{if } \beta_j < C_r; \\ \text{or } j = j_{\text{rand}}; \\ x_{i,j,G}, \text{ otherwise.} \end{cases} \quad (12)$$

rand/2/bin:

$$u_{i,j,G} = \begin{cases} x_{r1,j,G} + F(x_{r2,j,G} - x_{r3,j,G}) + F(x_{r4,j,G} \\ -x_{r5,j,G}), \text{if } \beta_j < C_r \text{or } j = j_{\text{rand}}; \\ x_{i,j,G}, \text{ otherwise.} \end{cases} \quad (13)$$

Subcarrier-1	Subcarrier-2	$\cdots$	Subcarrier-N
4	15	$\cdots$	k

Fig. 2. Encoding of individuals for subcarrier allocation.

current-to-rand/1:

$$\vec{u}_{i,G} = \vec{x}_{i,G} + \beta_j(\vec{x}_{r1,G} - \vec{x}_{i,G}) + F(\vec{x}_{r2,G} - \vec{x}_{r3,G}). \quad (14)$$

The Control Parameter Settings used:

$$F = [1.0, 1.0, 0.8], C_r = [0.1, 0.9, 0.2].$$

V. RESOURCE ALLOCATION IN MULTIUSER OFDM USING CODE

Our objective is to maximize the sum capacity of the system, subject to the constraints of total maximum power and proportional rate for each user, given by (1) and constraints C1–C5. Further, it is assumed that no two users can share a particular subcarrier and all subchannels are assumed to share equal power. Finally, the bits of each user are modulated into N M-level quadrature amplitude modulation OFDM symbols and transmitted simultaneously on N orthogonal subcarriers and then inverse fast Fourier transform module combines these symbols and return an OFDMA symbol. With the equal power allocation, the transmit rate of kth user on the nth subcarrier can be calculated as follows:

$$r_{k,n} = \log_2\left(1 + \frac{\frac{P_{\text{total}}}{N} h_{k,n}^2}{N_o \frac{B}{N}}\right). \quad (15)$$

In general, the algorithm begins with a randomly initiated population of M, D dimensional real-valued parameter vectors. Each vector, also known as genome/chromosome, forms a candidate solution to the multidimensional optimization problem. Each individual of the population corresponds to a subchannel allocation. It is coded as a vector of length N whose indices represent the subchannels, and the value of each vector entry is an integer in the range [1,K] representing the user that has been assigned the subchannel corresponding to that entry. For instance, the nth entry of an individual has value of k implies that subchannel n is assigned user k. Fig. 2 depicts the coding of a particular individuals in one generation. Entire population is made up of M such individuals in each generation.

The steps involved in subchannel allocation for multiuser OFDM system using CoDE are shown in Fig. 3.

A. Constraint Handling

An efficient and adequate constraint-handling technique is a key element in the design of optimization algorithm. Although the use of penalty functions is the most common technique for constraint-handling, there are a lot of different approaches for dealing with constraints [37]. A comprehensive discussion about constraint handling is presented in [38]. In constraint handling using penalty approach, a penalty is added to

Input: M: The number of individuals at each generation i.e., population size.
Max_FES : Maximum number of function evaluations.
The strategy candidate pool: rand/1/bin, rand/2/bin, current-to-best/1.
The parameter candidate pool: [F=1.0, C_r=0.1], [F=1.0, C_r=0.9], and [F=0.8, C_r=0.2].
Step 1: Set G = 0.
Step 2: Allocate equal power (P_{total}/Number of subchannels) to all subchannels.
Step 3: Coding of individuals: Each individual of the population corresponds to a subchannel allocation. It is coded as a vector of length N whose indices represent the subchannels, and the value of each vector entry is an integer in the range [1,K] representing the user that has been assigned the subchannel corresponding to that entry. For instance, the $m\text{th}$ entry of an individual has value of n, implies that subchannel m is assigned to user n.
Step 4: Initial population: The initial population of size M can be randomly generated, with high-quality individuals possibly being fed into the population. A fine individual could be either a good subchannel allocation generated by appropriate randomization, or the suboptimal solutions existing in literature. With a carefully selected starting population, the time required for CoDE to reach an optimum solution would be substantially reduced.
Step 5: Evaluate the objective function values $f\left(\vec{x}_{1,0}\right), f\left(\vec{x}_{2,0}\right), \cdots, f\left(\vec{x}_{M,0}\right)$.
Step 6: Set *FES* = M.
Step 7: While *FES* $<$ *max_FES* **do**
Step 8: $P_{G+1} = \Phi$.
Step 9: for i =1:M **do**
Step 10: Use the three strategies each with a control parameter setting randomly selected from the parameter pool, to generate three trial vectors $\vec{u}_{i_1,G}$, $\vec{u}_{i_2,G}$, and $\vec{u}_{i_3,G}$ for the target vector.
Step 11: Evaluate the objective function values of the three trial vectors $\vec{u}_{i_1,G}$, $\vec{u}_{i_2,G}$, and $\vec{u}_{i_3,G}$.
Step 12: Choose the best trial vector $\left(\vec{u}^*_{i_1,G}\right)$ from the three trial vectors $\vec{u}_{i_1,G}$, $\vec{u}_{i_2,G}$, and $\vec{u}_{i_3,G}$.
Step 13:$P_{G+1} = P_{G+1} \cup$ select $\left(\vec{x}_{i,G}, \vec{u}^*_{i,G}\right)$.
Step 14: *FES* = *FES* + 3.
Step 15: end for
Step 16: G = G + 1.
Step 17: end while
Output: The individual with the smallest objective function value in the population.

Fig. 3. Pseudo code for subchannel allocation using CoDE.

the objective function to penalize an individual for constraint violation so that the constrained optimization is converted to unconstrained optimization. The optimization might be inefficient with this technique. In this study, a dynamic constraint handling approach is adopted in order to improve the efficiency, i.e., reducing the computation time. The dynamic constraint handling called dynamic-objective constraint-handling method (DOCHM) is adopted from the work by Lu and Chen [39] in our work.

By defining auxiliary function $F(X)$, the dynamic constraint handling convert the original problem into bi-objective optimization problem min($F(X)$, $f(X)$) where $F(X)$ is treated as the first objective function and $f(X)$ is the second (the main) objective. The auxiliary function $F(X)$ will be merely used to determine whether or not an individual (candidate solution) is within the feasible region and how close a solution is to the feasible region. If an individual lies outside the feasible region, the algorithm will take $F(X)$ as its optimization objective. Otherwise, the algorithm will instead optimize the real objective function $f(X)$. During the optimization process, if an individual leaves the feasible region, it will once again optimize $F(X)$. Therefore, the optimizer has the ability to dynamically drive the individuals into the feasible region. The dynamic constraint handling can be illustrated in the following pseudo-code:

If $F(X)$ = 0 (constraints are satisfied)
  $f(X)$ = $f(X)$ (the main objective function)
else
  $f(X)$ = $F(X)$ (the auxiliary objective function)
end

The auxiliary objective function is defined as:

$$F(X) = \sum_{i=1}^{D} \max(0, d_i) \tag{16}$$

where X is solution variables, D is dimension of the problem and d_i represents the distance of $i\text{th}$ individual (candidate solution), represented by '*' marks, to the constraint violation boundary.

For the resource allocation problem under consideration there are five constraints (C1–C5) defined in Section II. Constraint C1 limits the total power which can be allocated to all the users over all subchannels to P_{total}. According to constraint C2, if a user is allocated a particular subchannel, the algorithm should allocate minimum finite power to that user on that subchannel. In our proposed solution, the constraints C1 and C2 are handled by allocating equal power, which is equal to P_{total}/number of subchannels, on all subchannels.

According to constraints C3 and C4, no two users can share a particular subchannel. These constraints are handled in coding of individuals, as described in Step 3 in Figs. 2 and 3.

Finally, in constraint C5, $\{\gamma_i\}_{i=1}^{K}$ is a set of predetermined values that are used to ensure proportional fairness among users. The fairness index is defined as:

$$F = \frac{\left(\sum_{k=1}^{K} \gamma_k\right)^2}{K \sum_{k=1}^{K} \gamma_k^2} \tag{17}$$

with the maximum value of 1 to be the greatest fairness case in which all users would achieve the same data rate. Since the problem formulation in (1) is to allocate resources to satisfy the rate constraints strictly for each channel realization, we define a quantity to measure how well the rate constraints are satisfied. The imbalance coefficient is defined as:

$$f = \frac{1}{K} \sum_{k=1}^{K} \left[\gamma_k - \frac{\sum_{k=1}^{K} \gamma_i}{K} \right] \tag{18}$$

In order to handle this constraint we used DOCHM as described above.

B. Stopping Criterion

Although the objective of min-max optimization is usually clear, i.e., the global optimum should be found, it is not easy to decide when the execution of an optimization algorithm should be terminated. For practical applications, the choice of stopping criteria can significantly influence the duration of an optimization process. Due to different stopping criteria, an optimization run might be terminated before the population has converged, or computational resources might be wasted because the optimization run is terminated too lengthy.

A good work on stopping criteria especially for PSO and DE optimizations has been presented by Zielinski and Laur [40]. They suggested that it would be better to use stopping criteria that consider knowledge from the state of the optimization run. The time of termination would be determined adaptively, so function evaluations could be saved. According to their work, a good technique for stopping criteria is distribution-based criteria. It considers the diversity in the population. If the diversity is low, the individuals (candidate of solutions) are close to each other after a sufficient number of iterations η, so it is assumed that convergence has been obtained. In general, the distribution-based criteria either in variable (population) space or objective function space are classified as reliable means for detecting convergence [40].

In this study, standard deviation of populations is used to check the diversity. If the standard deviation σ_d is below a threshold (small number, ε), the optimization stops. It can be formulated as follows:

$$\sigma_d = \sqrt{\frac{1}{\eta} \sum_{j=1}^{\eta} (x^j_{\mathrm{best},d} - \overline{x}_{\mathrm{best},d})^2} < \varepsilon(\max(x_{\mathrm{best},d}) - \min(x_{\mathrm{best},d})), \text{ for } d = 1, 2, \cdots, D \tag{19}$$

where $x^j_{\mathrm{best},d}$ represents the best individual in $j\mathrm{th}$ generation (iteration) for $d\mathrm{th}$ dimension and $\overline{x}_{\mathrm{best},d}$ is the mean value of the best individuals.

Table 1. Parameters for stopping criterion.

Definition	Value
Maximum iteration (if stopping criterion fails)	100
Number of iteration for which stopping criterion applies	40
Standard deviation threshold for which stopping criterion applies	1%

VI. SIMULATION AND RESULTS

In the following we present simulation results and comparisons of proposed algorithm with that of no fairness method [4], linear method [12], genetic algorithm based subcarrier allocation (GABSA) [13], genetic algorithm based power allocation (GABPA) and immune clonal optimization [41]. For comparison with GABPA approach, we modified GA used in [13] and use it for power allocation, while the subcarriers were allocated using the method proposed in [12]. In our simulation, the wireless channel is modeled as a frequency selective channel consisting of six independent Rayleigh multipaths. Furthermore, each multipath component was modeled as Clarke's flat fading model [9]. The power delay profile was assumed to be exponentially decaying with e^{-2l}, where l is the multipath index. Therefore relative power of the six multipath components are $[0, -8.69, -17.37, -26.06, -34.74, -43.43]$ dB. The total available bandwidth and transmit power were 1 MHz and 1 W, respectively. The power spectral density of additive white Gaussian noise was -80 dBW/Hz, and the total bandwidth of 1 MHz is divided into 64 subchannels. The maximum path loss difference was 40 dB. Stopping criterion used for CoDE, GABPA, GABSA, and immune clonal optimization [41] are shown in Table 1.

A. Sum Capacity versus Number of Users

Fig. 4 shows the variation of sum capacity with the number of users, for a fixed number of subchannels (N = 64). The population size was also fixed to 30 and SNR was fixed to 10 dB. The number of users was varied from 2 to 16 in increment of 2. A total of 100 times of samples are used for each number of users. This figure shows the comparisons of the sum capacity achieved by the proposed algorithm with that of no fairness method in [4], linear [12] and immune clonal optimization [41]. It is evident from Fig. 4 that the use of CoDE for subchannel allocation for OFDMA systems provides consistently higher than the linear method as well as immune clonal method. Since no fairness was considered in [4] it achieves maximum capacity.

Moreover, as the number of users increases, the sum capacity also increases; this is because of added multiuser diversity gain. Multiuser diversity is obtained by opportunistic user scheduling at either the transmitter or the receiver. The effect of multiuser diversity is predominant in systems with large number of users, as with the increasing number of users in the system, the probability that a given subchannel is in a deep fade for all users decreases. The main advantage of using CoDE algorithm over the immune clonal method is better sum capacity without the need of any parameter tuning.

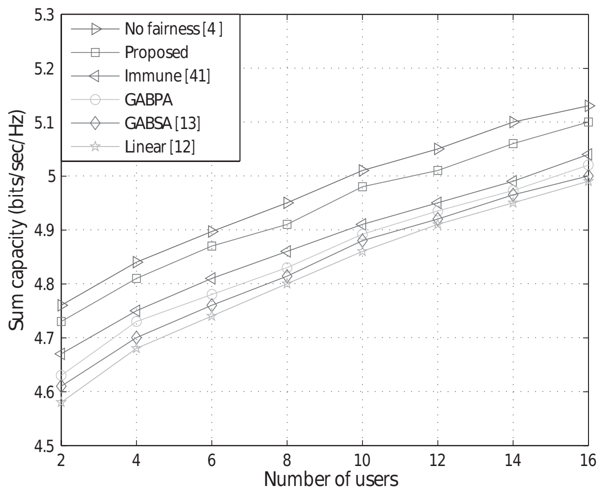

Fig. 4. Sum capacity versus number of users (K) for $N = 64$.

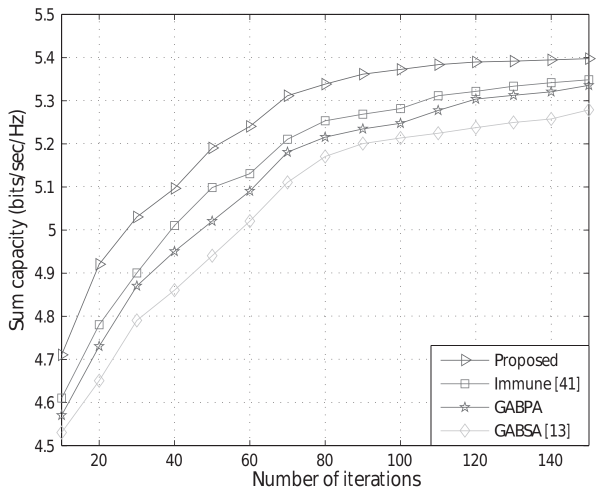

Fig. 5. Sum capacity versus number of iterations ($K = 16, N = 64$).

B. Sum Capacity versus Number of Iterations

In order to study the effect of number of iterations on sum capacity, we fixed the number of users to 16 and population size to 30. Since, no fairness method [4] and linear method are not iterative methods, these methods were not used for comparisons. The stopping criterion using standard deviation was not considered for this set of simulation, and the algorithm was allowed to run for a fixed number of iterations. As it is evident from Fig. 5, the sum capacity initially increased with the number of iterations and then gradually saturated for the higher values. It is also evident from fig. 5 that the proposed method provides better gain in sum capacity and also converges faster than immune clonal optimization and GA based approaches. This fact makes CoDE aided subchannel allocation a suitable choice for practical wireless systems such as LTE and WiMAX (802.16e), where the convergence rate plays a very important role as the wireless channel changes rapidly. The fact that the channel is assumed to be constant during the allocation makes convergence rate a very important parameter for wireless systems. The faster convergence of CoDE as compared to immune clonal optimization algorithm can be attributed to equal power allocation. Moreover, no parameter tuning is required in CoDE algorithm.

C. Sum Capacity versus SNR

Fig. 6 shows the comparison of sum capacity achieved by proposed algorithm with no fairness method, linear and immune clonal optimization for different values of SNR. The number of users was fixed 16 and population size was fixed to 30. As expected, it can be observed from Fig. 6 that the sum capacity increases with the average SNR and the proposed algorithm consistently outperforms the linear and immune clonal optimization algorithm.

D. Proportional Fairness

Fig. 7 shows the achieved sum capacities in a multiuser OFDM system with 4 users plotted against the change in proportional rate constraint defined in Table 2. The simulation parameters are the same as those in the previous sections. The average channel power of user 1 to user 3 is the same, while the average channel power of user 4 is 10 dB higher than the other three users. As the fairness index increases, that is the imbalance coefficient as defined in (18) becomes large, higher sum capacity is achieved. This is reasonable because user 4 has higher average SNR and can utilize the resources more efficiently. The proposed scheme achieved almost similar fairness as achieved by the schemes in linear and immune, although in the proposed algorithm only subchannel allocation was performed as compared to both power and subchannel allocation in [12] and [41]. This result reaffirms the fact that subchannel allocation provides much higher capacity at lower computational cost than joint subchannel and power allocation [41], at the cost of only slight degradation in the fairness of resource allocation.

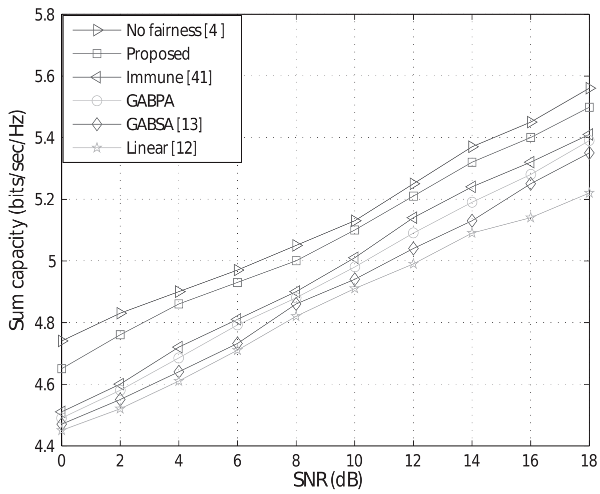

Fig. 6. Sum capacity versus SNR ($K = 16, N = 64$).

As expected, the proposed algorithm achieved slightly lower sum capacity as compared to the algorithm proposed in [4]. Since the algorithm in [4] is not constrained by fairness requirement, it allocates all the resources to the users with the best

Table 2. Proportional fairness comparison.

Index	Rate constraint	f (Proposed)	f[41]	f[12]	f[13]	f (GABPA)
1	$\gamma_1 : \gamma_2 : \gamma_3 : \gamma_4 = 1 : 1 : 1 : 1$	0	0	0	0	
2	$\gamma_1 : \gamma_2 : \gamma_3 : \gamma_4 = 1 : 1 : 1 : 4$	1.7421	1.6875	1.7312	1.7455	1.7387
3	$\gamma_1 : \gamma_2 : \gamma_3 : \gamma_4 = 1 : 1 : 1 : 8$	10.3213	9.7625	10.2332	10.3312	10.3013
4	$\gamma_1 : \gamma_2 : \gamma_3 : \gamma_4 = 1 : 1 : 1 : 16$	34.4613	33.75	35.52	35.11	34.88

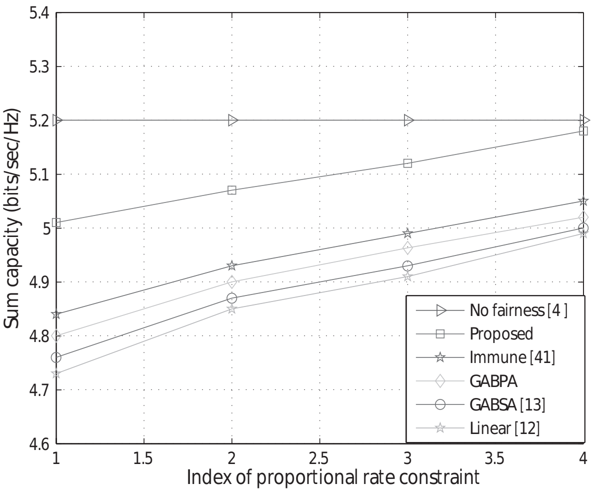

Fig. 7. Sum capacity versus index of proportional rate constraint (see Table 2 for index values).

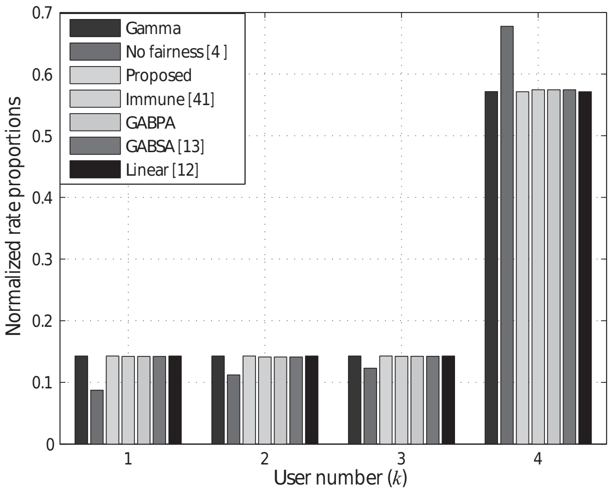

Fig. 9. Normalized capacity ratios per user for 4 users averaged over 100 channels, with the required normalized proportions γ shown as the leftmost bar for each user.

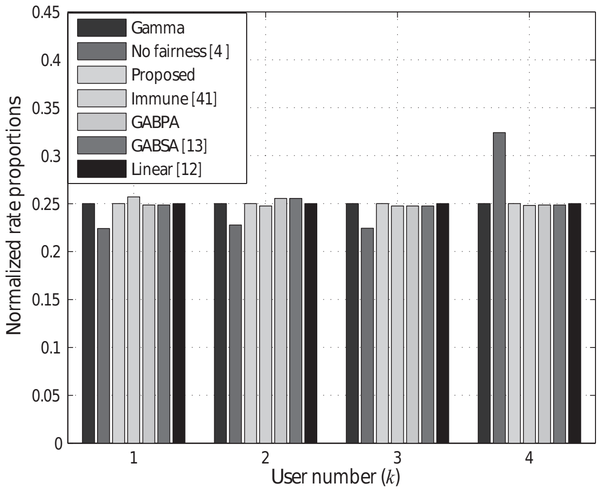

Fig. 8. Normalized capacity ratios per user for 4 users averaged over 100 channels, with the required normalized proportions γ shown as the leftmost bar for each user.

channel gains on them. However, it may leave some users without any channel allocated to them and hence not fair.

Figs. 8 and 9 show the normalized proportions of the capacities for each user for the case of 4 users averaged over 100 channel samples. The normalized capacities are given by $R_k / \sum_{k=1}^{4} R_k$. This is compared to the normalized proportionality constraints $\{\gamma\}_{k=1}^{4}$. The proportional rate constraints of $\gamma_1 : \gamma_2 : \gamma_3 : \gamma_4 = 1 : 1 : 1 : 1$ and $\gamma_1 : \gamma_2 : \gamma_3 : \gamma_4 = 1 : 1 : 1 : 4$, were used for simulation results in Figs. 8 and 9 respectively. The first column denotes the ideal distributions i.e., $\gamma_k / \sum_{k=1}^{4} \gamma_k$. It can be observed that the capacity obtained after subchannel allocation using the proposed algorithm closely follows the proportional rate constraints. It can also be observed that the proportionality obtained by proposed algorithm is fairly close to the method in [41], linear method [12], GABSA [13], and GABPA algorithms. This result reaffirms the fact that subchannel allocation with equal power allocation can provide similar fairness as can be obtained by joint power and subchannel allocation as well as separate subchannel and power allocation. However, the complexity of subchannel allocation with equal power allocation is much less than that of joint subchannel and power allocation.

The algorithm in [4] allocates resource to users with best gain on it and does not consider the fairness; hence, when user 4 has better channel conditions, it obtains almost all the resources and other users get smaller resource.

Comparison of the imbalance coefficient obtained by proposed method with that of obtained by immune clonal optimization is shown in Table 2. It can be observed from the table , that the joint subchannel and power allocation [41] achieves slightly lower imbalance coefficient as compared to the all the other methods used in this work, which means that the joint subchannel and power allocation is only slightly better in proportional allocation of resources as compared to only subchannel allocation and separate subchannel and power allocation schemes. The cost of better proportional fairness is higher computational cost. In wireless communication where the channels are highly dynamic, algorithms with lower computational complexity are preferred. Moreover, the assumption of perfect channel state information at transmitter and receiver also restricts the practical systems to use algorithms with lower computational cost. Analysis of computational complexity is presented in following subsection.

E. Comparison with Optimal Solution

In this subsection we compare the performance of proposed scheme with respect to optimal solution. For this comparison we studied the effect of variation in the fairness coefficient ratio (defined in C5) γ_1/γ_2 on the sum capacity achieved by proposed approaches in comparison to optimal solution. The fairness index defined in (17) can be calculated for different values of fairness coefficient ratios (shown on x-axis of Fig. 10) used for this comparison. With the aim to reduce the time for calculating the optimal solution using exhaustive search, number of users and subchannels were fixed to 2 and 10 respectively. A total of 200 channel realizations were simulated and the the average of sum capacities obtained were then plotted in Fig. 10. It can be observed from the figure that, for the case of no path loss difference between the two users, the sum capacity was almost constant and hence not very sensitive to the fairness constraint ratio γ_1/γ_2. On the other hand, for the case of path loss difference between two users the sum capacity varies significantly with the fairness constraint ratio. For instance, in the case, when the user 1 mean channel power ($P_{\text{avg}}(1)$) was 10 dB higher than the user 2 mean channel power ($P_{\text{avg}}(2)$), the sum capacity reduced with the reduction in γ_1/γ_2. This result is in consistence with the expected result, as γ_1/γ_2 decreases user 2 gets more priority. Therefore, user 2 is assigned significant portion of the available resources, which, consequently, reduces the achieved capacity, because the mean channel power of user 1 is 10 dB higher than user 2. It can also be observed from fig. 10 that the proposed scheme achieves about 95% and 97% of the optimal sum capacity. Although in a real wireless communication systems, the number of users and subchannels will be much larger, we expect the proposed approaches to perform even better and further close to optimum. Since the EAs are expected to perform better for the case of large parameters.

F. Complexity Analysis

In order to analyze the computational complexity of the algorithm, recall that K refers to the total number of users in the system. N refers to the number of subchannels, which is a power of 2 and much larger than K. Furthermore, M denotes the number of individuals at each generation, i.e, the population size, G denotes the number of generations for which the algorithm is allowed to run.

For the above defined parameters the complexity of proposed algorithm is $M \times G \times$ (complexity of function evaluation in each generation). The complexity of function evaluation in each generation is mainly governed by the complexity of fitness function evaluation and complexity of trial vector generation. The complexity of fitness function evaluation is $O(N)$ for $N >> K$. Similarly, the complexity of trail vector generation is also $O(N)$ for each trail vector. Therefore, the total complexity of propose algorithms can be evaluated to $O(M \times G \times N)$. The method

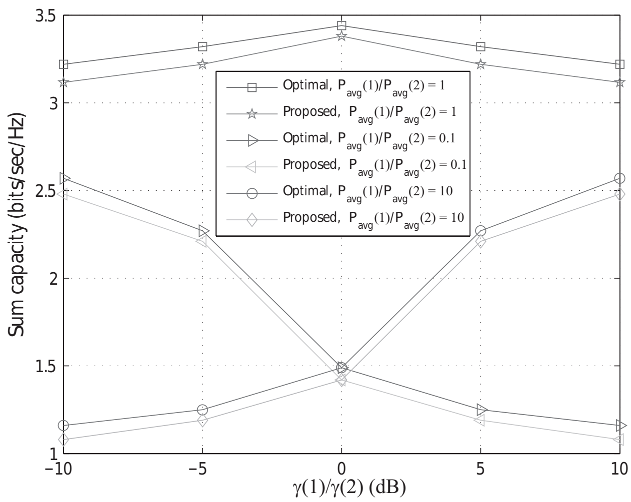

Fig. 10. Performance comparison of proposed scheme and optimal algorithms for the case of two users and ten subchannels.

in [41] uses immune clonal optimization to allocate subchannels followed by power allocation. Effectively, it requires searching the whole solution space two times as compared to proposed algorithm. The complexity of immune clonal optimization was claimed to be $O(M \times G \times (NQ + NZ))$ where Q and Z are parameters related to subchannel and power allocation respectively. In light of above discussion it is clear that the computational complexity of proposed algorithm is much less than immune clonal optimization method.

VII. CONCLUSION

In this paper, we have proposed the use of CoDE algorithm to solve the problem of subchannel allocation in the downlink of OFDMA systems. The results produced by the simulations indicate that the algorithm performs better in terms of sum capacities as compared to both non-evolutionary and evolutionary algorithms. The sum capacity increases with the increase number of users. The sum capacity also increases initially with the increase in number of iterations but rapidly saturates to a near optimal value. This result suggests that CoDE aided subchannel allocation can provide significant gain in capacity even with small number of iterations. Moreover, in CoDE aided subchannel allocation the search and subchannel allocation is performed simultaneously as compared to traditional methods where the subchannels are first sorted in accordance of their gains and then allocation is performed. This significantly reduces the complexity of CoDE aided allocation. Hence it may be concluded that the proposed algorithm is order of magnitude faster as compared to the other methods. This fact makes CoDE aided subchannel allocation a suitable choice for practical wireless systems such as LTE and WiMAX (802.16e) where the convergence rate plays a very important role as the wireless channel changes rapidly. The fact that the channel is assumed to be constant during the allocation makes convergence rate a very important parameter for wireless systems. The future scope of this paper could be to use multiple antennas on both transmitter and receiver site, which can provide further gain in capacity because of spatial multiplexing.

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