QoS Aware Scheduling with Optimization of Base Station Power Allocation in Downlink Cooperative OFDMA Systems

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Abstract—Quality-of-Service (QoS) aware scheduling in cooperative orthogonal frequency division multiple access (OFDMA) systems has long been a critical yet challenging research topic for achieving full system utilization. The optimal performance of such systems can only be achieved by joint optimization of various resources (power, bandwidth and etc). In this paper, we investigate the optimization of base station power allocation with QoS requirements in cooperative OFDMA systems. We formulate the QoS aware resource allocation problem and exploit its structure to derive an efficient solution. By employing Lagrangian relaxation, the problem decouples on each subcarrier into a hierarchy of subproblems. Combined with an iterative procedure, some separable and parallel structures could be exploited to obtain an efficient solution. Simulation results demonstrate that our proposed method outperforms previous works in terms of spectrum efficiency and OoS satisfaction.

Index Term-Relay, OFDMA, Scheduling, Power Allocation

I. Introduction

Cooperative relaying has recently emerged as a promising technology to achieve virtual spatial diversity in wireless communication networks [1]. Combined with orthogonal frequency division multiple access (OFDMA), cooperative OFDMA systems are strong candidates for future 4th generation (4G) wireless communication and are currently under standardization by the IEEE 802.16j task group [2]. Scheduling in those systems is essential in realizing full benefits of cooperative OFDMA systems. The optimal performance of such systems can only be achieved by joint optimization of the various resources available.

Scheduling in cooperative systems has attracted attention from the research community in recent years, aiming at maximizing spectrum efficiency [3]-[5] or power efficiency [6] under resource limitations. In [3], the QoS aware resource-allocation problem in cooperative OFDMA system is investigated and a greedy algorithm is designed to solve the problem without any optimality consideration. To overcome the short-comings of the greedy algorithm, in [4], Zhang *et al* proposed a scheduling algorithm based on dual decomposition, for a tutorial on dual decomposition, refer to [7] for more detail. However, as is noted both algorithms proposed in [3] and [4] lie in the basic assumption that the power at both the source node and the relay nodes should be pre-determined. Such an

assumption, on one hand, renders the problem much easier to handle, but on the other hand, results in some losses in system performance. In practice, the source node and relay nodes are operating below a prescribed maximum allowable value and the efficient allocation of power at those nodes is quite crucial for maintaining the system throughput. Therefore, in our paper, we focus on the optimization of source power allocation with QoS requirement in downlink cooperative OFDMA systems.

The remaining sections of the paper are organized as follows. In Section II, we describe the cooperative OFDMA system model and formulate the QoS aware Scheduling problem. A dual decomposition algorithm is proposed to tackle the problem in Section III. Section IV illustrates the effectiveness of the algorithms by numerical simulations. Finally, the conclusions are drawn in Section V.

II. SYSTEM MODEL AND PROBLEM FORMULATION

A. System Model

Consider a wireless cellular network consisting of one base station (BS), multiple relay stations (RSs) and multiple mobile stations (MSs), each of which is equipped with a single antenna. The set containing K RSs is denoted $R = \{r_1, r_2, \ldots, r_K\}$ and M MSs form the set $M = \{m_1, m_2, \ldots, m_M\}$. All stations share a total number of N subcarriers denoted $N = \{n_1, n_2, \ldots, n_N\}$ in the cell. For the nth subcarrier, the channel gains between BS and mth MS, BS and kth RS, kth RS and mth MS are denoted $h^n_{d,m}, h^n_{a,k}$ and $h^n_{b,km}$, respectively. The broadband channel is assumed to experience frequency-selective Rayleigh fading and full channel state information (CSI) is obtained via channel estimation and fed back to a central unit, where the scheduling algorithm is implemented to obtain a solution.

The BS establishes a radio link with MS either in cooperative mode or non-cooperative mode. We assume the BS operates under time-division-duplex (TDD) mode. Thus, for non-cooperative mode, the BS transmits data streams with power $P_{s,0m}^n$ to m_m on the nth subcarrier over two time slots and the instantaneous rate can therefore be derived as

$$c_{0m}^{n} = \log(1 + P_{s,0m}^{n} d_{m}^{n}) \tag{1}$$

for cooperative mode, the BS transmits data streams with power $P^n_{s,km}$ on the nth subcarrier, then the r_k forwards the signal with $P^n_{r,km}$ to the mth Ms on the same subcarrier in the second time slot. When amplify-and-forward (AF) protocol is adopted, the instantaneous rate of relay pair (k,m) on the nth subcarrier can be derived as [1]

$$c_{km,AF}^{n} = \frac{1}{2} \log(1 + \text{SNR}_{km,AF}^{n})$$

$$= \frac{1}{2} \log(1 + \frac{P_{s,km}^{n} a_{k}^{n} P_{r,km}^{n} b_{km}^{n}}{1 + P_{s,km}^{n} a_{k}^{n} + P_{r,km}^{n} b_{km}^{n}}) \quad (2)$$

where $a_k^n=|h_{a,k}^n|^2/\sigma_{r,nk}^2$, $b_{b,km}^n=|h_{b,km}^n|^2/\sigma_{m,n}^2$, and $d_m^n=|h_{d,m}^n|^2/\sigma_{m,n}^2$; $\sigma_{m,n}^2$, and $\sigma_{r,nk}^2$ represent the noise variances at RSs and MS within one OFDMA subchannel.

B. Various Constraints

In [3] and [4], the process of relay selection and subcarrier allocation is realized by introducing the binary assignment variables x_{km}^n , with $x_{km}^n=1, k\neq 0$ representing the BS communicates with m_m via relay r_k on the nth subcarrier, otherwise $x_{km}^n=0$. Moreover, we could let $x_{0m}^n=1$, if data streams are transmitted directly from the BS to the mth MS and $x_{0m}^n=0$, if it is not. Therefore, the subcarrier constraint representing each subcarrier can only be occupied by one MS, can be written as

$$\sum_{k=0}^{K} \sum_{m=1}^{M} x_{km}^{n} = 1, \quad \forall n$$
 (3)

Two kinds of services are considered in our problem, namely, best-effort (BE) services and non-real-time (nRT) services which are fully discussed in [8]. As is demonstrated in [4], only nRT services can be incorporated as contraints in our model. The nRT services constraints can be placed as

$$\sum_{k=0}^{K} \sum_{n=1}^{N} c_{km}^{n} x_{km}^{n} \ge \bar{c}_{m}, \quad m \in M$$
 (4)

where \bar{c}_m is the minimum rate requirement for nRT user m, and M denotes the set containing all nRT users. Some existing work such as [3] and [4], assume that the BS and RSs power allocation is pre-determined. In our work, we consider the optimization of base station power allocation, with uniform allocation of RSs power, thus the power constraint at the BS can be posed as

$$\sum_{m=1}^{M} \sum_{n=1}^{N} \sum_{k=0}^{K} P_{s,km}^{n} \leq \bar{P}_{s}$$

$$P_{s,km}^{n} \geq 0, \quad \forall k, n, m$$
(5)

where \bar{P}_s the is prescribed maximum allowable power at BS and all power allocated should have nonnegative values.

C. Optimization Problem

With all preliminaries introduced, the optimization problem for BS power allocation, relay selection and subcarrier assignment in downlink cooperative OFDMA networks can be formulated as follows

$$\max_{X,P_{s}} \sum_{n=1}^{N} \sum_{k=0}^{K} \sum_{m=1}^{M} c_{km}^{n} x_{km}^{n}$$

$$s.t. \sum_{k=1}^{K} \sum_{m=1}^{M} x_{km}^{n} = 1, \quad \forall n$$

$$x_{km}^{n} \in \{0,1\}, \quad \forall k, m, n$$

$$\sum_{n=1}^{N} \sum_{k=0}^{K} c_{km}^{n} x_{km}^{n} \ge \bar{c}_{m}, m \in M$$

$$\sum_{m=1}^{M} \sum_{n=1}^{N} \sum_{k=0}^{K} P_{s,km}^{n} x_{km}^{n} \le \bar{P}_{s}$$

$$P_{s,km}^{n} \ge 0, \quad \forall k, n, m$$

$$c_{km}^{n} \in \{c_{km,AF}^{n}, c_{0m}^{n}\}, \quad \forall k, m, n$$

$$(6)$$

where X and P are $(K+1)\times M\times N$ arrays consisting all binary assignment variables x_{km}^n and $P_{s,km}^n$. Our objective is to maximize the sum rate with both the power and QoS constraints satisfied.

III. SCHEDULE ALGORITHM WITH OPTIMIZATION OF BASE STATION POWER ALLOCATION

In this section, we tackle the optimization problem (6) within the framework of Lagrangian formulism [7]. Only AF scheme is considered in our derivation.

A. Relaxation via Lagrangian Duality

Observe that the primal problem (6) couples at each subcarrier, making the direct decomposition impossible. Therefore, by introducing *Power and QoS prices*, the Lagrangian associated with (6) is derived as follows

$$L(X, P_s)$$

$$= \sum_{n=1}^{N} \sum_{k=0}^{K} \sum_{m=1}^{M} c_{km}^n x_{km}^n + \sum_{m \in M} \mu_m (\sum_{n=1}^{N} \sum_{k=0}^{K} c_{km}^n x_{km}^n - \bar{c}_m)$$

$$+ \lambda_{BS} (\bar{P}_s - \sum_{m=1}^{M} \sum_{n=1}^{N} \sum_{k=0}^{K} P_{s,km}^n x_{km}^n)$$

$$= \sum_{n=1}^{N} (\sum_{m=1}^{M} \sum_{k=0}^{K} + \sum_{m \in M} \sum_{k=0}^{K} \mu_m c_{km}^n x_{km}^n)$$

$$- \sum_{m=1}^{M} \sum_{k=0}^{K} \lambda_{BS} P_{s,km}^n x_{km}^n) - \sum_{m \in M} \mu_m \bar{c}_m + \lambda_{BS} \bar{P}_s$$
 (7)

where $\lambda_{\rm BS}$ is the dual variable for BS power constraint and $\mu = [\mu_1, \mu_2, \dots, \mu_{|M|}]$, is the vector of dual variables for nRT service constraints, where |M| denotes the total number of nRT users. Thus, the Lagrangian dual function $g(\lambda_{\rm BS}, \mu)$ can

be formulated [9]

$$\max_{X,P_s} L(X, P_s)
s.t. \sum_{k=0}^{K} \sum_{m=1}^{M} x_{km}^n = 1, \quad \forall n
x_{km}^n \in 0, 1, \quad \forall k, m, n
P_{s,km}^n \ge 0, \quad \forall k, m, n
c_{km}^n \in \{c_{km,AF}^n, c_{0m}^n\}, \quad \forall k, m, n$$
(8)

the corresponding Lagrangian dual problem can be obtained [9]:

$$\min_{\lambda_{\rm BS},\mu} g(\lambda_{\rm BS},\mu)
s.t.\lambda_{\rm BS} \ge 0, \mu \succeq 0$$
(9)

where \succeq denotes the component-wise inequality for two vectors of the same length. Mathematically, the convex nature of the dual problem enables us to solve (8) via an iterative algorithm that is guaranteed to coverage to a global minimal. Via Lagrangian relaxation, we could remove the coupling between subcarriers, and dual objective function $g(\lambda_{\rm BS},\mu)$ decomposes on each subcarrier into N subproblems which can be solved in parallel with $(\lambda_{\rm BS},\mu)$ specified. The subproblem at the nth subcarrier is equivalent to

$$\max_{X^{n}, P_{s}^{n}} \sum_{m=1}^{M} \sum_{k=0}^{K} c_{km}^{n} x_{km}^{n} + \sum_{m \in M} \sum_{k=0}^{K} \mu_{m} c_{km}^{n} x_{km}^{n} \\
- \sum_{m=1}^{M} \sum_{k=0}^{K} \lambda_{BS} P_{s,km}^{n} x_{km}^{n} \\
s.t. \sum_{k=0}^{K} \sum_{m=1}^{M} x_{km}^{n} = 1, \\
x_{km}^{n} \in \{0, 1\}, \quad \forall k, m \\
P_{s,km}^{n} \ge 0, \quad \forall k, m \\
c_{km}^{n} \in \{c_{km,AF}^{n}, c_{0m}^{n}\}, \quad \forall k, m$$
(10)

where X^n and P^n_s are matrices with elements x^n_{km} and $P^n_{s,km}$. To simplify the notation (10), $\bar{\mu}_m$ is introduced so that (10) can be simplified as

$$\max_{X^{n}, P_{s}^{n}} \sum_{m=1}^{M} \sum_{k=0}^{K} \left((1 + \bar{\lambda}_{m}) c_{km}^{n} - \lambda_{BS} P_{s,km}^{n} \right) x_{km}^{n}$$

$$s.t. \sum_{k=0}^{K} \sum_{m=1}^{M} x_{km}^{n} = 1,$$

$$x_{km}^{n} \in \{0, 1\}, \quad \forall k, m$$

$$P_{s,km}^{n} \ge 0, \quad \forall k, m$$

$$c_{km}^{n} \in \{c_{km}^{n} A_{F}, c_{0m}^{n}\}, \quad \forall k, m, n$$
(11)

where $\bar{\mu}_m = \mu_m$, if $m \in M$, otherwise, $\bar{\mu}_m = 0$. Since the schedule variable X is an all-zero matrix except for one non-zero entry, the optimal solution for (11) can be readily given

bv

$$(x_{km}^n)^* = \begin{cases} 1, & (k,m) = \arg\max_{k,m} (1+\bar{\lambda}_m) c_{km}^n - \lambda_{\rm BS} P_{s,km}^n \\ 0, & \text{otherise} \end{cases}$$
(12)

and the corresponding $(P_{s,km}^n)^*$ can be calculated. Therefore, we focus on solving (11) through further decomposition.

B. Solutions of Individual Subproblems

In the following deduction, we solve the subproblems with $(\lambda_{\rm BS}, \mu)$ given. First, we discuss the case for direct transmission. The associated subproblem can be written as

$$\max_{P_{s,0m}^n} (1 + \bar{\mu}_m) \log(1 + P_{s,0m}^n d_m^n) - \lambda_{BS} P_{s,0m}^n$$

$$s.t. P_{s,0m}^n \ge 0$$
(13)

using the Karush-Kuhn-Tucker(KKT) conditions [9], the closed-form solution can be obtained

$$(P_{s,0m}^n)^* = \left(\frac{1+\bar{\mu}_m}{\lambda_{\rm BS}} - \frac{1}{d_m^n}\right)^+$$
 (14)

For the suboptimal problems corresponding to AF scheme, (11) could be written as

$$\max_{\substack{P_{s,k}^n \\ P_{s,k}^n }} \frac{1}{2} (1 + \bar{\mu}_m) \log(1 + \frac{\alpha_{km}^n \beta_k^n P_{s,k}^n}{1 + \alpha_{km}^n + \beta_k^n P_{s,k}^n}) - \lambda_{\text{BS}} P_{s,km}^n$$

$$s.t. P_{s,km}^n \ge 0$$
(15)

where $\alpha_{km}^n=P_{r,km}^nb_{km}^n$ and $\beta_k^n=\alpha_k^n$. A closed-form solution can also be obtained:

$$(P_{s,km}^n)^* = \frac{1}{\beta_k^n} \left[-1 + \frac{\alpha_{km}^n}{2} \left(\sqrt{1 + \frac{2(1 + \bar{\mu}_m)\beta_k^n}{\lambda_{BS}\alpha_{km}^n}} - 1 \right) \right]^+$$
(16)

With all the subproblems solved, the solution of (12) and $(P_{s,km}^n)^*$ can be determined with specified $(\lambda_{\rm BS},\mu)$.

C. Optimization of the Dual Problem via Projected Subgradient Algorithm

By employing projected subgradient algorithm to minimize (9), our proposed algorithm can be described as

- 1) Initialize (λ_{BS}^0, μ^0) ;
- 2) Given (λ_{BS}^l, μ^l) , solve (K+1)N maximization problem at each subcarrier in parallel, then combine the results to obtain $(X_l^*(l), P_s^*(l))$;
- 3) Perform projected subgradient updates for (λ_{BS}^l, μ^l)

$$\lambda_{\text{BS}}^{l+1} = \lambda_{\text{BS}}^{l} - s(l) \left(\bar{P}_{S} - \sum_{k=0}^{K} \sum_{n=1}^{N} (P_{s,k}^{n})_{l}^{*} (x_{km}^{n})_{l}^{*} \right)^{+}$$

$$\mu_{m}^{l+1} = \mu_{m}^{l} - s(l) \left(\sum_{k=0}^{K} \sum_{n=1}^{N} (c_{km}^{n})_{l}^{*} (x_{km}^{n})_{l}^{*} - \bar{c}_{m} \right)^{+}$$

$$m = 1, 2, \dots, |M| \quad (17)$$

4) Return to step 2 until convergence.

If the step sizes s(l) is chosen to be the non-summable diminishing step lengths, the projected subgradient method above is guaranteed to converge to the global minimal, thus obtaining the suboptimal solution of the primal problem accordingly.

D. Complexity Analysis

Computational complexity of our proposed algorithm is analyzed. For each one iteration, all NM(K+1) subproblems need to be solved to the dual problem to update the iterative variables. Since the update is implemented with respect to (M+1) iterative variables, the complexity of the outer projected subgradient method is $O(M+K)^2$ [11]. The overall complexity for the AF mode is $O(M^3NK)$. Observe the algorithm can be accelerated by solving the M(K+1) subproblem at each subcarrier in parallel. With CSI fed back to the central controller, the algorithm can be implemented efficiently.

IV. SIMULATION RESULTS

In this section, simulations are conducted to verify the performance of our proposed approach. The following scenario is considered. The BS is located at the centre of the cell with a radius of $r_1 = 1km$ and four fixed RSs are placed on a circle with their location coordinates are (0,0.5), (0,-0.5), (-0.5,0) and (0.5,0) in kilometers. The MSs are randomly distributed in the coverage area of the cell with a radius between $r_1 = 0.95km$ and $r_2 = 1km$. The broadband channel is modeled to experience both frequency selective and large-scaling fade. By adopting Clarke's model, the frequency selective channel is simulated by six independent Rayleigh multipaths, and a modified COST231-Hata propagation model is further utilized with path loss $128 + \log(R)$, where R denotes the distance in kilometers. The lognormal shadowing is assumed to have a mean of zero with a deviation of 8dB. The total bandwidth is 1.25MHz and the power spectral density of noise is assumed to be -155dBm/Hz. The total power at BS is bounded by 1W. We compare our proposed algorithm with algorithms in [3] and [4] from the perspectives of different performance measure, e.g., average sum rate, satisfaction index and fairness index. Fig.1-2 illustrate the average sum rates and fairness index achieved by each algorithm. Jain's Fairness Index is employed as a measure of average fairness [12]. A scenario of different number of BE users is considered. First, we note from Fig.1-2 that when all MSs are BE users, algorithms in [3] and [4] are equivalent and are optimal solutions of the primal problem under the uniform power allocation assumption. Second, due to the multi-user diversity and the all-BE-users assumption, the average sum rate is a non-decreasing function of the number of MSs. Finally, from Fig.2, the average sum criterion favors the user with better CSI, making the fairness index degrade dramatically, which conforms to the traditional point of view. Our proposed algorithm performs quite well in term of the average sum rate. Fig.3-5 illustrate the average sum rates, satisfaction index and fairness index achieved by each algorithm. We employ the satisfaction index as a measure of average QoS satisfaction,

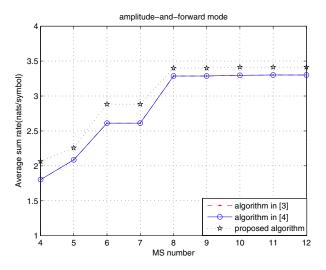


Fig. 1. Average sum rate vs. MS numbers with all BE users

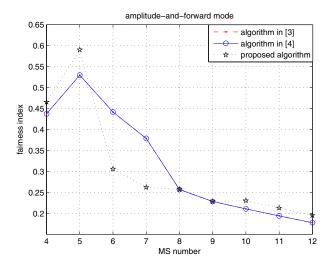


Fig. 2. Fairness index vs. MS number with all BE users

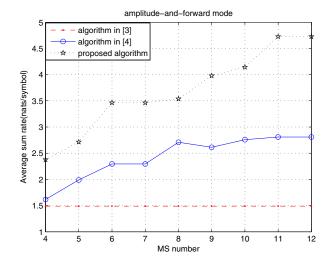


Fig. 3. Average sum rate vs. MS number with all nRT users with $\bar{c}_m=1$

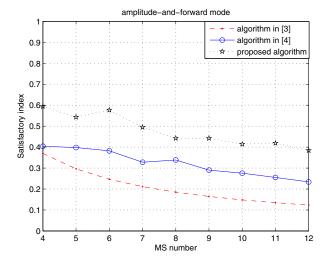


Fig. 4. Satisfaction index MS number with all nRT users with $\bar{c}_m=1$

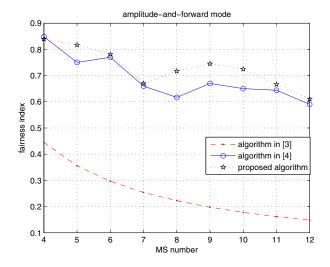


Fig. 5. Fairness index MS number with all nRT users with $\bar{c}_m=1$

which is formally defined as $\frac{1}{M}\sum_{m=1}^{M}\min(\frac{c_m}{\bar{c}_m},1)$ [4]. We consider the scenario where all MSs are nRT users with $\bar{c}_m=1$. Contrary to Fig.1, the average sum rate displayed in Fig.4 is not a non-decreasing function of the number of MSs, owing to the QoS constaints posed by each nRT user. As is observed from Fig.4-5, with the increasing number of nRT users, the system cannot provide enough bits to satisfy all the users. As the satisfaction index decreases simultaneously, our proposed algorithm improves satisfaction index compared with the algorithms in [3] and [4].

V. CONCLUSION

In this paper, we consider QoS aware scheduling with optimization of base station power allocation in cooperative OFDMA systems, where BE and nRT services are supported simultaneously. We formulate the problem model and tackle the problem via dual decomposition. Simulation results reveal

that our proposed algorithm outperforms the previous work in terms of the average sum rate and QoS satisfaction.

VI. ACKNOWLEDGMENT

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