Dual Decomposition Based Power Allocation for Downlink OFDM Non-Coherent Cooperative Transmission System

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***Abstract*—In this paper, we study the subchannel power allocation problem to maximize the total throughput of the downlink orthogonal frequency division multiplexing (OFDM) multiple access points (APs) systems with non-coherent cooperative transmission. Although the problem has been claimed as a non-convex optimization problem, we prove that the duality gap between the original problem and its dual optimization problem is nearly zero when the number of subchannel is large, which implies solving the problem in the dual domain. Then, the problem is solved with the standard Lagrange dual decomposition method with an acceptable deviation. In addition, in order to reduce the complexity of the dual decomposition based method, we propose a suboptimal low-complexity algorithm, at a minor cost of the total throughput. Numerical results are also given to verify the proposed schemes.**

I. Introduction

Transmit power allocation across multiple subchannels is one of the most key techniques for increasing system throughput in orthogonal frequency division multiplexing (OFDM) system. The power allocation problem in the single access point (AP) case has been studied well [1]-[6]. In [1]-[3], the optimal solution, named as single AP "water-filling" scheme is derived via Lagrange dual method [7]. Suboptimal schemes with low complexity are proposed in [4] and [5] with equal power allocation. The optimal and efficient algorithm is proposed in [6] with a polynomial complexity with respect of number of subchannel. Recently, power allocation problem in the multi-AP cooperative transmission system is drawing more and more attentions [8] [9], in which each user can be served by multiple APs grouping as a multi-antenna system. Therefore, spacial multiplexing and diversity can be exploited to improve the system performance, and the power allocation becomes more complicated than in the single AP case.

In the downlink case, one of the important approaches of cooperative transmission is the non-coherent cooperative transmission [10]. Due to its slight requirements on the user feedback and the processing at receivers, non-coherent cooperative transmission is much easier to be implemented in the practical system. The non-coherent cooperative transmission power allocation (CT-PA) problem is studied in [11] to maximize the total throughput. The authors proved that the problem is a non-convex optimization problem, which in general can not be solved with standard convex optimization techniques [7]. As a result, a complicated matrix elimination analysis method is used in [11] to derive the optimal solution. However, based on the optimization theory [7], if we can prove that the duality gap between the CT-PA problem and its dual optimization problem is zero, the problem can be solved in the dual domain due to that, the dual problem is always convex and can be solved with standard dual optimization techniques.

Hence, in this paper, we study the CT-PA problem by analyzing the duality gap between the original problem and its dual optimization problem. In [12], the duality gap of the general non-convex maximization problem is studied. The authors prove that if the optimal value of the non-convex problem is a concave function of the constraints, the duality gap between the problem and its dual optimization problem is zero, which means the dual problem has an identical optimal solution with the original problem. Moreover, a *time-sharing* condition is derived to judge the concavity efficiently. Based on the theory of [12], we prove that the duality gap of the CT-PA problem is nearly zero when the number of subchannel is large, which implies solving the problem in the dual domain. Then, the CT-PA problem is solved by the standard dual decomposition method [13], which decouples the original optimization problem into several easier subproblems. With the subgradient dual update method [14], the optimal solution of the dual problem is obtained approximately equalling to the optimal solution of the original CT-PA problem. In addition, to reduce the complexity of the dual decomposition method, a suboptimal power allocation scheme is proposed with lower complexity and good performance. Numerical results demonstrate that the dual decomposition method achieves a nearly optimal solution, and the performance gap between optimal solution and the proposed suboptimal scheme is very limited. Moreover, the proposed suboptimal scheme can converge to the optimal solution fast in many cases.

The remainder of this paper is organized as follows. The system model for two-AP cooperative transmission is described in section II. In section III, the duality gap between the CT-PA problem and its dual optimization problem is analyzed. Then, the CT-PA problem is solved with the dual decomposition method in the section IV, along with the low-complexity suboptimal scheme. Simulation results are given in section V and the paper is concluded in section VI.

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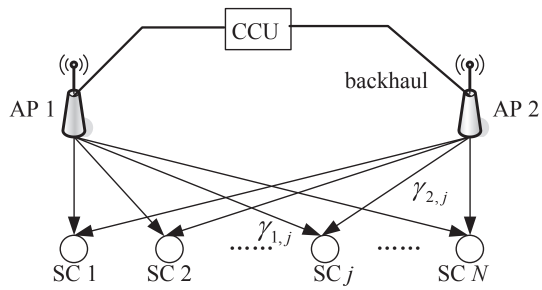

Fig. 1. OFDM downlink cooperative transmission with two APs

II. System Model

We consider the downlink of an OFDM two-AP multiuser system with non-coherent cooperative transmission shown by Fig. 1. Each subchannel can be a single or group of subcarriers. Assuming that the two APs are connected to a centralized control unit (CCU) with an efficient backhaul. The CCU has the perfect channel state information and users' data of all users, and the transmit power on each subchannel from different APs can be jointly controlled. To focus on the power allocation, we assume the subchannel allocation has been fixed among users by allocating each subchannel to at most one user. Therefore, the channel condition on each subchannel is constant during the power allocation. Based on the Shannon theorem, the throughput on subchannel n with non-coherent joint transmission is given as

$$r_n(p_{1,n}, p_{2,n}) = B\log_2(1+\sum_{i=1}^{2}\gamma_{i,n}p_{i,n}) \tag{1}$$

where the $\gamma_{i,n}$ denotes the channel-gain-to-noise-ratio (CNR) of AP i on subchannel n. The $p_{i,n}$ is the transmit power from AP i on subchannel n and B is the bandwidth of each subchannel. Assuming the total number of subchannels is N, the total throughput maximizing cooperative transmission power allocation (CT-PA) problem under per-AP power constraints is formulated as

$$\begin{aligned} \text{maximize} \quad & R(\mathbf{P}_1,\mathbf{P}_2) = \sum_{n=1}^{N} r_n(p_{1,n},p_{2,n}) \\ \text{subject to} \quad & \sum_{n=1}^{N} p_{i,n} \le P_i, i=1,2 \\ & p_{i,n} \ge 0, i=1,2, n=1,2,...,N \end{aligned} \tag{2}$$

where $\mathbf{P}_i = [p_{i,1}, ..., p_{i,n}, ..., p_{i,N}]$ denotes the power vector on each subchannel of AP i and P_i is the maximum transmit power of AP i.

The authors in [11] proved that the problem (2) is a non-convex optimization problem whose globally optimal solution can not be directly obtained by KKT (Karush-Kuhn-Tuker) condition [7]. However, the next section shows that the duality gap between (2) and its dual problem is zero, which implies the globally optimal solution can be obtained in the dual domain, due to that the dual problem is always convex.

III. Duality Gap of the CT-PA Problem

In this section, the general theory of duality gap of non-convex optimization problem is first given. Then we prove that the duality gap between the CT-PA problem (2) and its dual problem is nearly zero when the number of subchannel is large.

A. Duality Gap of Non-convex Optimization Problem

Referring to [12], we first introduce the condition under which the duality gap of general non-convex optimization problems in multiple subchannel systems. With N subchannels and K users, the optimization problem has a general form as follows.

$$\begin{aligned} \text{maximize} \quad & f(\{\mathbf{x}_n\}) = \sum_{n=1}^{N} f_n(\mathbf{x}_n) \\ \text{subject to} \quad & \sum_{n=1}^{N} \mathbf{h}_n(\mathbf{x}_n) \preceq \mathbf{P} \end{aligned} \tag{3}$$

where $\mathbf{x}_n \in \mathbb{R}$ are vectors of optimization variables, $f_n(\cdot)$ are $\mathbb{R}^K \to \mathbb{R}$ functions which are not necessarily concave, and $\mathbf{h}_n(\cdot)$ are $\mathbb{R}^K \to \mathbb{R}^L$ functions also not necessarily convex. Power constraints are denoted by an L-vector $\mathbf{P}$. The Lagrangian of (3) is defined as

$$L(\{\mathbf{x}_n\},\lambda) = \sum_{n=1}^{N} f_n(\mathbf{x}_n) + \lambda^T \left(\mathbf{P} - \sum_{n=1}^{N}\mathbf{h}_n(\mathbf{x}_n)\right) \tag{4}$$

where λ is the vector of Lagrange dual variables. The dual optimization problem of (4) is given as

$$\begin{aligned} \text{minimize} \quad & g(\lambda) = \max_{\{\mathbf{x}_n\}} L(\{\mathbf{x}_n\},\lambda) \\ \text{subject to} \quad & \lambda \succeq \mathbf{0} \end{aligned} \tag{5}$$

where $g(\lambda)$ is the dual objective. According to duality theory, $g^* \ge f^*$ where f^* and g^* are the optimal values of primal and dual problems (4) and (5), respectively. The duality gap d^* is defined as $d^* = g^* - f^*$. When $f_n(\mathbf{x}_n)$'s are concave and $\mathbf{h}_n(\mathbf{x}_n)$'s are convex, (3) is a convex optimization problem whose duality gap is guaranteed to be zero. However, even if (3) is non-convex, duality gap may be also zero according to the following theorem [12]:

***Theorem** 1:* If the maximum value f^* of the optimization problem (3) is a concave function of $\mathbf{P}$, the duality gap is zero, even if (3) is non-convex.

Furthermore, the authors in [12] proved that if a ***time-sharing*** condition, defined as follows, is satisfied, the concavity described above can be derived.

***Definition** 1:* Let $\mathbf{x}_n^*$ and $\mathbf{y}_n^*$ be optimal solutions to the optimization problem (3) with constraints $\mathbf{P} = \mathbf{P_x}$ and $\mathbf{P} = \mathbf{P_y}$ for each n, respectively. An optimization problem of the form (3) is said to satisfy the time-sharing condition if for any $\mathbf{P_x}$, $\mathbf{P_y}$ and for any $0 \le v \le 1$, there always exists a feasible solution $\mathbf{z}_n$, such that $\sum_{n=1}^{N}\mathbf{h}_n(\mathbf{z}_n) \le v\mathbf{P_x} + (1-v)\mathbf{P_y}$, and $f(\{\mathbf{z}_n\}) \ge vf^*(\{\mathbf{x}_n^*\}) + (1-v)f^*(\{\mathbf{y}_n^*\})$.

Then, set $\mathbf{P_z} = v\mathbf{P_x} + (1-v)\mathbf{P_y}$ and $\mathbf{z}_n^*$ as the optimal solution with $\mathbf{P} = \mathbf{P_z}$. According to the time-sharing condition, there is a feasible $\mathbf{z}_n$ with constraint $\mathbf{P} = \mathbf{P_z}$ such that

$f(\{\mathbf{z}_n\}) \geq vf^*(\{\mathbf{x}_n^*\}) + (1-v)f^*(\{\mathbf{y}_n^*\})$. This means that $f^*(\{\mathbf{z}_n^*\}) \geq f(\{\mathbf{z}_n\}) \geq vf^*(\{\mathbf{x}_n^*\}) + (1-v)f^*(\{\mathbf{y}_n^*\})$, thus proving the concavity.

Hence, with Theorem 1 and the time-sharing condition, the duality gap theory for non-convex optimization problem is established.

B. Duality Gap of CT-PA Problem

In this subsection, we check the duality gap between the CT-PA problem (2) and its dual problem with the Theorem 1 and time-sharing condition. Correspond to the general form of (3), the CT-PA problem (2) can be considered as $\mathbf{x}_n = [p_{1,n}, p_{2,n}]^T$, $f_n = r_n$, $f = R$, $\mathbf{h}_n(\mathbf{x}_n) = [p_{1,n}, p_{2,n}]^T$ and $\mathbf{P} = [P_1, P_2]^T$.

Now, let $\mathbf{x}_n^* = [p_{1,n,x}^*, p_{2,n,x}^*]$ and $\mathbf{y}_n^* = [p_{1,n,y}^*, p_{2,n,y}^*]$ be the optimal solutions of (2) for each n with power constraints $\mathbf{P}_x = [P_{1,x}, P_{2,x}]^T$ and $\mathbf{P}_y = [P_{1,y}, P_{2,y}]^T$, respectively. Let the maximum total throughput for these two cases be R_x^* and R_y^*. Assuming that the power is allowed to be continuously distributed within a subchannel, a power allocation $\mathbf{z}_n = [p_{1,n,z}, p_{2,n,z}]^T$ is constructed by taking the union of $\mathbf{x}_n^*$ and $\mathbf{y}_n^*$ that, each subchannel is further divided into two parts, v proportion of which has power $p_{i,n,z} = p_{i,n,x}^*, i = 1, 2$, and $(1-v)$ proportion of which has power $p_{i,n,z} = p_{i,n,y}^*, i = 1, 2$. Then we have $\sum_{n=1}^N p_{i,n,z} = \int p_{i,n,z} \leq vP_{i,x} + (1-v)P_{i,y}$, i.e. $\sum_{n=1}^N \mathbf{h}_n(\mathbf{z}_n) \leq v\mathbf{P}_\mathbf{x} + (1-v)\mathbf{P}_\mathbf{y}$. Further, such power allocation $\mathbf{z}_n$ also achieves a total throughput $vR_x^* + (1-v)R_y^*$, i.e. $R(\{\mathbf{z}_n\}) = vR^*(\{\mathbf{x}_n^*\}) + (1-v)R^*(\{\mathbf{y}_n^*\})$.

Hence, with the $\mathbf{z}_n$, the time-sharing condition is satisfied by allowing the power to be continuously distributed within a subchannel. Similar to [12], the CT-PA problem becomes approximately continuous power distribution in each subchannel when the number of subchannel N is large. Hence, when N goes large, the time-sharing condition approximately holds for (2), and the maximum value of (2) is nearly a concave function of the power constraint $\mathbf{P}$ as shown in Fig. 2.

Therefore, the duality gap between the CT-PA problem (2) and its dual problem is nearly zero when the number of subchannel N goes large. This implies solving the CT-PA problem in the dual domain with an acceptable deviation.

IV. Dual Decomposition based Solution and Suboptimal Scheme

According to the analysis on the duality gap, the optimal solution of the CT-PA problem is obtained with dual decomposition method in this section. In order to reduce the complexity, a suboptimal scheme with low complexity is also given.

A. Dual Decomposition based Solution

The Lagrangian function of (2) is given by

$$L(\mathbf{P}_1, \mathbf{P}_2, \lambda) = \sum_{n=1}^N r_n(p_{1,n}, p_{2,n}) + \sum_{i=1}^2 \lambda_i (P_i - \sum_{n=1}^N p_{i,n})$$
$$= \sum_{n=1}^N L_n(p_{1,n}, p_{2,n}, \lambda) + \sum_{i=1}^2 \lambda_i P_i \tag{6}$$

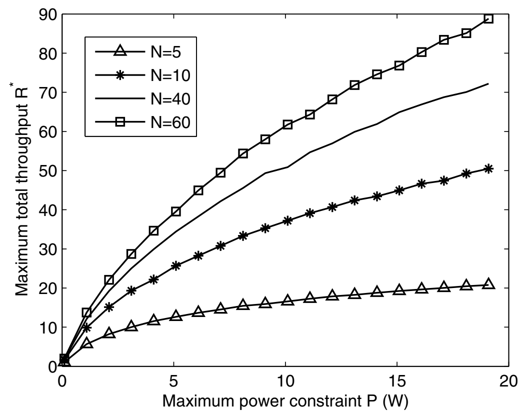

Fig. 2. The maximum value of CT-PA problem (2) vs. the constraint $\mathbf{P}$ assuming $P_1 = P_2$

where $L_n(p_{1,n}, p_{2,n}, \lambda) = r_n(p_{1,n}, p_{2,n}) - \sum_{i=1}^2 \lambda_i p_{i,n}$. The $\lambda_i \geq 0, i = 1, 2$ is the Lagrange multiplier associated with the power constraint and $\lambda = [\lambda_1, \lambda_2]^T$. Then, the dual optimization problem is

$$\begin{aligned} &\text{minimize} \quad g(\lambda) = \max_{\mathbf{P}_1, \mathbf{P}_2} L(\mathbf{P}_1, \mathbf{P}_2, \lambda) \\ &\text{subject to} \quad \lambda \succeq \mathbf{0} \end{aligned} \tag{7}$$

where $g(\lambda)$ is the Lagrange dual function. According to the duality gap analysis, there is $g^* \approx R^*$ where g^* and R^* are the optimal values of (7) and (2), respectively. With dual decomposition, $g(\lambda)$ becomes

$$g(\lambda) = \sum_{n=1}^N g_n(\lambda) + \sum_{i=1}^2 \lambda_i P_i \tag{8}$$

where $g_n(\lambda) = \max_{p_{1,n}, p_{2,n}} L_n(p_{1,n}, p_{2,n}, \lambda)$. Hence, the dual decomposition results in N independent maximization subproblems on each subchannel n with fixed λ. For simplicity, we denote $L_n(p_{1,n}, p_{2,n}, \lambda)$ as L_n. For the nth maximization subproblem given above, $n = 1, 2, ..., N$, we have

$$\frac{\partial L_n}{\partial p_{i,n}} = \frac{B\gamma_{i,n}}{(1 + \sum_{i=1}^2 \gamma_{i,n} p_{i,n}) \ln 2} - \lambda_i = 0, i = 1, 2 \tag{9}$$

With the non-negative power constraint, the solution maximizing $g_n(\lambda)$ is given as

$$p_{i,n}^* = \left[\frac{B}{\lambda_i \ln 2} - \frac{1 + \gamma_{i',n} p_{i',n}^*}{\gamma_{i,n}}\right]^+ \tag{10}$$

where $i \neq i', i, i' = 1, 2$, and the function $[\cdot]^+ = \max(\cdot, 0)$. According to (10), if $p_{1,n}^*$ and $p_{2,n}^*$ are both positive, there is

$$\frac{\gamma_{1,n}}{\gamma_{2,n}} = \frac{\lambda_1}{\lambda_2} \tag{11}$$

Hence, if (11) doesn't hold, one of $p_{1,n}^*$ and $p_{2,n}^*$ is zero, i.e. the subchannel n is transmitted by only one of the two APs.

Algorithm 1 Dual decomposition method

1: **Initialize:** $l=0,\ \lambda_i^l=\lambda_0,\ s_i^l=s_0,\ i=1,2,\varepsilon=M$;
2: Search over all possible combinations of Φ_1,Φ_2,Φ_c;
3: Calculate $p_{i,n}^*(\lambda^l)$ with (12) for each combination;
4: Obtain $g_n(\lambda^l)$ and $g(\lambda^l)$ with (14) and (8);
5: **While** $\varepsilon\geq\varepsilon_0$ **do**
6: Update λ_i^{l+1} with (15), $l=l+1$;
7: Obtain $p_{i,n}^*(\lambda^l),\ g_n(\lambda^l),\ g(\lambda^l)$ with (12), (14), (8);
8: $\varepsilon=|g(\lambda^{l-1})-g(\lambda^l)|$;
9: **End while**
10: Set the final power allocation as $p_{i,n}^*=p_{i,n}^*(\lambda^l)$, $i=1,2,n=1,2,...,N$.

$\lambda_0,s_0,\varepsilon_0$ are small positive values, M is a large number;

Therefore, the solution (10) is rewritten as

$$\begin{cases} p_{i,n}^*=\left[\dfrac{B}{\lambda_i\ln 2}-\dfrac{1}{\gamma_{i,n}}\right]^+, p_{i',n}^*=0, n\in\Phi_i \\ p_{i,n}^*=\dfrac{B}{\lambda_i\ln 2}-\dfrac{1+\gamma_{i',n}p_{i',n}^*}{\gamma_{i,n}}, n\in\Phi_c \end{cases} \tag{12}$$

where $i,i'=1,2,i\neq i'$. Φ_i denotes the set of subchannels only transmitted by AP i, in which there is $\frac{\gamma_{1,n}}{\gamma_{2,n}}\neq\frac{\lambda_1}{\lambda_2}$, and Φ_c is the set of subchannels transmitted simultaneously by both two APs, in which $\frac{\gamma_{1,n}}{\gamma_{2,n}}=\frac{\lambda_1}{\lambda_2}$. Note that if there is more than one subchannel that simultaneously transmitted by both two APs, i.e. there exits subchannels $n,n'\in\Phi_c$, and $n\neq n'$, then according to (11) we have

$$\frac{\gamma_{1,n}}{\gamma_{2,n}}=\frac{\gamma_{1,n'}}{\gamma_{2,n'}} \tag{13}$$

which rarely happens in the practical system due to the large randomness of channel conditions. Hence, at most one subchannel is transmitted simultaneously by both two APs, i.e. $|\Phi_c|\leq 1$ where $|\Phi_c|$ denotes the size of Φ_c.

By searching all possible combinations of $\Phi_i,i=1,2$ and Φ_c, the $g_n(\lambda)$ can be obtained by

$$g_n(\lambda)=\max_{\Phi_1,\Phi_2,\Phi_c} r_n(p_{1,n}^*,p_{2,n}^*)-\sum_{i=1}^{2}\lambda_i p_{i,n}^* \tag{14}$$

where $p_{i,n}^*$ is calculated with (12), $i=1,2$, and $n=1,2,...,N$. With subgradient method [12], λ_i is updated by

$$\lambda_i^{l+1}=\left[\lambda_i^l-s_i^l(P_i-\sum_{n=1}^{N}p_{i,n}^*(\lambda^l))\right]^+, i=1,2 \tag{15}$$

where l is the iteration number and s_i^l is the positive step-size sequence, $i=1,2$. $\lambda^l=(\lambda_1^l,\lambda_2^l)$ and $p_{i,n}^*(\lambda^l)$ is obtained from (12) with $\lambda_i^l,i=1,2$. The above subgradient update is guaranteed to converge to the optimum as long as s_i^l is sufficiently small [14]. When the optimal $\lambda_i^*,i=1,2$ are reached, the $p_{i,n}^*$ can be obtained by substituting λ_i^* into (12) and combining with (14), the optimal $\Phi_i,i=1,2$ and Φ_c is indicated. The dual decomposition method is given in **Algorithm 1**.

Algorithm 2 Suboptimal power allocation scheme

1: **Initialize**: $t=0$, $p_{i,n}^t=0,i=1,2,n=1,2,...,N$;
2: **For** t=1:T **do**
3: Compute the SAPWF solution $p_{1,n}^t$ for AP 1 according to (16) conjugating with $p_{2,n}^{t-1}$, $n=1,...,N$;
4: Compute the SAPWF solution $p_{2,n}^t$ for AP 2 according to (16) conjugating with $p_{1,n}^t$, $n=1,...,N$;
5: **End for**
6: Set the final power allocation as $p_{i,n}^*=p_{i,n}^T$, $i=1,2,n=1,2,...,N$.

B. Suboptimal power allocation scheme

Notice that calculating (14) needs to search over about $2^N+N\times 2^{N-1}$ combinations of Φ_1,Φ_2,Φ_c, leading to an exponential complexity with respect of N, not mention the complexity of the dual updating. This makes the dual decomposition method impractical especially when N is large. In order to reduce the complexity, we propose a suboptimal power scheme with much lower complexity.

Suppose the power from AP i on each subchannel, $p_{i,n}$, is fixed, according to (10), the optimal power allocation from AP $i'\neq i$ is given as

$$p_{i',n}=\left[\frac{B}{\lambda_{i'}\ln 2}-\frac{1+\gamma_{i,n}p_{i,n}}{\gamma_{i',n}}\right]^+, n=1,...,N \tag{16}$$

which can be seen as a single AP "water-filling" (SAPWF) power allocation [3] from AP i' considering the conjugation with the power allocation from AP i. Then, by iteratively applying the SAPWF for each one of the two APs alternatively considering the conjugation with the power allocation of another AP, the achieved total throughput continuously increases and the power allocation from both two APs approximates to the optimum.

According to this, a suboptimal power allocation scheme is proposed in **Algorithm 2** by performing the above iterative procedure until the total throughput doesn't increase any more, or for a given iteration times. By employing the fast algorithm in [6] which only needs at most N iterations to obtain the SAPWF solution, the maximal iteration time of Algorithm 2 is $T\times 2N$, where T is the alternation number of calculating power allocation for AP 1 and 2. Selecting the T less than N, the complexity of Algorithm 2 increases polynomially with N, which is much lower than the dual decomposition method.

V. Numerical Results

In this section, the performance of dual decomposition method (DDM) and the proposed suboptimal scheme are compared with the optimal solution. The performance of equal power allocation (EPA) is also evaluated, in which both the two APs equally distribute the transmit power across all subchannels. Without loss of generality, we assume the subchannel bandwidth is normalized, and the maximum transmit power on each AP is identical denoted as P. The channel conditions $\gamma_{i,n}$ are randomly selected. We also denote T as the iterative alternation number of the proposed suboptimal scheme as described in Algorithm 2.

Fig. 3 illustrates the total throughput achieved by each compared scheme with different P and $N = 50$. It can be seen that the dual decomposition method achieves nearly optimal solution with an ignored deviation, and the performance gap between the optimum and the proposed suboptimal scheme is very narrow within a small T. And as the T increases, the suboptimal scheme approximates to the optimal solution. All the proposed schemes have a greatly improvement compared with the equal power allocation.

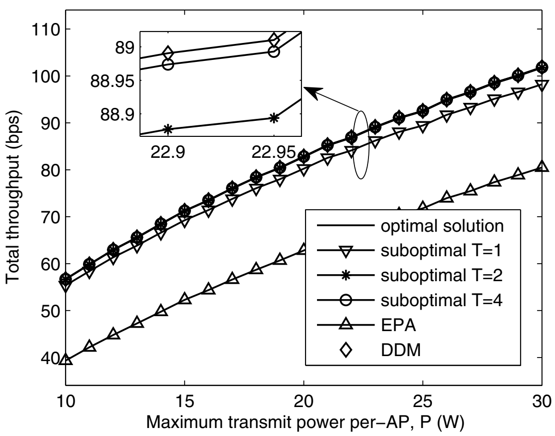

Fig. 3. Total throughput vs. maximum transmit power per-AP

The convergence behavior of the proposed suboptimal power allocation scheme is evaluated in the Fig. 4, with different P and N. It can be seen that, with the very small $T \leq 3$, the performances achieved by the suboptimal scheme have already been very close to the optimum. And as the T increases to $T \geq 6$, the suboptimal scheme converges to the optimal solution. Due to the strong dependence on the channel conditions, the accurate number of the iteration, T, required for the suboptimal scheme to converge to the optimum is unpredictable with arbitrary P and N. However, the Fig. 4 implies that the suboptimal scheme can achieve the nearly optimal performance within a very small number of iteration, and converge fast to the optimum in many cases.

VI. Conclusion

In this paper, we study the power allocation problem to maximize the total throughput of a two-AP OFDM downlink system with the non-coherent cooperative transmission. By proving the duality gap of the original non-convex problem is nearly zero as the number of subchannel goes large, the problem is solved with dual decomposition method. In addition, a suboptimal power allocation scheme is also proposed to reduce the complexity. Efficient power allocation algorithm for more than two APs is an open issue for the future study.

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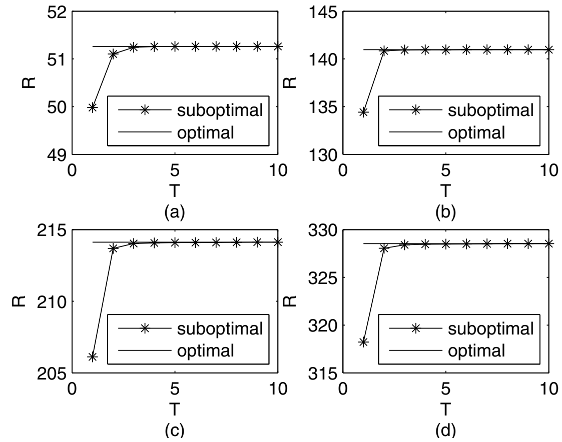

Fig. 4. Covergence behavior of the proposed suboptimal scheme: (a) P=20, N=20; (b) P=50, N=50; (c) P=60, N=100; (d) P=80, N=200.

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