Joint Uplink and Downlink Resource Allocation in Full-duplex OFDMA Networks

Sa Xiao^{†*}, Shengjie Guo^{*}, Xiangwei Zhou^{*}, Daquan Feng[†], Yi Yuan-Wu[‡], Geoffrey Ye Li[§], and Wei Guo[†] [†] National Key Lab on Communications, UESTC, Chengdu, China

* Division of Electrical and Computer Engineering, Louisiana State University, Baton Rouge, LA, USA

[‡] Orange Lab Network, Department of Wireless Technology Evolution, Paris, France

[§] School of Electrical and Computer Engineering, Georgia Institute of Technology, Atlanta, GA, USA

Abstract—In this paper, we study resource allocation in fullduplex OFDMA networks. We explore the joint optimization of subcarrier assignment, uplink-downlink user pairing, and power allocation to maximize the overall throughput with consideration of self-interference and inter-node interference. By using the dual method, we can decompose the original optimization problem into a primal problem and a dual problem. We adopt the concave-convex procedure to transform the primal problem into a tractable form through sequential convex approximations while we utilize the sub-gradient method to solve the dual problem. Simulation results show that the proposed algorithm can always achieve better throughput in comparison with the existing algorithms.

I. INTRODUCTION

THE exponential growth of smart phones and mobile services leads to an increasing demand on high data rate access, which can be hardly accommodated under traditional wireless communication techniques. To efficiently utilize the spectrum resource as well as to alleviate the huge infrastructure investment of operators, *full-duplex* (FD) communications have been considered as a promising technique in LTE-advanced networks [1], [2].

FD communications allow wireless equipment to transmit and receive signals simultaneously over the same frequency band, thus can potentially double the spectrum efficiency and provide flexible access [2]. *Self-interference* (SI), leaking from the FD equipment's transmission to its reception, is the major obstacle for FD communications to be widely used in practice. Although extensive research has been done to suppress SI, it still cannot be totally cancelled and significantly affects the performance of FD communications [3], [4]. Besides, cochannel inter-node interference also exists for simultaneously transmitting users in FD communication systems. To fully exploit the potential of FD communications, novel resource allocation algorithms, which can efficiently control interference, are required.

The resource allocation problems in FD communication systems differ from each other significantly in optimization objectives (throughput maximization, outage minimization, and energy efficiency maximization), practical constraints (individual power, minimum data rate, and minimum *signal-tointerference-plus-noise ratio* (SINR) constraint), and system architectures (cellular, relaying, and heterogeneous networks). Among these problems, the resource allocation in FD OFDMA networks is of fundamental importance and involves many design challenges. Compared with the traditional OFDMA cellular network, it requires perfect coordination of the subcarrier assignment and power allocation in uplink and downlink users to avoid severe interference. In addition, the combinatorial nature of subcarrier assignment and the non-convex nature of power allocation render the resource allocation problem in FD OFDMA networks very challenging to solve, which is worth exploring.

There has been some preliminary work regarding the resource allocation in FD OFDMA networks. In [5], a matchingbased resource allocation algorithm has been proposed to maximize the overall system throughput. It is assumed that one user can be assigned only one subcarrier and equal power allocation scheme is adopted. The performance of the algorithm in [5] can be further improved if more sophisticated subcarrier assignment and power allocation are considered. In [6] and [7], the dual method is used to optimize the subcarrier assignment, user pairing, and power allocation in FD OFDMA networks. However, SI is assumed to be perfectly cancelled in the above work.

Different from the aforementioned work, we propose a general resource allocation algorithm for FD OFDMA networks in this paper, which considers both SI and inter-node interference and jointly optimizes the subcarrier assignment, user pairing, and power allocation. By using the dual method, the optimization problem is equivalently decomposed into one primal problem and one dual problem. The *concave-convex procedure* (CCCP) is adopted to transform the primal problem into a tractable form through sequential convex approximations. The sub-gradient method is adopted to solve the dual problem. Simulation results show that the proposed algorithm can always achieve better throughput in comparison with the existing algorithms.

The rest of the paper is organized as follows. In Section II, we describe the system model and formulate the optimization

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problem. To solve the problem, we develop our resource allocation algorithm in Sections III. Then we present simulation results in Section IV. Finally, conclusions are drawn in Section V.

II. SYSTEM MODEL AND PROBLEM FORMULATION

In this section, we first introduce the system model and then formulate the resource allocation problem for FD OFDMA networks.

A. System Description

We consider a single-cell FD OFDMA system, that consists of a BS, M uplink users (UUs), and N downlink users (DUs), as shown in Figure 1. The BS is equipped with one FD antenna for simultaneous downlink transmission and uplink reception. Each of the M + N users employs a single halfduplex (HD) antenna to ensure low hardware complexity. Since the transmission is based on OFDM, the entire spectrum is divided into K orthogonal subcarriers with flat fading. For analysis simplification, we assume the BS has perfect channel state information (CSI) of all the links and can schedule proper resources for users according to the instantaneous CSI and practical quality-of-service requirements of users.



Fig. 1: System model for an FD OFDMA network.

To suppress SI, both analog and digital cancellation schemes are implemented at the BS. However, due to non-ideal channel estimation and signal processing in practice, residual SI still exists after interference cancellation [3]. Therefore, the impact of SI needs to be considered when designing resource allocation algorithms.

As in Figure 1, we use $h_{m,k}^u$, $h_{n,k}^d$, \hat{h}_k , and $h_{m,n,k}$ to denote the channel power gain of uplink, downlink, SI, and inter-node interference channels, where m, n, and k are the indices of the UU, DU, and subcarrier, respectively. If subcarrier k is assigned to UU m and DU n, the corresponding SINRs at the BS and DU n can be written as

$$SINR_{m,k}^{u} = \frac{p_{m,k}^{u} h_{m,k}^{u}}{p_{m,k}^{d} \hat{h}_{k} + \delta_{N}^{2}}$$
(1)

and

$$SINR_{n,k}^{d} = \frac{p_{n,k}^{a}h_{n,k}^{a}}{p_{m,k}^{u}h_{m,n,k} + \delta_{N}^{2}},$$
(2)

respectively, where $p_{m,k}^u$ and $p_{n,k}^d$ denote the transmission powers of UU m and the BS, respectively, while δ_N^2 denotes the power of additive white Gaussian noise.

B. Problem Formulation

Due to the exclusive subcarrier assignment constraint for both uplink and downlink, each subcarrier can be assigned to at most one UU-DU pair. Thus we define binary variable $x_{m,n,k} \in \{0,1\}$ as an indictor for subcarrier assignment and user pairing. Specially, if subcarrier k is assigned to user pair (m,n), we have $x_{m,n,k} = 1$, and otherwise $x_{m,n,k} = 0$.

Our objective is to maximize the overall throughput of the system via joint optimization of the subcarrier assignment, user pairing, and power allocation. Denote P_m^{\max} and P_b^{\max} as the total transmission powers at UU m and the BS, respectively. Then the optimization problem can be formulated as

$$\max_{x_{m,n,k}, p_{m,k}^{u}, p_{n,k}^{d}} \sum_{k=1}^{K} \sum_{n=1}^{N} \sum_{m=1}^{M} x_{m,n,k} \left(\omega_{m}^{u} \log \left(1 + \text{SINR}_{m,k}^{u} \right) + \omega_{n}^{d} \log \left(1 + \text{SINR}_{n,k}^{d} \right) \right),$$
(3)

subject to
$$\sum_{n=1}^{N} \sum_{m=1}^{M} x_{m,n,k} \le 1, \quad \forall k,$$
 (3a)

$$\sum_{k=1}^{K} p_{m,k}^{u} \le P_{m}^{\max}, \quad \forall m,$$
(3b)

$$\sum_{k=1}^{N} \sum_{k=1}^{K} p_{n,k}^{d} \le P_{b}^{\max},$$
(3c)

$$p_{m,k}^{u} \ge 0, \ p_{n,k}^{d} \ge 0, \ \forall m, n, k,$$
 (3d)

$$p_{m,k}^u = 0$$
, if $x_{m,n,k} = 0$, $\forall m, k$, (3e)

$$p_{n,k}^d = 0, \text{ if } x_{m,n,k} = 0, \ \forall n,k,$$
 (3f)

where ω_m^u and ω_n^d are predetermined positive weights for UU m and DU n, respectively, which are used to prioritize different classes of services. Constraint (3a) is originated from the fact that each subcarrier can be assigned to at most one user pair while constraints (3b)-(3f) guarantee the valid power allocation for the UUs and the BS. It should be noted that there may exist $p_{m,k}^u = 0$ or $p_{n,k}^d = 0$ for $x_{m,n,k} = 1$. In this case, subcarrier k is used in the HD mode and no SI or inter-node interference exists over the subcarrier.

III. RESOURCE ALLOCATION FOR FD COMMUNICATIONS

It can be seen that problem (3) is a mixed integer and non-linear programming problem, and thus the brute-forced method is required to find the optimal solution. However, the total $(NM)^K$ possible subcarrier assignments complicate the problem especially when K, M, and N are large. According to [8], the duality gap of a non-convex resource allocation problem in a multi-subcarrier system is negligible when the number of subcarriers is sufficiently large. Therefore, we can solve the dual problem instead of the original problem. The associated Lagrange dual problem is written as

$$\min_{\mathbf{r},\lambda} G(\mathbf{r},\lambda), \qquad (4)$$

subject to
$$\gamma_m \ge 0, \ \forall m, \ \lambda \ge 0,$$
 (4a)

where $\mathbf{r} = [\gamma_1, ..., \gamma_M]$ and λ denote the Lagrange multipliers associated with (3b) and (3c), respectively, and $G(\mathbf{r}, \lambda)$ denotes the dual objective function given by

$$G(\mathbf{r},\lambda) = \max_{x_{m,n,k}, p_{m,k}^{u}, p_{n,k}^{d}} \sum_{k=1}^{K} \sum_{n=1}^{N} \sum_{m=1}^{M} x_{m,n,k} \left(\omega_{m}^{u} \log\left(1\right) + \operatorname{SINR}_{m,k}^{u}\right) + \omega_{n}^{d} \log\left(1 + \operatorname{SINR}_{n,k}^{d}\right)\right)$$
$$- \sum_{m=1}^{M} \gamma_{m} \left(\sum_{k=1}^{K} p_{m,k}^{u} - P_{m}^{\max}\right)$$
$$- \lambda \left(\sum_{n=1}^{N} \sum_{k=1}^{K} p_{n,k}^{d} - P_{b}^{\max}\right), \qquad (5)$$
subject to (3a), (3d), (3e), and (3f).

A. Solving Primal Problem

To solve the dual problem, we first need to find the optimal primal variables $\left\{x_{m,n,k}^{*}, p_{m,k}^{u}^{*}, p_{n,k}^{d}^{*}\right\}$ for given Lagrange multipliers **r** and λ . From (5), the primal optimization problem is rewritten as

$$\max_{\substack{x_{m,n,k}, p_{m,k}^u, p_{n,k}^d \\ \text{subject to}}} \sum_{k=1}^K \sum_{n=1}^N \sum_{m=1}^M x_{m,n,k} L_{m,n,k} \left(p_{m,k}^u, p_{n,k}^d \right), \quad (6)$$

where

$$L_{m,n,k}\left(p_{m,k}^{u}, p_{n,k}^{d}\right) = \omega_{m}^{u} \log\left(1 + \text{SINR}_{m,k}^{u}\right) - \gamma_{m} p_{m,k}^{u} + \omega_{n}^{d} \log\left(1 + \text{SINR}_{n,k}^{d}\right) - \lambda p_{n,k}^{d}.$$
 (7)

The primal optimization problem consists of two layers. The inner one is power allocation, determining the optimal transmission powers at UUs and the BS to maximize the $L_{m,n,k}$ at all possible user pairs and subcarrier assignments. The outer one is the decision process of joint user pairing and subcarrier assignment. The two layers can be decomposed. Therefore, we separately optimize the inner and outer layers to obtain the optimal solution to (6).

1) Inner Layer Problem

Without loss generality, we consider the power allocation for an assignment unite (m, n, k). The associated power allocation problem is written as

$$\max_{V_P \in \mathcal{S}_P} L_{m,n,k}\left(V_P\right),\tag{8}$$

where $V_P = [p_{m,k}^u; p_{n,k}^d]$ and S_P is the set of V_P satisfying (3d).

From (8), we can observe that γ_m and λ serve as pricing constants to coordinate the demand of data rate and the supply of transmission power. A higher value of γ_m or λ discourages UU m or the BS from expending power. Therefore, there must exist thresholds for γ_m and λ such that the optimal transmission power at UU m or the BS will be zero when γ_m or λ excesses its threshold. A possible expression of the thresholds is given in the following theorem, which is proved in Appendix A.

Theorem 1: Denote $\hat{\gamma}_m = \frac{\omega_m^u h_{m,k}^u + \omega_n^d h_{m,n,k}}{\delta_N^2 \ln 2}$ and $\hat{\lambda} = \frac{\omega_m^u \hat{h}_k + \omega_n^d h_{n,k}^d}{\delta_N^2 \ln 2}$. For the optimization problem given in (8), if $\gamma_m \geq \hat{\gamma}_m$, the optimal power of UU *m* should be set to zero, i.e., $p_{m,k}^u * = 0$, while if $\lambda \geq \hat{\lambda}$, we have $p_{n,k}^d * = 0$ for DU *n*. Based on Theorem 1, we analyze the behavior problem (8)

by decomposing it into three sub-problems as follows.

Sub-problem 1: If $\gamma_m \geq \widehat{\gamma}_m$, we have $p_{m,k}^{u^*} = 0$. Therefore, problem (8) can be rewritten as

$$\max_{p_{n,k}^d} \left\{ \omega_n^d \log \left(1 + \frac{h_{n,k}^d p_{n,k}^d}{\delta_N^2} \right) - \lambda p_{n,k}^d \right\}, \tag{9}$$

subject to
$$p_{n,k}^d \ge 0.$$
 (9a)

Obviously, Problem (9) is a convex optimization problem. Therefore, the optimal power for DU n follows the expression of conventional water-filling approach as

$$p_{n,k}^{d} = \left(\frac{\omega_n^d}{\lambda \ln 2} - \frac{\delta_N^2}{h_{n,k}^d}\right)^+, \tag{10}$$

where $(x)^{+} = \max(0, x)$.

Sub-problem 2: If $\lambda \geq \hat{\lambda}$, we have $p_{n,k}^d^* = 0$. Therefore, we can rewrite problem (8) as a power allocation problem for uplink and the optimal solution is similarly given by

$$p_{m,k}^{u}^{*} = \left(\frac{\omega_m^u}{\gamma_m \ln 2} - \frac{\delta_N^2}{h_{m,k}^u}\right)^+.$$
 (11)

Sub-problem 3: If $\gamma_m < \hat{\gamma}_m$ and $\lambda < \hat{\lambda}$, there may exist non-negative solutions for both $p_{m,k}^u$ and $p_{n,k}^d$. Thus the power allocation problem remains the same as in (8), which has a non-convex structure and is proved to be NP hard [9].

By rearranging the terms in the objective function, we can rewrite problem (8) as

$$\max_{V_P \in \mathcal{S}_P} \left\{ f_{cav} \left(V_P \right) + f_{vex} \left(V_P \right) \right\},\tag{12}$$

where $f_{cav}(V_P) = \omega_m^u \log\left(p_{m,k}^u h_{m,k}^u + p_{n,k}^d \hat{h}_k + \delta_N^2\right) + \omega_n^d \log\left(p_{n,k}^d h_{n,k}^d + p_{m,k}^u h_{m,n,k} + \delta_N^2\right)$ and $f_{vex}(V_P) = -\omega_m^u \log\left(p_{n,k}^d \hat{h}_k + \delta_N^2\right) - \omega_n^d \log\left(p_{m,k}^u h_{m,n,k} + \delta_N^2\right) - \gamma_m p_{m,k}^u - \lambda p_{n,k}^d$.

Clearly, $f_{cav}(V_P)$ is a strictly concave function in V_P , while $f_{vex}(V_P)$ is strictly convex. Thus problem (12) has a *difference of convex* (D.C.) structure [10]. Meanwhile, $f_{vex}(V_P)$ is differentiable. Therefore, problem (12) can be solved by the CCCP, which is one of the most powerful methods to deal with differentiable D.C. problems [11].

The main idea of the CCCP is to iteratively linearize $f_{vex}(V_P)$ by the first order Taylor expansion at the current fixed point. Denote $V_P^{(l)} = [p_u^{(l)}; p_d^{(l)}]$ as the fixed point at the *l*-th iteration. Then problem (12) can be solved by the following sequential programming

$$V_P^{(l+1)} = \underset{V_P \in \mathcal{S}_P}{\operatorname{arg\,max}} F\left(V_P\right)$$

$$\Phi\left(\beta, g_1, g_2\right) = \frac{\left(\left(\omega_m^u + \omega_n^d\right)g_1g_2 - \beta\left(g_1 + g_2\right)\delta_N^2 + \sqrt{\left(\beta\left(g_2 - g_1\right)\delta_N^2 - \left(\omega_m^u - \omega_n^d\right)g_1g_2\right)^2 + 4\omega_m^u\omega_n^d(g_1g_2)^2}\right)^+}{2\beta g_1g_2} \tag{16}$$

$$= \underset{V_P \in \mathcal{S}_P}{\operatorname{arg\,max}} \left\{ f_{cav} \left(V_P \right) + V_P{}^{\mathrm{T}} \nabla f_{vex} \left(V_P^{(l)} \right) \right\},$$
(13)

where V_P^{T} denotes the transpose of vector V_P , and $\nabla f_{cvex}\left(V_P^{(l)}\right)$ is the gradient of $f_{vex}\left(V_P\right)$ at $V_P^{(l)}$.

Let $\gamma'_m = \frac{\omega_n^d h_{m,n,k}}{h_{m,n,k} p_u^{(l)} + \delta_N^2} + \gamma_m \ln 2$ and $\lambda' = \frac{\omega_m^u \hat{h}_k}{\hat{h}_k p_d^{(l)} + \delta_N^2} + \lambda \ln 2$. We can rewrite $F(V_P)$ as

$$F(V_P) = \omega_n^d \log \left(\delta_N^2 + h_{m,n,k} p_{m,k}^u + h_{n,k}^d p_{n,k}^d \right) - \frac{\lambda' p_{n,k}^a}{\ln 2} + \omega_m^u \log \left(\delta_N^2 + h_{m,k}^u p_{m,k}^u + \hat{h}_k p_{n,k}^d \right) - \frac{\gamma'_m p_{m,k}^u}{\ln 2}.$$
 (14)

It is easy to verify that (14) is a concave function. Applying the KKT condition, we can obtain $V_P^{(l+1)}$ from the following theorem, which is proved in Appendix B.

Theorem 2: Define $Z_1 = \frac{\omega_m^u(h_{m,k}^u h_{n,k}^d - \hat{h}_k h_{m,n,k})}{(h_{n,k}^d \gamma_m' - h_{m,n,k} \lambda') \delta_N^2}$ and $Z_2 = \frac{\omega_n^d(h_{m,k}^u h_{n,k}^d - \hat{h}_k h_{m,n,k})}{(h_{m,k}^u \lambda' - \hat{h}_k \gamma_m') \delta_N^2}$. For the CCCP sequential programming specified in (13), $V_P^{(l+1)}$ can be expressed as follows.

If $Z_1 < 0$ or $Z_2 < 0$,

$$V_P^{(l+1)} = \begin{cases} [0; p'_2], & \text{if } F([0; p'_2]) \ge F([p'_1; 0]), \\ [p'_1; 0], & \text{if } F([p'_1; 0]) > F([0; p'_2]), \end{cases}$$
(15)

where $p'_1 = \Phi\left(\gamma'_m, h_{m,n,k}, h^u_{m,k}\right)$ and $p'_2 = \Phi\left(\lambda', h^d_{n,k}, \hat{h}_k\right)$ and $\Phi\left(\beta, g_1, g_2\right)$ is given in (16) at the top of this page.

If $Z_1 \ge 0$ and $Z_2 \ge 0$,

$$V_P^{(l+1)} = \begin{cases} [p_1^*; p_2^*], & \text{if } p_1^* \ge 0, p_2^* \ge 0, \\ [0; p_2'], & \text{if } p_1^* < 0, p_2^* \ge 0, \\ [p_1'; 0], & \text{if } p_1^* \ge 0, p_2^* < 0, \\ [0; 0], & \text{if } p_1^* < 0, p_1^* < 0, \end{cases}$$
(17)

where $p_1^* = \frac{\delta_N^2 (h_{n,k}^d Z_1 - \hat{h}_k Z_2 + \hat{h}_k - h_{n,k}^d)}{h_{m,k}^u h_{n,k}^d - \hat{h}_k h_{m,n,k}}$ and $p_2^* \frac{\delta_N^2 (h_{m,k}^u Z_2 - h_{m,n,k} Z_1 + h_{m,n,k} - h_{m,k}^u)}{h_{m,k}^u h_{n,k}^d - \hat{h}_k h_{m,n,k}}$ $h_{m,k}^u h_{n,k}^d - \hat{h}_k h_{m,n,k}$

The whole procedure of the CCCP algorithm is summarized in Table I and the algorithm is proved to be converge in our previous paper [10]. Therefore, we can always obtain the optimal power allocation for problem (8) through this method.

2) Outer Layer Problem

Given the optimal transmission powers, problem (6) becomes to be a 0-1 integer programming problem as follows

$$\max_{x_{m,n,k}} \sum_{k=1}^{K} \sum_{n=1}^{N} \sum_{m=1}^{M} x_{m,n,k} L_{m,n,k}^{*}, \qquad (18)$$

TABLE I: CCCP for D.C. Optimization

1: Initialize 2: $l = 0, \forall V_P^{(0)} \in S_P$, tolerance $\epsilon > 0$; 3: Repeat 4: $V_P^{(l+1)} = \underset{V_P \in S_P}{\operatorname{argmax}} \left\{ f_{cav} (V_P) + V_P^{\mathrm{T}} \nabla f_{vex} \left(V_P^{(l)} \right) \right\};$ 5: $l = l + 1;$ 6: Until $ V_P^{(l+1)} - V_P^{(l)} < \epsilon.$	Algorithm 1 CCCP Algorithm	
2: $l = 0, \forall V_P^{(0)} \in S_P$, tolerance $\epsilon > 0$; 3: Repeat 4: $V_P^{(l+1)} = \underset{V_P \in S_P}{\operatorname{argmax}} \left\{ f_{cav} \left(V_P \right) + V_P^{\mathrm{T}} \nabla f_{vex} \left(V_P^{(l)} \right) \right\};$ 5: $l = l + 1;$ 6: Until $ V_P^{(l+1)} - V_P^{(l)} < \epsilon.$	1:	Initialize
3: Repeat 4: $V_P^{(l+1)} = \underset{V_P \in S_P}{\operatorname{argmax}} \left\{ f_{cav} \left(V_P \right) + V_P^{\mathrm{T}} \nabla f_{vex} \left(V_P^{(l)} \right) \right\};$ 5: $l = l + 1;$ 6: Until $ V_P^{(l+1)} - V_P^{(l)} < \epsilon.$	2:	$l=0, \ \forall \ V_P^{(0)} \in \mathcal{S}_P$, tolerance $\epsilon > 0$;
4: $V_P^{(l+1)} = \underset{V_P \in S_P}{\operatorname{argmax}} \left\{ f_{cav} \left(V_P \right) + V_P^{\mathrm{T}} \nabla f_{vex} \left(V_P^{(l)} \right) \right\};$ 5: $l = l + 1;$ 6: Until $ V_P^{(l+1)} - V_P^{(l)} < \epsilon.$	3:	Repeat
5: $l = l + 1;$ 6: Until $ V_P^{(l+1)} - V_P^{(l)} < \epsilon.$	4:	$V_P^{(l+1)} = \operatorname*{argmax}_{V_P \in \mathcal{S}_P} \left\{ f_{cav} \left(V_P \right) + V_P{}^{\mathrm{T}} \nabla f_{vex} \left(V_P^{(l)} \right) \right\};$
6: Until $ V_P^{(l+1)} - V_P^{(l)} < \epsilon$.	5:	$l = l + 1; \qquad (1)$
	6:	Until $ V_P^{(l+1)} - V_P^{(l)} < \epsilon.$

subject to (3a),

where $L^*_{m,n,k}$ is obtained by substituting the optimal power into (7). It is easy to see that each subcarrier should be assigned to the user pair with the maximum value of $L_{m,n,k}^*$. Therefore, we have

$$x_{m,n,k}^{*} = \begin{cases} 1, & \text{if } (m,n) = \underset{(m',n')}{\arg\max} L_{m',n',k}^{*}, \forall k, \\ 0, & \text{otherwise.} \end{cases}$$
(19)

Clearly, $L_{m,n,k}^*$ serves as the optimal criterion for the user pairing and subcarrier assignment.

B. Solving Dual Problem

Here we solve the dual problem (4) to find the optimal dual variables γ_m and λ . Since the dual problem is always convex, the sub-gradient method can be used to minimize $G(\mathbf{r},\lambda)$ with guaranteed convergence [8]. Denote $\gamma_m^{(l)}$ and $\lambda^{(l)}$ as the dual variables at the *l*-th iteration. Then the dual variables at the (l+1)-th iteration can be obtained from

$$\gamma_m^{(l+1)} = \left(\gamma_m^{(l)} - s^{(l)} \left(P_m^{\max} - \sum_{k=1}^K p_{m,k}^u\right)\right)^+$$
(20)

and

$$\lambda^{(l+1)} = \left(\lambda^{(l)} - s^{(l)} \left(P_b^{\max} - \sum_{n=1}^N \sum_{k=1}^K p_{n,k}^d\right)\right)^+, \quad (21)$$

where $(P_m^{\max} - \sum_{k=1}^{K} p_{m,k}^u)$ and $(P_b^{\max} - \sum_{n=1}^{N} \sum_{k=1}^{K} p_{n,k}^d)$ are the sub-gradient of $G(\mathbf{r}, \lambda)$ while $s^{(l)}$ denotes an appropriate step size at the *l*-th iteration. To ensure the convergence of the above sub-gradient method, we adopt the diminishing step size in [8], which guarantees the sub-gradient method to converge with the computational complexity polynomial in the number of dual variables M + 1 [12].

IV. SIMULATION RESULTS

In this section, simulation results are presented to verify the performance of the proposed resource allocation algorithm. In



15 Average overall throughput (Mbits) 10 5 Proposed algorithm UF algorithm DF algorithm 0 L 32 40 34 36 38 42 p_b^{max} (dBm) (a) Uplink of proposed algorithm 12 Downlink of proposed algorithm Average throughput (Mbits) 10 8 6 4 2 0 40 42 32 34 36 38 P_b^{max} (dBm) (b)

Fig. 2: Average throughput vs P_m^{\max} when $P_b^{\max} = 36$ dBm. our simulation, the BS is deployed in the center of the cell with a maximum service distance of 150 meters while 6 UUs and 6 DUs are randomly distributed between the reference distance of 50 meters and the maximum service distance. There are 16 subcarriers with center carrier frequency of 2.5 GHz. Each subcarrier has a bandwidth of 180 kHz and a noise variance of -119 dBm [6]. Since there exists a strong line-of-sight component between the transmitting and receiving antennas at the BS, the SI channel is assumed to be Rician distributed [3]. The channel power gain of SI channel over subcarrier kcan be expressed as $\hat{h}_k = \xi \vartheta_k$, where $\xi = -110 \text{ dB}$ [4] is the SI cancellation constant and ϑ_k is a Rician random variable with the factor 6 dB. The uplink, downlink, and inter-node channels are modeled as Rayleigh fading channels as in [13] and the path-loss constant is set to be 4. To simplify analysis, we assume that all the UUs have the same total transmission power.

For comparison, we investigate the *uplink-first* (UF) and *downlink-first* (DF) algorithms [7] in our simulation. The UF algorithm in [7] first performs uplink resource allocation to maximize the uplink throughput, and then maximizes the downlink throughput treating inter-node interference as the noise. For the DF algorithm in [7], downlink resource allocation is first performed and then uplink resource allocation is operated to maximize the overall throughput. Note that both UF and DF algorithms consider only inter-node interference while ignoring SI.

Figures 2 and 3 demonstrate the performance of three algorithms for different maximum transmission powers of

Fig. 3: Average throughput vs P_b^{\max} when $P_m^{\max} = 24$ dBm. UUs and the BS, respectively. The results are based on 100 realizations of the user distribution. To have a fair comparison between the uplink and downlink performance, we assume $\omega_m^u = \omega_n^d = 1$ in our simulation. Thus the throughput metric in the figures is the actual throughput.

In Figure 2(a), we observe that the proposed algorithm always yields higher overall throughput than the other two algorithms. That is due to two facts. First, the proposed algorithm considers both SI and inter-node interference while the UF and DF algorithms ignore SI. Second, the proposed algorithm always jointly optimizes the uplink and downlink resource allocation while the UF and DF algorithms perform resource allocation for the UUs and the DUs separately. Meanwhile it can be observed in Figure 2(b) that the uplink throughput of the proposed algorithm increases while the downlink throughput decreases with the increase of P_m^{\max} . That is because that increasing P_m^{\max} encourages the UUs to utilize more resources for transmission. Thus additional throughput gain is obtained by the UUs while more inter-node interference is incurred to downlink transmission. However, the increase of P_m^{\max} also extends the feasible region of the optimization problem in (3), thus the overall throughput increases as shown in Figure 2(a).

In Figure 3(a), we also observe that the proposed algorithm always renders better throughput than the other two algorithms. Meanwhile, it can be observed in Figure 3(b) that the uplink throughput decreases with the increase of P_b^{\max} . That is because increasing P_b^{\max} will cause more SI to UUs.

V. CONCLUSIONS

In this paper, we formulated a resource allocation problem to maximize the overall throughput of FD OFDMA networks. With the dual method, the original optimization problem was decomposed into a primal problem and a dual problem. The CCCP was developed to solve the primal problem while the sub-gradient method was used to solve the dual problem. To evaluate the performance of proposed algorithm, we compared it with other algorithms by simulation and showed that the proposed algorithm can always achieve higher throughput.

APPENDIX A **PROOF OF THEOREM 1**

For notation simplification, we use p_1 , p_2 , and L to replace $p_{m,k}^u, p_{n,k}^d$, and $L_{m,n,k}$ respectively. Then we have

$$\frac{\partial L}{\partial p_1} \stackrel{\Delta}{=} \frac{\omega_m^u h_{m,k}^u}{\ln 2 \left(h_{m,k}^u p_1 + \hat{h}_k p_2 + \delta_N^2 \right)} - \frac{\omega_n^d h_{m,n,k}}{\ln 2 \left(h_{m,n,k} p_1 + \delta_N^2 \right)} + \frac{\omega_n^d h_{m,n,k}}{\ln 2 \left(h_{m,k}^d p_2 + h_{m,n,k} p_1 + \delta_N^2 \right)} - \gamma_m \\ < \frac{\omega_m^u h_{m,k}^u}{\ln 2 \delta_N^2} + \frac{\omega_n^d h_{m,n,k}}{\ln 2 \delta_N^2} - \gamma_m,$$

where the inequality is originated from the fact that $p_1 \ge 0$ and $p_2 \ge 0$. Therefore, if $\gamma_m \ge \widehat{\gamma}_m$ is satisfied, we have $\frac{\overline{\partial L}}{\partial p_1} < 0$. In other word, L is always decreasing in p_1 for $p_1 \ge 0$ and $p_2 \geq 0$. Therefore, the optimal p_1 for (8) should be set to zero. Similarly, if $\lambda \geq \hat{\lambda}$, we can obtain that $p_2 = 0$, which completes the proof.

APPENDIX B **PROOF OF THEOREM 2**

We first define $h_1 = h^u_{m,k}/\delta^2_N$, $h_2 = h^d_{n,k}/\delta^2_N$, $h_3 =$ \hat{h}_k/δ_N^2 , $h_4 = h_{m,n,k}/\delta_N^2$, $p_1 = p_{m,k}^u$, and $p_2 = p_{n,k}^d$ to simplify notation. Set $U_1 = 1 + h_1p_1 + h_3p_2$ and $U_2 =$ $1+h_4p_1+h_2p_2$. Then it is easy to see from (14) that $F(V_P)$ is valid and concave only when $U_1 \ge 0$ and $U_2 \ge 0$. Therefore, to solve problem (13), we first need to verify that if there exists a stationary point $[p_1^*; p_2^*]$ for $F(V_P)$ or not. Setting $\frac{\partial F}{\partial p_1} = 0$ and $\frac{\partial F}{\partial p_2} = 0$, we have

$$\begin{cases} \omega_{m}^{u}h_{1}/U_{1} + \omega_{n}^{d}h_{4}/U_{2} = \gamma_{m}', \\ \omega_{m}^{u}h_{3}/U_{1} + \omega_{n}^{d}h_{2}/U_{2} = \lambda'. \end{cases}$$
(22)

The above equation set can be easily solved if we consider $\frac{1}{U_1}$ and $\frac{1}{U_2}$ as variables, and the solution is $U_1^* = Z_1$ and $U_2^* = Z_2$.

1) If $Z_1 \ge 0$ and $Z_2 \ge 0$, there exists a stationary point for $F(V_P)$. Thus $[p_1^*; p_2^*]$ can be obtained by solving the following equation set

$$\begin{cases} h_1 p_1 + h_3 p_2 = Z_1 - 1, \\ h_4 p_1 + h_2 p_2 = Z_2 - 1, \end{cases}$$
(23)

and $p_1^* = \frac{h_2(Z_1-1)-h_3(Z_2-1)}{h_1h_2-h_3h_4}$ and $p_2^* = \frac{h_1(Z_2-1)-h_4(Z_1-1)}{h_1h_2-h_3h_4}$. If $p_1^* \ge 0$ and $p_2^* \ge 0$, we have $V^{(l+1)} = [p_1^*; p_2^*]$. If $p_1^* < 0$ and $p_2^* < 0$, $\frac{\partial F}{\partial p_1} < 0$ and $\frac{\partial F}{\partial p_2} < 0$ for $p_1 \ge 0$ and $p_2 \ge 0$. Thus $V^{(l+1)} = [0; 0]$.

If $p_1^* \ge 0$ and $p_2^* < 0$, it is easy to prove from the property of concave functions that the optimal p_2 for problem (13) equals zero. Thus we can obtain $p_1 = p'_1$ by solving the following equation

$$\frac{\omega_m^a h_1}{1+h_1 p_1} + \frac{\omega_n^a h_4}{1+h_4 p_1} = \gamma_m'.$$
 (24)

Similarly, if $p_1^* < 0$ and $p_2^* \ge 0$, we have $p_2 = p'_2$.

2) If $Z_1 < 0$ or $Z_2 < 0$, there exists no stationary point for $F(V_P)$. Thus the optimal p_1 and p_2 must be at the boundary of the feasible region defined by (3d). When $p_2 = 0$, we can obtain $p_1 = p_1'$ from (24). Similarly, we can obtain $p_2 =$ p'_2 when $p_1 = 0$. Then we compare the values of $F(V_P)$ in these two solutions and choose the one rendering the higher value of F. Therefore, $V_p^{(l+1)}$ can be expressed as (15), which completes the proof.

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