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JOINT OPTIMIZATION FOR FULL-DUPLEX CELLULAR COMMUNICATIONS VIA INTELLIGENT REFLECTING SURFACE

Zhangjie Peng[⋆,∗], *Cunhua Pan*[†], *Zhenkun Zhang*[⋆], *Xianzhe Chen*[⋆], *Li Li*[⋆], *and A. Lee Swindlehurst*[‡]

[⋆] College of Information, Mechanical and Electrical Engineering, Shanghai Normal University, Shanghai, China

[∗] Shanghai Engineering Research Center of Intelligent Education and Bigdata, Shanghai Normal University, Shanghai, China

[†] School of Electronic Engineering and Computer Science, Queen Mary University of London, London, UK

[‡] Department of Electrical Engineering and Computer Science, University of California, Irvine, CA, USA

ABSTRACT

The implementation of full-duplex (FD) theoretically doubles the spectral efficiency of cellular communications. We propose a multiuser FD cellular network relying on an intelligent reflecting surface (IRS). The IRS is deployed to cover a dead zone while suppressing user-side self-interference (SI) and co-channel interference (CI) by carefully tuning the phase shifts of its massive low-cost passive reflection elements. To ensure network fairness, we aim to maximize the weighted minimum rate (WMR) of all users by jointly optimizing the precoding matrix of the base station (BS) and the reflection coefficients of the IRS. Specifically, we propose a low-complexity minorization-maximization (MM) algorithm for solving the subproblems of designing the precoding matrix and the reflection coefficients, respectively. Simulation results confirm the convergence and efficiency of our proposed algorithm, and validate the advantages of introducing IRS to realize FD cellular communications.

***Index Terms*—** Intelligent reflecting surface, reconfigurable intelligent surface, full-duplex, max-min fairness.

1. INTRODUCTION

Full-duplex (FD) two-way communication in which two or more devices simultaneously exchange data at the same carrier frequency has received extensive research attention, as it can double the spectral-efficiency of the wireless communication system [1, 2]. FD two-way relaying has been studied in various scenarios [1, 3–5]. However, besides the loop-interference (LI) at the relay, FD two-way networks must also overcome back-propagation interference at the base station (BS) and the users. Therefore, existing networks suffer from low energy-efficiency and high hardware cost since energy-intensive transceivers and complex signal processing techniques are required to cope with the much more complex propagation environment.

Recently, the intelligent reflecting surfaces (IRSs) have attracted extensive attention from researchers as a means to improve both the spectral- and energy-efficiency of wireless communication networks [6]. An IRS comprises a large number of low-cost passive reflection elements, each independently imposing a continuously or discretely tunable phase shift on the incident signal [7, 8]. When the phase shifts are properly adjusted, the directly transmitted signal and the reflected signal can be superimposed constructively at the intended receivers or destructively at other unintended users, so as to realize directional enhancement or suppression of signals, while enabling fine-grained

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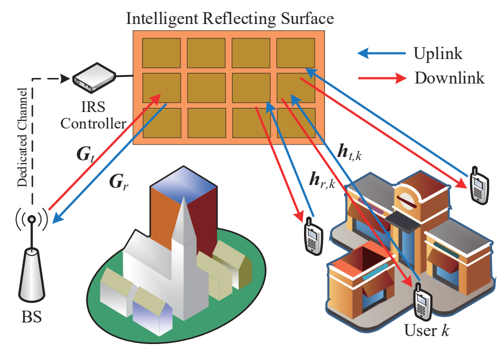

Fig. 1. Illustration of the IRS-aided FD cellular network between a MIMO BS and K SISO users.

3D passive beamforming. We emphasize that the IRS reflects signals through passive reflection, generating no new signals or thermal noise, and requiring no signal processing operations to deal with LI.

Due to these appealing features, joint precoding at the BS/AP and reflecting elements design at the IRS have been extensively studied in one-way communication networks [9–16]. However, there is a paucity of investigations on the study of the integration of IRS in two-way communications [17–19]. Additionally, the fairness between uplink and downlink transmissions needs to be guaranteed in FD communication, which has not been taken into account in these studies.

In this paper, we propose to employ an IRS in an FD cellular network to provide signal coverage for users in blind areas, as shown in Fig. 1. Specifically, unlike the relay schemes in [20], in our proposed system, both the uplink and downlink transmissions can occur simultaneously and operate at the same frequency via the reflection of the IRS, and thus potentially doubles the spectral-efficiency. In order to guarantee fairness, the max-min fairness (MMF) criterion is chosen as the optimization metric, which is a complex non-differentiable objective function (OF). We propose a low-complexity algorithm based on alternating optimization and the Minorization-Maximization (MM) algorithm to solve this problem. According to the simulation results, our proposed algorithm has a high convergence speed, and the FD cellular network can achieve high communication performance.

2. SIGNAL MODEL AND PROBLEM FORMULATION

2.1. Signal Transmission Model

We consider the IRS-based FD cellular communication system shown in Fig. 1, where one BS and K users exchange data at the same time and the same frequency. Due to severe path loss and blockages, no direct link between the BS and the users is assumed to exist. To resolve this issue, an IRS containing M passive reflection elements is deployed to establish additional non-line-of-sight (NLoS) links. The BS is equipped with $N_{\rm t} > 1$ transmit antennas and $N_{\rm r} > 1$ receive antennas. Each user is equipped with one transmit antenna and one receive antenna. The kth user transmits signals with fixed power P_k. Denoting $\mathbf{F} = [\mathbf{f}_1, \cdots, \mathbf{f}_K] \in \mathbb{C}^{N_t \times K}$ as the collection of beamforming vectors of the BS, the power constraint of the BS is

$$\mathcal{S}_F = \left\{ \mathbf{F} | \mathrm{Tr} \left[\mathbf{F}^{\rm H} \mathbf{F} \right] \leq P_{\max} \right\}, \quad (1)$$

where $P_{\max}$ is the maximum transmit power. All the data symbols sent by the BS and the users are assumed to be independent Gaussian with unit power. The phase adjustment of the IRS to the reflected signals is modeled as a set of reflection coefficients $\boldsymbol{\phi} = [\phi_1, \cdots, \phi_M]^{\rm T}$, or equivalently as a matrix $\boldsymbol{\Phi} = diag(\boldsymbol{\phi})$, where $|\phi_m|^2 = 1, \forall m = 1, \cdots, M$.

We assume that the channel state information (CSI) of all channels is quasi-static and perfectly known at the BS. Though this assumption is idealistic, it allows us to explore the performance upper bounds for the IRS-based FD network. The baseband channels from the BS to the IRS, from the IRS to the BS, from user k to the IRS, and from the IRS to user k are denoted by $\mathbf{G}_{\rm t} \in \mathbb{C}^{M \times N_{\rm t}}$, $\mathbf{G}_{\rm r} \in \mathbb{C}^{M \times N_{\rm r}}$, $\mathbf{h}_{{\rm t},k} \in \mathbb{C}^{M \times 1}$, and $\mathbf{h}_{{\rm r},k} \in \mathbb{C}^{M \times 1}$, respectively. Additionally, we denote the loop channels between the transmit and receive antenna(s) of user k and the BS by h_{kk} and $\mathbf{H}_{\rm B}$, respectively. Let us define $\mathcal{K} = \{1, \cdots, K\}$. Denoting the set of receive beamformers at the BS by $\mathcal{U}_{\rm U} = \{\mathbf{u}_{{\rm U},k}, \forall k \in \mathcal{K}\}$, in [21] the mean squared error (MSE) of the estimated signal at the BS corresponding to user k was derived as

$$\begin{aligned} e_{{\rm U},k} = &\sum_{m=1}^{K} P_m \mathbf{u}_{{\rm U},k}^{\rm H} \mathbf{G}_{\rm r}^{\rm H} \boldsymbol{\Phi} \mathbf{h}_{{\rm t},m} \mathbf{h}_{{\rm t}.m}^{\rm H} \boldsymbol{\Phi}^{\rm H} \mathbf{G}_{\rm r} \mathbf{u}_{{\rm U},k} \\ &- 2\mathrm{Re} \left\{ \sqrt{P_k} \mathbf{u}_{{\rm U},k}^{\rm H} \mathbf{G}_{\rm r}^{\rm H} \boldsymbol{\Phi} \mathbf{h}_{{\rm t},k} \right\} + \sigma_{\rm U}^2 \mathbf{u}_{{\rm U},k}^{\rm H} \mathbf{u}_{{\rm U},k} + 1, \end{aligned} \quad (2)$$

where $\sigma_{\rm U}^2$ denotes the the average power of the total noise resulting from the interference cancellation at the BS. Similarly, defining the LI coefficient $\rho_{\rm L}$ and the self-interference (SI) coefficient $\rho_{\rm S}$ with $0 \leq \rho_{\rm L}, \rho_{\rm S} \leq 1$ to respectively model the residual LI and SI components of the interference elimination methods applied by the users, the MSE of the estimated signal at user k can be derived as

$$\begin{aligned} e_{{\rm D},k} = &\sum_{m=1}^{K} u_{{\rm D},k}^* u_{{\rm D},k} \mathbf{h}_{{\rm r},k}^{\rm H} \boldsymbol{\Phi} \mathbf{G}_{\rm t} \mathbf{f}_m \mathbf{f}_m^{\rm H} \mathbf{G}_{\rm t}^{\rm H} \boldsymbol{\Phi}^{\rm H} \mathbf{h}_{{\rm r},k} \\ &+ \sum_{m=1}^{K} \rho P_m u_{{\rm D},k}^* u_{{\rm D},k} \mathbf{h}_{{\rm r},k}^{\rm H} \boldsymbol{\Phi} \mathbf{h}_{{\rm t},m} \mathbf{h}_{{\rm t},m}^{\rm H} \boldsymbol{\Phi}^{\rm H} \mathbf{h}_{{\rm r},k} \\ &- 2\mathrm{Re} \left\{ u_{{\rm D},k}^* \mathbf{h}_{{\rm r},k}^{\rm H} \boldsymbol{\Phi} \mathbf{G}_{\rm t} \mathbf{f}_k \right\} + \sigma_{{\rm D},k}^2 u_{{\rm D},k}^* u_{{\rm D},k} + 1, \end{aligned} \quad (3)$$

where coefficient ρ is equal to 1 except when $m \neq k$, in which case it is equal to $\rho_{\rm S}$, and $\sigma_{{\rm D},k}^2$ represents the average sum power of the residual LI and additive white Gaussian noise (AWGN) at user k.

2.2. Problem Formulation

We introduce two sets of auxiliary variables: $\mathcal{W}_{\rm D} = \{w_{{\rm D},k} \geq 0, \forall k \in \mathcal{K}\}$ and $\mathcal{W}_{\rm U} = \{w_{{\rm U},k} \geq 0, \forall k \in \mathcal{K}\}$. Using the equivalence between the achievable rates and the mean-square error, tractable lower bounds for the maximum downlink and uplink achievable rates (nat/s/Hz) of user k can be derived as follows [21]

$$r_{{\rm D},k} (\mathbf{F}, \boldsymbol{\phi}, \mathcal{U}_{\rm D}, \mathcal{W}_{\rm D}) = \log |w_{{\rm D},k}| - w_{{\rm D},k} e_{{\rm D},k} + 1, \quad (4)$$

$$r_{{\rm U},k} (\boldsymbol{\phi}, \mathcal{U}_{\rm U}, \mathcal{W}_{\rm U}) = \log |w_{{\rm U},k}| - w_{{\rm U},k} e_{{\rm U},k} + 1. \quad (5)$$

For a given reflection coefficient vector $\boldsymbol{\phi}$, $r_{{\rm D},k}$ and $r_{{\rm U},k}$ are concave functions for each set of variables when the others are fixed.

To guarantee fairness among the users, we propose to maximize the weighted minimum rate (WMR) of all users by jointly optimizing the precoding matrix of the BS and the reflection coefficients of the IRS, subject to maximum transmit power and unit modulus constraints. Denoting $\mathcal{L} = \{\rm D, U\}$, we introduce a weighting factor $\omega_{l,k} \geq 1$ for $\forall l, k$ to represent the inverse of the priority of the corresponding user. Then, the WMR maximization problem can be formulated as

$$\max_{\substack{\mathcal{U}_l, \mathcal{W}_l, l \in \mathcal{L} \\ \mathbf{F}, \boldsymbol{\phi}}} \quad \min_{l \in \mathcal{L}, k \in \mathcal{K}} \{\omega_{l,k} r_{l,k}\} \quad (6a)$$

$$\text{s.t.} \quad \mathbf{F} \in \mathcal{S}_F, \quad (6b)$$

$$\boldsymbol{\phi} \in \mathcal{S}_{\boldsymbol{\phi}}, \quad (6c)$$

where the set $\mathcal{S}_F$ is defined in (1), and the set $\mathcal{S}_{\boldsymbol{\phi}}$ defined as $\mathcal{S}_{\boldsymbol{\phi}} = \{\boldsymbol{\phi} | |\phi_m| = 1, 1 \leq m \leq M\}$ imposes the unit-modulus constraint on $\boldsymbol{\phi}$. This problem is non-convex due to constraint (6c). In the following, an efficient algorithm is provided to solve this problem.

3. LOW-COMPLEXITY ALGORITHM

In this section, we derive an MM-based alternating optimization algorithm for efficiently solving the formulated problem (6).

3.1. Outer Iteration

From the lower bounds (4) and (5), although additional variables are introduced, we see that the variables in Problem (6) are not coupled. This motivates us to adopt an alternating optimization approach, where the variables $\mathcal{U}_{\rm D}$, $\mathcal{U}_{\rm U}$, $\mathcal{W}_{\rm D}$, $\mathcal{W}_{\rm U}$, $\mathbf{F}$ and $\boldsymbol{\phi}$ are alternately updated to maximize the WMR of all users.

We first introduce the following theorem proposed in [21].

Theorem 1 *For given $\mathbf{F}$, $\boldsymbol{\phi}$, $\mathcal{W}_{\rm D}$ and $\mathcal{W}_{\rm U}$, the optimal $\mathcal{U}_{\rm D}$ and $\mathcal{U}_{\rm U}$ are respectively given by*

$$\begin{aligned} u_{{\rm D},k}^{\rm opt} = \mathbf{h}_{{\rm r},k}^{\rm H} \boldsymbol{\Phi} \mathbf{G}_{\rm t} \mathbf{f}_k \Bigg(&\sum_{m=1}^{K} \mathbf{h}_{{\rm r},k}^{\rm H} \boldsymbol{\Phi} \mathbf{G}_{\rm t} \mathbf{f}_m \mathbf{f}_m^{\rm H} \mathbf{G}_{\rm t}^{\rm H} \boldsymbol{\Phi}^{\rm H} \mathbf{h}_{{\rm r},k} \\ &+ \sum_{m=1}^{K} \rho P_m \mathbf{h}_{{\rm r},k}^{\rm H} \boldsymbol{\Phi} \mathbf{h}_{{\rm t},m} \mathbf{h}_{{\rm t},m}^{\rm H} \boldsymbol{\Phi}^{\rm H} \mathbf{h}_{{\rm r},k} + \sigma_{{\rm D},k}^2 \Bigg)^{-1}, \end{aligned} \quad (7)$$

$$\mathbf{u}_{{\rm U},k}^{\rm opt} = \frac{\sqrt{P_k} \mathbf{G}_{\rm r}^{\rm H} \boldsymbol{\Phi} \mathbf{h}_{{\rm t},k}}{\sum_{m=1}^{K} P_m \mathbf{G}_{\rm r}^{\rm H} \boldsymbol{\Phi} \mathbf{h}_{{\rm t},m} \mathbf{h}_{{\rm t},m}^{\rm H} \boldsymbol{\Phi}^{\rm H} \mathbf{G}_{\rm r} + \sigma_{\rm U}^2 \mathbf{I}_{N_{\rm r}}}, \ \forall k. \quad (8)$$

And for given $\mathbf{F}$, $\boldsymbol{\phi}$, $\mathcal{U}_{\rm D}$ and $\mathcal{U}_{\rm U}$, the optimal $\mathcal{W}_{\rm D}$ and $\mathcal{W}_{\rm U}$ are respectively given by

$$w_{{\rm D},k}^{\rm opt} = e_{{\rm D},k}^{-1}, \quad w_{{\rm U},k}^{\rm opt} = e_{{\rm U},k}^{-1}, \quad \forall k. \quad (9)$$

Theorem 1 provides closed-form solutions for $\mathcal{U}_{\rm D}$, $\mathcal{U}_{\rm U}$, $\mathcal{W}_{\rm D}$ and $\mathcal{W}_{\rm U}$, and our main task is thus translated into optimizing the precoding matrix $\mathbf{F}$ and the reflection coefficient vector $\boldsymbol{\phi}$. Note that the precoding matrix $\mathbf{F}$ is not related to the rate of the uplink transmission $r_{{\rm U},k}$, so by defining $h_{{\rm D},k}(\mathbf{F}) = \omega_{{\rm D},k} r_{{\rm D},k}(\mathbf{F})$ for $\forall l, k$, the subproblem corresponding to $\mathbf{F}$ can be formulated as

$$\max_{\mathbf{F}} \quad \delta_{{\rm D},k}(\mathbf{F}) = \min_{k \in \mathcal{K}} \{h_{{\rm D},k}(\mathbf{F})\} \quad (10a)$$

$$\text{s.t.} \quad \mathbf{F} \in \mathcal{S}_F. \quad (10b)$$

It can be derived that $h_{\mathrm{D},k}(\mathbf{F})$ has a quadratic form as follows

$$h_{\mathrm{D},k}(\mathbf{F}) = 2\mathrm{Re}\left\{\mathrm{Tr}\left(\mathbf{C}_k^{\mathrm{H}}\mathbf{F}\right)\right\} - \mathrm{Tr}\left(\mathbf{F}^{\mathrm{H}}\mathbf{B}_k\mathbf{F}\right) + \mathrm{const}_k. \quad (11)$$

where the definitions of $\mathbf{B}_k$, $\mathbf{C}_k$ and const_k are given in [21, III-B]. Similarly, with the following definition

$$\begin{aligned} h_{l,k}(\boldsymbol{\phi}) &\triangleq \omega_{l,k} r_{l,k}(\boldsymbol{\phi}) \\ &= 2\mathrm{Re}\left\{\mathbf{a}_{l,k}^{\mathrm{H}}\boldsymbol{\phi}\right\} - \boldsymbol{\phi}^{\mathrm{H}}\mathbf{A}_{l,k}\boldsymbol{\phi} + \mathrm{const}_{l,k},\ \forall l,k, \quad (12) \end{aligned}$$

the subproblem for the optimization of $\boldsymbol{\phi}$ can be formulated as

$$\max_{\boldsymbol{\phi}} \quad \delta_{l,k}(\boldsymbol{\phi}) = \min_{l\in\mathcal{L},k\in\mathcal{K}} \{h_{l,k}(\boldsymbol{\phi})\} \quad (13a)$$

$$\text{s.t.} \quad \boldsymbol{\phi} \in \mathcal{S}_{\phi}. \quad (13b)$$

where the definitions of $\mathbf{a}_{l,k}$, $\mathbf{A}_{l,k}$ and $\mathrm{const}_{l,k}$ are given in [21, III-C].

3.2. Inner Iteration

As shown in 3.1, there are two complex subproblems (10) and (13) to solve in the outer iteration. In this subsection, we propose a modified MM algorithm to efficiently solve these two problems.

First, we introduce the following differentiable smooth approximation for the objective functions $\delta_{\mathrm{D},k}(\mathbf{F})$ and $\delta_{l,k}(\boldsymbol{\phi})$ [22]:

$$\delta_{\mathrm{D},k}(\mathbf{F}) \approx f(\mathbf{F}) = -\frac{1}{\mu}\log\left(\sum_{k\in\mathcal{K}}\exp\{-\mu h_{\mathrm{D},k}(\mathbf{F})\}\right), \quad (14)$$

$$\delta_{l,k}(\boldsymbol{\phi}) \approx f(\boldsymbol{\phi}) = -\frac{1}{\mu}\log\left(\sum_{l\in\mathcal{L}}\sum_{k\in\mathcal{K}}\exp\{-\mu h_{l,k}(\boldsymbol{\phi})\}\right), \quad (15)$$

where $\mu > 0$ is a smoothing parameter. For $\mu > 0$, the following inequalities hold:

$$f(\mathbf{F}) \le \delta_{\mathrm{D},k}(\mathbf{F}) \le f(\mathbf{F}) + \frac{1}{\mu}\log(K), \quad (16)$$

$$f(\boldsymbol{\phi}) \le \delta_{l,k}(\boldsymbol{\phi}) \le f(\boldsymbol{\phi}) + \frac{1}{\mu}\log(2K). \quad (17)$$

The function $-\frac{1}{\mu}\log\left(\sum_{x\in\mathcal{X}}\exp\{-\mu x\}\right)$ has been proved in [14] to be increasing and concave with respect to (w.r.t.) x. Note that quadratic functions $h_{\mathrm{D},k}(\mathbf{F})$ and $h_{l,k}(\boldsymbol{\phi})$ are concave w.r.t. $\mathbf{F}$ and $\boldsymbol{\phi}$, respectively, so $f(\mathbf{F})$ and $f(\boldsymbol{\phi})$ are concave functions w.r.t. $\mathbf{F}$ and $\boldsymbol{\phi}$, respectively. It should be noted that an appropriate strategy for initializing and adjusting μ should be chosen. On the one hand, in the early stage of the outer iteration, a large μ may trap $\mathbf{F}$ and $\boldsymbol{\phi}$ in a local stationary point far from the optimal solutions of Problem (10) and (13). On the other hand, in order to ensure that the algorithm converges to a globally optimal solution, a large μ is required to improve the approximation accuracy in the later stage.

The MM algorithm [23, 24] is widely used for resource allocation in wireless communication networks [11, 14, 15]. Specifically, instead of the original subproblems (10) and (13), we iteratively solve two series of more tractable surrogate problems whose OFs *minorize* the original ones. Denote the optimal solutions of the surrogate problems at the nth iteration by $\mathbf{F}^n$ and $\boldsymbol{\phi}^n$. The resulting sequences of $\mathbf{F}^n$ and $\boldsymbol{\phi}^n$ are guaranteed to respectively converge to the Karush-Kuhn-Tucker (KKT) point of Problem (10) and (13) [14], and the sequences of OF values $\left\{f\left(\mathbf{F}^1\right), f\left(\mathbf{F}^2\right), \dots\right\}$ and $\left\{f\left(\boldsymbol{\phi}^1\right), f\left(\boldsymbol{\phi}^2\right), \dots\right\}$ must be monotonically non-decreasing.

To obtain the surrogate problems, we introduce the following theorems [21]:

Theorem 2 *For any feasible* $\mathbf{F}$, $f(\mathbf{F})$ *is minorized with a quadratic function at solution* $\mathbf{F}^n$ *as follows*

$$\tilde{f}(\mathbf{F}|\mathbf{F}^n) = 2\mathrm{Re}\left\{\mathrm{Tr}\left[\mathbf{V}^{\mathrm{H}}\mathbf{F}\right]\right\} + \alpha\mathrm{Tr}\left[\mathbf{F}^{\mathrm{H}}\mathbf{F}\right] + \mathrm{cons}F. \quad (18)$$

In (18), $\mathbf{V}$ *and* $\mathrm{cons}F$ *are respectively defined as*

$$\begin{aligned} \mathbf{V} &= \sum_{k\in\mathcal{K}} g_{\mathrm{D},k}(\mathbf{F}^n)\left(\mathbf{C}_k - \mathbf{B}_k^{\mathrm{H}}\mathbf{F}^n\right) - \alpha\mathbf{F}^n, \\ \mathrm{cons}F &= f(\mathbf{F}^n) + \alpha\mathrm{Tr}\left[(\mathbf{F}^n)^{\mathrm{H}}\mathbf{F}^n\right] \\ &\quad - 2\mathrm{Re}\left\{\mathrm{Tr}\left[\sum_{k\in\mathcal{K}} g_{\mathrm{D},k}(\mathbf{F}^n)\left(\mathbf{C}_k^{\mathrm{H}} - (\mathbf{F}^n)^{\mathrm{H}}\mathbf{B}_k\right)\mathbf{F}^n\right]\right\}. \end{aligned}$$

Refer to [21, Theroem 1] for the more details of this theorem.

Theorem 3 *For any feasible* $\boldsymbol{\phi}$, $f(\boldsymbol{\phi})$ *is minorized at solution* $\boldsymbol{\phi}^n$ *with the following function:*

$$\tilde{f}(\boldsymbol{\phi}|\boldsymbol{\phi}^n) = 2\mathrm{Re}\left\{\mathbf{v}^{\mathrm{H}}\boldsymbol{\phi}\right\} + \mathrm{cons}\phi. \quad (19)$$

In (19), $\mathbf{v}$ *and* $\mathrm{cons}\phi$ *are respectively defined as*

$$\begin{aligned} \mathbf{v} &= \mathbf{d} - \beta\boldsymbol{\phi}^n, \\ \mathrm{cons}\phi &= f(\boldsymbol{\phi}^n) + 2M\beta - 2\mathrm{Re}\left\{\mathbf{d}^{\mathrm{H}}\boldsymbol{\phi}^n\right\}. \end{aligned}$$

Refer to [21, Theroem 2] for more details.

Then, we can formulate the surrogate problem corresponding to $\mathbf{F}$ at each inner iteration by replacing the OF of Problem (10) with (18), as follows

$$\max_{\mathbf{F}} \quad 2\mathrm{Re}\left\{\mathrm{Tr}\left[\mathbf{V}^{\mathrm{H}}\mathbf{F}\right]\right\} + \alpha\mathrm{Tr}\left[\mathbf{F}^{\mathrm{H}}\mathbf{F}\right] + \mathrm{cons}F \quad (21a)$$

$$\text{s.t.} \quad \mathbf{F} \in \mathcal{S}_F. \quad (21b)$$

Introduce the Lagrangian multiplier ζ and construct the following Lagrangian function

$$\begin{aligned} \mathcal{L}(\mathbf{F},\zeta) &= 2\mathrm{Re}\left\{\mathrm{Tr}\left[\mathbf{V}^{\mathrm{H}}\mathbf{F}\right]\right\} + \alpha\mathrm{Tr}\left[\mathbf{F}^{\mathrm{H}}\mathbf{F}\right] + \mathrm{cons}F \\ &\quad - \zeta\left(\mathrm{Tr}\left[\mathbf{F}^{\mathrm{H}}\mathbf{F}\right] - P_{\max}\right). \quad (22) \end{aligned}$$

By setting the first-order derivative of $\mathcal{L}(\mathbf{F},\zeta)$ w.r.t. $\mathbf{F}$ to zero, and considering the power constraint $\mathrm{Tr}\left[\mathbf{F}^{\mathrm{H}}\mathbf{F}\right] \le P_{\max}$, the optimal solution for $\mathbf{F}$ at each inner iteration can be derived as

$$\mathbf{F}^{\mathrm{opt}} = \begin{cases} -\mathbf{V}/\alpha, & \text{if } \frac{\mathrm{Tr}\left[\mathbf{V}^{\mathrm{H}}\mathbf{V}\right]}{\alpha^2} \le P_{\max}; \\ -\sqrt{\frac{P_{\max}}{\mathrm{Tr}\left[\mathbf{V}^{\mathrm{H}}\mathbf{V}\right]}}\mathbf{V}, & \text{otherwise.} \end{cases} \quad (23)$$

By replacing the OF of Problem (13) with (19), the surrogate problem corresponding to $\boldsymbol{\phi}$ at each iteration is formulated as

$$\max_{\boldsymbol{\phi}} \quad 2\mathrm{Re}\left\{\mathbf{v}^{\mathrm{H}}\boldsymbol{\phi}\right\} + \mathrm{cons}\phi \quad (24a)$$

$$\text{s.t.} \quad \boldsymbol{\phi} \in \mathcal{S}_{\phi}. \quad (24b)$$

It is readily derived that the optimal solution of $\boldsymbol{\phi}$ at each inner iteration is given by

$$\boldsymbol{\phi}^{\mathrm{opt}} = \exp\{j\angle\mathbf{v}\}, \quad (25)$$

where $\angle(\cdot)$ and $\exp\{\cdot\}$ are element-wise operations.

Algorithm 1 MM-based alternating optimization algorithm

1: Initialize iteration number $n = 1$ and feasible $\mathbf{F}^1$ and $\boldsymbol{\phi}^1$. Calculate $\text{Obj}\left(\mathbf{F}^1, \boldsymbol{\phi}^1\right)$. Set μ, ι, maximum number of iterations $n_{\max}$ and error tolerance ε_{e};
2: Given $\mathbf{F}^n$ and $\boldsymbol{\phi}^n$, calculate $\mathcal{U}_{\text{D}}^{n+1}$ and $\mathcal{U}_{\text{U}}^{n+1}$ following (7) and (8);
3: Given $\mathbf{F}^n$, $\boldsymbol{\phi}^n$, $\mathcal{U}_{\text{D}}^{n+1}$ and $\mathcal{U}_{\text{U}}^{n+1}$, calculate $\mathcal{W}_{\text{D}}^{n+1}$ and $\mathcal{W}_{\text{U}}^{n+1}$ following (9);
4: Calculate $\mathbf{F}_1 = \mathfrak{M}_F\left(\mathbf{F}^n\right)$ and $\mathbf{F}_2 = \mathfrak{M}_F\left(\mathbf{F}_1\right)$;
5: Calculate $\mathbf{Q}_1 = \mathbf{F}_1 - \mathbf{F}^n$ and $\mathbf{Q}_2 = \mathbf{F}_2 - \mathbf{F}_1 - \mathbf{Q}_1$;
6: Calculate step factor $\varpi = -\frac{\|\mathbf{Q}_1\|_F}{\|\mathbf{Q}_2\|_F}$;
7: Calculate $\mathbf{F}^{n+1} = \mathbf{F}^n - 2\varpi\mathbf{Q}_1 + \varpi^2\mathbf{Q}_2$.
8: If $\mathbf{F}^{n+1} \notin \mathcal{S}_F$, scale $\mathbf{F}^{n+1} \leftarrow \frac{\sqrt{P_{\max}}}{\|\mathbf{F}^{n+1}\|}\mathbf{F}^{n+1}$;
9: If $\text{Obj}\left(\mathbf{F}^{n+1}, \boldsymbol{\phi}^n\right) < \text{Obj}\left(\mathbf{F}^n, \boldsymbol{\phi}^n\right)$, set $\varpi \leftarrow (\varpi - 1)/2$ and go to step 8;
10: Calculate $\boldsymbol{\phi}_1 = \mathfrak{M}_\phi\left(\boldsymbol{\phi}^n\right)$ and $\boldsymbol{\phi}_2 = \mathfrak{M}_\phi\left(\boldsymbol{\phi}_1\right)$;
11: Calculate $\mathbf{q}_1 = \boldsymbol{\phi}_1 - \boldsymbol{\phi}^n$ and $\mathbf{q}_2 = \boldsymbol{\phi}_2 - \boldsymbol{\phi}_1 - \mathbf{q}_1$;
12: Calculate step factor $\varpi = -\frac{\|\mathbf{q}_1\|_F}{\|\mathbf{q}_2\|_F}$;
13: Calculate $\boldsymbol{\phi}^{n+1} = \exp\left\{\angle\left(\boldsymbol{\phi}^n - 2\varpi\mathbf{q}_1 + \varpi^2\mathbf{q}_2\right)\right\}$;
14: If $\text{Obj}\left(\mathbf{F}^{n+1}, \boldsymbol{\phi}^{n+1}\right) < \text{Obj}\left(\mathbf{F}^{n+1}, \boldsymbol{\phi}^n\right)$, set $\varpi \leftarrow (\varpi - 1)/2$ and go to step 13;
15: Set $\mu \leftarrow \mu^\iota$;
16: If $\left|\text{Obj}\left(\mathbf{F}^{n+1}, \boldsymbol{\phi}^{n+1}\right) - \text{Obj}\left(\mathbf{F}^n, \boldsymbol{\phi}^n\right)\right| / \text{Obj}\left(\mathbf{F}^n, \boldsymbol{\phi}^n\right) < \varepsilon_{\text{e}}$ or $n \geq n_{\max}$, terminate. Otherwise, set $n \leftarrow n + 1$ and go to step 2.

3.3. Algorithm Development

Note that the convergence speed of the proposed MM algorithm is limited by the tightness of the smooth approximation $f\left(\mathbf{F}\right)$ and $f\left(\boldsymbol{\phi}\right)$ as well as the minorizing functions $\tilde{f}\left(\mathbf{F}|\mathbf{F}^n\right)$ and $\tilde{f}\left(\boldsymbol{\phi}|\boldsymbol{\phi}^n\right)$. To address this issue, we introduce SQUAREM [25] theory to accelerate the convergence of the proposed MM algorithm. Finally, our proposed MM-based alternating optimization algorithm is summarized in Algorithm 1, where the OF of Problem (6) evaluated at $\mathbf{F}^n$ and $\boldsymbol{\phi}^n$ is denoted as $\text{Obj}\left(\mathbf{F}^n, \boldsymbol{\phi}^n\right)$, and the MM-update strategy of $\mathbf{F}$ given in (23) and that of $\boldsymbol{\phi}$ given in (25) are denoted as the nonlinear fixed-point iteration maps $\mathfrak{M}_F\left(\cdot\right)$ and $\mathfrak{M}_\phi\left(\cdot\right)$, respectively. As shown in step 15, we define an adjustment factor ι to gradually increase μ.

The MM method yields monotonically non-decreasing values for (14) and (15), and both steps 9 and 14 in Algorithm 1 ensure that the value of the OF in Problem (6) is non-decreasing. Additionally, the value of the OF must have an upper bound, due to the limitations on the maximum transmit power $P_{\max}$ and the number of reflection elements M. Hence, Algorithm 1 is guaranteed to converge. The overall complexity of Algorithm 1 is of order $\mathcal{O}(K^2N_{\text{t}}M + K^2N_{\text{r}}M + K^2N_{\text{t}}^2 + K^3N_{\text{t}} + KM^3 + KN_{\text{t}}M^2 + K^2M^2)$ [21].

4. SIMULATION RESULTS

In our simulation, we consider a system with $K = 3$ users, whose plane coordinates are uniformly and randomly generated in a rectangular region centered at $(120\text{ m}, 0)$ with length 40 m and width 20 m. The coordinates of the BS and the IRS are assumed to be $(0, 0)$ and $(10\text{ m}, 20\text{ m})$, respectively. The height of the BS, the IRS, and the users are 30 m, 10 m, and 1.5 m, respectively. The path loss is taken to be -30 dB at a reference distance of 1 m, and we set the path loss exponents of all the reflection links as $\alpha_{\text{IRS}} = 2.2$ [15]. The small-scale fading is assumed to be Rician distributed with Rician factor 3. The other parameters are set as follows: Channel bandwidth 10 MHz, noise power density -174 dBm/Hz, SI coefficient $\rho_{\text{S}} = 1$, weighting factors $\omega_{l,k} = 1, \forall l, k$, user transmit power $P_k = 50$ mW, $\forall k$,

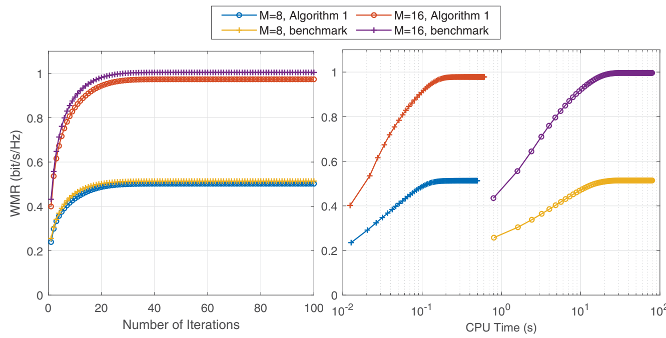

Fig. 2. Convergence behaviour of proposed Algorithm 1 versus the number of iterations and CPU time for $M = [8, 16]$.

number of BS antennas $N_{\text{t}} = N_{\text{r}} = 4$, maximum BS transmit power $P_{\max} = 1$ W, initial smoothing parameter $\mu = 3$, adjustment factor $\iota = 1.05$, error tolerance $\varepsilon_{\text{e}} = 10^{-6}$. All experiments are performed on a PC with a 2.59 GHz i7-9750H CPU and 16 GB RAM.

Note that Problem (10) is a second-order cone programming problem, which can be optimally solved by existing optimization solvers. To verify the efficiency of our proposed Algorithm 1, we introduce a benchmark algorithm in which the MOSEK solver [26] replaces the MM algorithm to solve Problem (10).

Fig. 2 plots the WMR versus the number of iterations and the CPU time when the number of reflection elements is $M = 8$ and 16, demonstrating the convergence behaviour of Algorithm 1 and the benchmark algorithm. We see that both algorithms converge within 40 iterations, which confirms the high efficiency of the outer iteration of the proposed algorithm. Thanks to MOSEK's high precision in solving the SOCP, the converged WMR of the benchmark algorithm is slightly higher. However, due to its advantage in computational complexity, Algorithm 1 converges much faster in terms of CPU time. Additionally, it is interesting to observe that even when the number of reflection coefficients doubles, the convergence speed in terms of both number of iterations and CPU time does not significantly increase. This indicates that our proposed algorithm will maintain good convergence performance and relatively low complexity even for the case of large M. The simulation results show an achievable WMR of about 0.5 bit/s/Hz when $M = 8$ and 1 bit/s/Hz when $M = 16$, confirming the feasibility of using an IRS to realize FD cellular communication. Given the much lower power consumption of passive reflection, the IRS shows great potential as an alternative to FD relays in this application.

5. CONCLUSIONS

In this paper, we have proposed a multiuser FD cellular network based on an IRS. Specifically, with appropriately adjusted phase shifts, the IRS can create effective reflective paths between the BS and the users, while simultaneously mitigating the interference at the users. To ensure network fairness, we investigated the WMR maximization problem, where the BS precoding matrix and the IRS reflection coefficients were jointly optimized subject to maximum transmit power and unit-modulus constraints. An efficient MM algorithm with closed-form solutions in each iteration was proposed to solve the subproblems corresponding to these two variables. Our simulation results showed that the proposed algorithm has a very good convergence speed in terms of both the number of iterations and CPU time, and achieves high communication performance indicating the energy consumption advantage of IRS in FD cellular communication.

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