Downlink Scheduling with Transmission Strategy Selection for Multi-Cell MIMO Systems

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***Abstract*—In this paper, we study downlink scheduling with transmission strategy selection in multi-cell multiple-input multiple-output (MIMO) systems. Depending on the level of inter-cell interference experienced by a user, the scheduler can choose between two MIMO transmission strategies, namely, spatial multiplexing and interference alignment. We formulate an optimization problem which aims to jointly select a user and the corresponding transmission strategy for each base station in order to maximize the overall system utility while stabilizing all transmission queues. We first develop a centralized dynamic scheduling scheme with transmission strategy selection by using a stochastic network optimization approach. To reduce the communication overhead, we then propose a distributed scheduling algorithm which only requires limited message exchange between the base stations. We also consider the impact of imperfect channel state information on the scheduling schemes and propose an efficient rate adjustment method to improve the performance for this case. Simulation results show that the performance of the proposed distributed scheduling scheme is close to that of the centralized scheduling scheme, and both schemes achieve a better performance than schemes employing a single transmission strategy.**

***Index Terms*—Scheduling, spatial multiplexing, interference alignment, stochastic network optimization.**

I. Introduction

NEXT generation wireless communication systems, such as the 3rd Generation Partnership Project (3GPP) Long Term Evolution Advanced (LTE-Advanced) system [2], aim to provide high speed data services with limited radio resources. Multi-cell processing combined with multiple-input multiple-output (MIMO) transmission has been proposed as a promising solution to improve spectral efficiency and system throughput [3]. The conventional spatial multiplexing MIMO transmission strategy can achieve high data rates by transmitting multiple data streams simultaneously [4]. However, in multi-cell systems where the same carrier frequency is reused by several adjacent cells, the performance of spatial multiplexing is limited due to inter-cell interference [5]. Specifically, the performance degradation for the cell-edge users who experience significant inter-cell interference is severe, which may limit the overall system performance.

Recently, interference alignment has emerged as an effective technique to suppress inter-cell interference in multi-cell MIMO systems [6]. The main idea is that base stations jointly design precoding and decoding matrices based on the channel state information (CSI) of all individual links such that the signals transmitted from interfering base stations are aligned onto the same spatial dimension at each user so that the desired signal can be separated and successfully decoded. In the literature, several interference alignment strategies have been proposed for multi-cell MIMO systems [7]–[9], and progress has been made in designing efficient interference alignment algorithms [10], [11]. With interference alignment, multiple concurrent interference-free transmissions are achievable and the performance of cell-edge users can be improved. However, since an additional spatial dimension is sacrificed for accommodating interference rather than transmitting user data, interference alignment may be outperformed by spatial multiplexing when the inter-cell interference is insignificant. Therefore, in a multi-cell system with users who experience various levels of inter-cell interference, the performance can be improved by allowing the base stations to choose between different MIMO transmission strategies.

In addition to choosing the transmission strategy, scheduling plays an important role in improving the system performance [12], [13]. For time slotted systems, where the time frame is divided into slots, in each time slot, the downlink scheduling scheme selects a set of users to be served with the objective to optimize certain performance metrics such as stability, throughput, and fairness [14]–[16]. In the literature, several scheduling schemes have been proposed for MIMO systems under different queueing models, such as the infinitely backlogged model. The scheduling objective is to maximize the throughput or a utility function which reflects a certain fairness criterion [17], [18]. However, most existing scheduling schemes are designed for a single-cell scenario where inter-cell interference is not considered. The scheme in [19] considers scheduling in the presence of inter-cell interference, but only studies a non-cooperative scenario where base stations schedule their transmissions independently without any interference mitigation technique. Joint scheduling, power allocation, and precoder design has been studied for multi-cell systems in [20]. However, the scheme proposed in [20] considers only spatial multiplexing transmission for the infinitely backlogged model.

In our previous work [1], we proposed to use two MIMO

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transmission strategies, spatial multiplexing and interference alignment, to optimize the system performance, and designed a centralized scheduling scheme based on a two-cell infinitely backlogged queueing model. In this paper, we consider a multi-cell system where each base station maintains a finite data buffer and users experience different levels of inter-cell interference. We first focus on the design and analysis of scheduling schemes with perfect CSI at the base stations, and then describe their extension to the realistic scenario of imperfect CSI. The major contributions of this work are summarized as follows.

- We formulate a discrete-time stochastic optimization problem which aims to jointly select a user and the corresponding transmission strategy for each base station in order to maximize the overall system utility while stabilizing all data queues. Based on a stochastic optimization approach, we develop a centralized dynamic scheduling scheme with transmission strategy selection for multi-cell MIMO systems.
- To reduce the communication overhead, we propose a distributed scheduling scheme which only requires limited message exchange among the base stations. In this scheme, each base station first determines the optimal scheduling decisions for a fixed transmission strategy. Then, to arrive at the final scheduling decisions, the base stations coordinate with each other by exchanging the value of one variable.
- When the CSI is imperfect at the base stations, the data rate calculated assuming perfect CSI is not accurate and outages may occur during the transmission. To address this issue, we propose a rate adjustment scheme to improve the transmission success probability. We show that this approach improves the performance significantly compared to the case without rate adjustment.
- Simulation results show that the proposed scheduling schemes are superior compared to scheduling schemes with a single transmission strategy. The proposed distributed scheduling scheme achieves a performance that is close to that of the centralized scheduling scheme, and both schemes achieve a better performance than weighted sum-rate maximization scheduling.

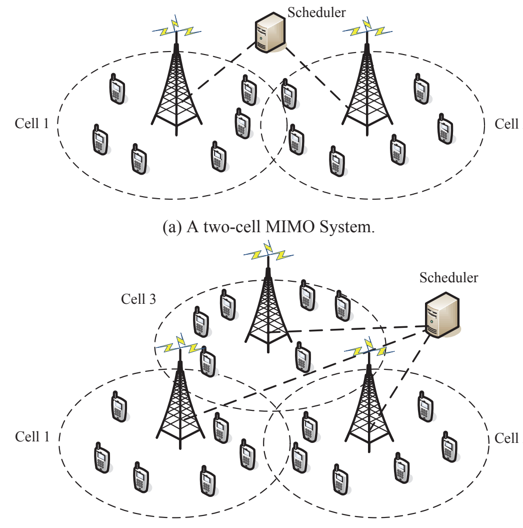
The rest of this paper is organized as follows. In Section II, we describe the system model and formulate the joint scheduling and transmission strategy selection problem. In Section III, we develop the centralized and distributed dynamic scheduling schemes, and discuss the impact of imperfect CSI. Simulation results are presented in Section IV, and conclusions are drawn in Section V.

II. System Model and Problem Formulation

In this section, we first introduce the system model, and then we formulate a dynamic scheduling problem considering transmission strategy selection, system stability, and fairness among users.

A. System Model

We consider the downlink of a MIMO system with $M > 1$ cells (i.e., a cluster of adjacent cells in wireless cellular



(a) A two-cell MIMO System.

(b) A three-cell MIMO System.

Fig. 1. Multi-cell MIMO systems. (a) Two-cell case; (b) Three-cell case. Each cell $i \in \mathcal{I}$ has K_i users.

systems), where the same carrier frequency is used in all cells. Examples of such systems with $M = 2$ and $M = 3$ are shown in Figs. 1 (a) and (b), respectively. In each cell, a base station equipped with N_T transmit antennas is located at the cell center and serves a number of users, each of which is equipped with N_R receive antennas. The base stations are connected with each other (or connected to a central controller) via backhaul links with limited capacity. We assume that the base stations can exchange control messages such as CSI and scheduling decisions but do not share user data. We consider a time slotted system, where each time frame is divided into slots of equal length. Each base station serves at most one user in a time slot. We assume a frequency flat block fading channel model, where the channel gain remains constant during a time slot and is independent and identically distributed (i.i.d.) in different time slots[1]. We denote the set of cells as $\mathcal{I} = \{1, 2, \ldots, M\}$, and the number of users in cell $i \in \mathcal{I}$ as K_i. The set of users in cell i is denoted as $\mathcal{K}_i$. The signal received at user $k \in \mathcal{K}_i$ can be represented as

$$y_{ik} = \sqrt{g_{ik}}\, \mathbf{H}_{ik} x_i + \sum_{j \neq i,\ j \in \mathcal{I}} \sqrt{g_{jk}}\, \mathbf{H}_{jk} x_j + n_{ik}, \quad i \in \mathcal{I}, \quad (1)$$

where x_i is the signal transmitted by the ith base station, $\mathbf{H}_{ik} \in \mathbb{C}^{N_R \times N_T}$ is the channel matrix from the ith base station to user k, whose elements are i.i.d. and follow a complex Gaussian distribution with zero mean and unit variance ($\mathcal{CN}(0,1)$), g_{ik} is the distance-dependent average path gain from the ith base station to user k, and n_{ik} is the additive white Gaussian noise (AWGN) with complex Gaussian distribution $\mathcal{CN}(0,1)$. The first term on the right hand side in (1) represents the desired signal and the second term corresponds to the inter-cell interference.

Similar to some previous works (e.g., [12], [16]), we assume that mobile devices are able to perfectly estimate the desired

[1] This i.i.d. channel model has been widely adopted for performance analysis in the literature [12], [19], [20]. However, the proposed scheduling scheme in this paper can also be extended to non-i.i.d. channel models, which is an interesting topic for future work.

channel and the interference channel, and this perfect CSI is available to the base station via feedback (or estimation via the uplink in time-division duplexing systems) at the beginning of each time slot. The base stations can exchange the CSI to make scheduling decisions. In practice, a mobile device can estimate the CSI of each of its links based on the pilot signal received from the corresponding base stations, i.e., we can use existing approaches such as linear minimum mean square error (LMMSE) estimation [21] with successive interference cancellation (SIC) [22] to estimate the CSI of each link. Since the CSI is obtained via estimation and may be erroneous, we discuss the impact of imperfect CSI in Section III-C.

B. System Stability

We consider the scenario where the data to be transmitted arrive at their associated base station according to a stationary process. The base station maintains a transmission queue for each of its intended users. Let $Q_{ik}[t]$ represent the queue backlog for user k at the ith base station at the beginning of time slot t. We denote the corresponding data arrival rate and service rate for user k during time slot t as $A_{ik}[t]$ and $R_{ik}[t]$, respectively. Then, the system queues evolve according to the following stochastic difference equation

$$\begin{aligned} Q_{ik}[t+1] &= \max\{Q_{ik}[t] - R_{ik}[t], 0\} + A_{ik}[t], \\ & \quad \forall\ k \in \mathcal{K}_i,\ i \in \mathcal{I}. \end{aligned} \tag{2}$$

We define stability of the above queueing system as follows [23, p. 19].

Definition 1: A discrete-time queue Q_{ik} is strongly stable if $\limsup_{t\to\infty} \frac{1}{t}\sum_{\tau=0}^{t-1} \mathbb{E}[Q_{ik}[\tau]] < \infty$. The system is stable if all queues in the system are strongly stable.

The above definition implies that the system is stable when the average backlog of each queue is bounded. It has been shown in [23, p. 19] that to guarantee the stability of the system, the average data arrival rate of each queue should be no larger than the corresponding average service rate. That is, $\overline{A}_{ik} \le \overline{R}_{ik}$, $\forall\ k \in \mathcal{K}_i, i \in \mathcal{I}$, where

$$\overline{A}_{ik} = \lim_{t\to\infty} \frac{1}{t}\sum_{\tau=0}^{t-1} A_{ik}[\tau] \ \text{ and } \ \overline{R}_{ik} = \lim_{t\to\infty} \frac{1}{t}\sum_{\tau=0}^{t-1} R_{ik}[\tau]. \tag{3}$$

System stability is important since the total buffer size of a base station is finite in practice. Therefore, the downlink scheduling scheme should guarantee that all queues in the system are strongly stable.

C. MIMO Transmission Strategies

To achieve high data rates in MIMO systems, we consider two physical layer transmission strategies, namely, spatial multiplexing and interference alignment, which are described below.

i) *Spatial multiplexing*: For a MIMO link without interference, the transmitter can deliver multiple data streams to the receiver using spatial multiplexing [4, p. 334]. For an $N_T \times N_R$ MIMO link from the ith base station to user k, $N = \min\{N_T, N_R\}$ data streams are multiplexed by using a precoding matrix $\mathbf{V}_{ik}$ at the transmitter and are reconstructed with a decoding matrix $\mathbf{U}_{ik}$ at the receiver. The matrices $\mathbf{V}_{ik}$ and $\mathbf{U}_{ik}$ are obtained from the singular value decomposition (SVD) of the channel matrix $\mathbf{H}_{ik}$,

$$\mathbf{H}_{ik} = \mathbf{U}_{ik}^{\mathrm{H}} \mathbf{\Lambda}_{ik} \mathbf{V}_{ik}, \tag{4}$$

where $\mathbf{U}_{ik} \in \mathbb{C}^{N_R\times N_R}$ and $\mathbf{V}_{ik} \in \mathbb{C}^{N_T\times N_T}$ are unitary matrices, $\mathbf{\Lambda}_{ik} \in \mathbb{R}^{N_R\times N_T}$ is a rectangular matrix with non-negative main diagonal elements $\{\lambda_{ik,1}, \ldots, \lambda_{ik,N}\}$ and all other elements equal to zero. By applying the above precoding and decoding matrices, the MIMO link is transformed into several parallel Gaussian channels, which can support multiple data streams. The total power P is distributed among the data streams using waterfilling to maximize the achievable rate (assuming there is no interference). The power allocated to the mth data stream for user k in cell i is $P_{ik,m} = \max\left\{\mu - \frac{1}{\lambda_{ik,m}^2}, 0\right\}$, where μ is chosen to satisfy $\sum_{m=1}^{N} P_{ik,m} = P_T$.

The achievable data rate using spatial multiplexing in the presence of inter-cell interference can be derived for the multi-cell MIMO system. In particular, the data rate for user k in cell i is [8]

$$\begin{aligned} R_{ik}^{\mathrm{SM}} &= \log_2 \det\Bigg(\mathbf{I}_{N_R} + \left(g_{ik}\mathbf{H}_{ik}\mathbf{\Phi}_{SM,i}\mathbf{H}_{ik}^{\mathrm{H}}\right) \\ &\qquad \cdot\Bigg(\mathbf{I}_{N_R} + \sum_{j\ne i} g_{jk}\mathbf{H}_{jk}\mathbf{\Phi}_{SM,j}\mathbf{H}_{jk}^{\mathrm{H}}\Bigg)^{-1}\Bigg), \end{aligned} \tag{5}$$

where $\mathbf{I}_{N_R}$ is the $N_R \times N_R$ identity matrix, $\mathbf{\Phi}_{SM,i} = \mathbf{V}_{ik}\mathbf{Q}_{ik}\mathbf{V}_{ik}^{\mathrm{H}}$ is the covariance matrix of the transmitted signal at the ith base station, and $\mathbf{Q}_{ik}$ is an $N_T \times N_T$ diagonal matrix with allocated power $P_{ik,m}$ ($m \in \{1, \ldots, N\}$) as main diagonal elements.

ii) *Interference alignment*: When users experience significant inter-cell interference, the performance of spatial multiplexing is limited [5]. To combat interference and improve the data rate, interference alignment can be used. It allows interference-free concurrent transmissions at the expense of sacrificing some degrees of freedom. Interference alignment requires cooperation of the base stations to jointly design the transmit and receive matrices such that the interference and the desired signal lie in orthogonal subspaces at the receiver [6]. Specifically, the ith base station may transmit d_i ($d_i \le N-1$) data streams to user k by designing precoding matrix $\widetilde{\mathbf{V}}_{ik}$ and decoding matrix $\widetilde{\mathbf{U}}_{ik}$ such that

$$\widetilde{\mathbf{U}}_{ik}^{\mathrm{H}}\mathbf{H}_{jk}\widetilde{\mathbf{V}}_{jk} = \mathbf{0}, \quad \forall\ j \in \mathcal{I},\ j \ne i, \tag{6}$$

and

$$\mathrm{rank}\left(\widetilde{\mathbf{U}}_{ik}^{\mathrm{H}}\mathbf{H}_{ik}\widetilde{\mathbf{V}}_{ik}\right) = d_i, \tag{7}$$

where $\widetilde{\mathbf{U}}_{ik} \in \mathbb{C}^{N_R\times d_i}$, $\widetilde{\mathbf{V}}_{ik} \in \mathbb{C}^{N_T\times d_i}$ are truncated unitary matrices, and $\mathbf{0}$ is a $d_i \times d_i$ all-zero matrix. If we can find $\widetilde{\mathbf{U}}_{ik}$ and $\widetilde{\mathbf{V}}_{ik}$, $\forall\ i \in \mathcal{I}, k \in \mathcal{K}_i$ that satisfy (6) and (7), then interference can be suppressed at the desired receiver. By employing the interference alignment strategy, the achievable rate for user k in cell i is

$$R_{ik}^{\mathrm{IA}} = \log_2 \det\left(\mathbf{I}_{d_i} + g_{ik}\hat{\mathbf{H}}_{ik}\mathbf{\Phi}_{IA,i}\hat{\mathbf{H}}_{ik}^{\mathrm{H}}\right), \tag{8}$$

where $\hat{\mathbf{H}}_{ik} = \widetilde{\mathbf{U}}_{ik}^{\mathrm{H}} \mathbf{H}_{ik} \widetilde{\mathbf{V}}_{ik}$, and $\mathbf{\Phi}_{IA,i} = (P_T/d_i)\mathbf{I}_{d_i}$ is the covariance matrix of the data symbols to be transmitted (without precoding) at the ith base station (with equal power allocation for all data streams). For example, in a three-cell MIMO system with $N_T = N_R = 2$, we can design 2×1 precoding vectors ($\mathbf{v}_i, i = 1, 2, 3$) and decoding vectors ($\mathbf{u}_i, i = 1, 2, 3$) with $d_i = 1$ such that each base station can transmit one data stream successfully to its intended receiver without any interference. Specifically, we can choose $\mathbf{v}_1$ to be one of the eigenvectors of $\mathbf{H}_{\mathbf{v}_1} = \mathbf{H}_{12}^{-1}\mathbf{H}_{32}\mathbf{H}_{31}^{-1}\mathbf{H}_{21}\mathbf{H}_{23}^{-1}\mathbf{H}_{13}$, and choose $\mathbf{v}_2 = \mathbf{H}_{23}^{-1}\mathbf{H}_{13}\mathbf{v}_1$ and $\mathbf{v}_3 = \mathbf{H}_{31}^{-1}\mathbf{H}_{21}\mathbf{H}_{23}^{-1}\mathbf{H}_{13}\mathbf{v}_1$. It can be shown that these precoding vectors satisfy $\mathbf{H}_{13}\mathbf{v}_1 = \mathbf{H}_{23}\mathbf{v}_2$, $\mathbf{H}_{31}\mathbf{v}_3 = \mathbf{H}_{21}\mathbf{v}_2$, and $\mathbf{H}_{12}\mathbf{v}_1 = \mathbf{H}_{32}\mathbf{v}_3$, which implies that the interference at each receiver can be aligned in the same subspace and the desired signal can be successfully decoded by choosing a decoding vector orthogonal to that subspace. A more detailed explanation of this design can be found in [10]. Note that in this paper, we do not consider optimization of the power allocation for interference alignment. To simplify the analysis, we assume equal power allocation for all data streams. This assumption has also been widely used in other works (e.g. [7], [8]).

Although interference alignment can suppress the inter-cell interference, the signal power that lies in the interference subspace is lost. When the interference is not significant, spatial multiplexing may achieve a better performance [1]. Therefore, for a system with users who experience different levels of inter-cell interference, a proper transmission strategy selection is desirable for each user when scheduling the transmission.

D. Problem Formulation

In the above system, the downlink scheduling problem is to maximize a utility function by selecting in each cell a user to be served and a corresponding MIMO transmission strategy. The utility function is usually chosen as a concave, non-decreasing function of the service rates and should reflect a certain fairness criterion. In this paper, we consider the proportional fair utility [24], which is a function of the long term average service rates ($\overline{R}_{ik}$) of all users ($k \in \mathcal{K}_i, i \in \mathcal{I}$) in the system. Let vector $\overline{\mathbf{R}} = (\overline{R}_{ik}, k \in \mathcal{K}_i, i \in \mathcal{I})$. The considered utility function is denoted as $\phi(\overline{\mathbf{R}}) = \sum_{k \in \mathcal{K}_i, i \in \mathcal{I}} \log(\overline{R}_{ik})$. Since the data rate for a user that is served by one base station depends on the interference coming from other base stations, in order to optimize the system performance, coordination among the base stations is necessary to determine the scheduling decision. To simplify the analysis, in this paper, we propose to use the same transmission strategy at all base stations. This is reasonable since interference alignment requires all base stations to cooperate, i.e., each base station transmits only one data stream during a time slot. Nevertheless, we note that the analysis can be extended to scenarios where different transmission strategies are used by different base stations. We introduce $s[t]$ as the indicator of the transmission strategy that is selected in time slot t, where

$$s[t] = \begin{cases} 1, & \text{if spatial multiplexing is used,} \\ 0, & \text{if interference alignment is used,} \end{cases} \tag{9}$$

and define $\mathcal{S} = \{0, 1\}$. We further introduce $l_k[t]$ to denote whether user k is selected in time slot t, where $l_k[t] = 1$ if user k is selected and $l_k[t] = 0$ otherwise. Then, the joint scheduling and transmission strategy selection problem can be formulated as

$$\begin{aligned} \underset{l_k[t] \in \mathcal{S}, s[t] \in \mathcal{S}}{\text{maximize}} \quad & \phi(\overline{\mathbf{R}}) \\ \text{subject to} \quad & \sum_{k \in \mathcal{K}_i} l_k[t] = 1, \quad \forall\, i \in \mathcal{I}, \quad t \in \{1, 2, \dots\} \\ & \overline{R}_{ik} \geq \overline{A}_{ik}, \qquad \forall\, k \in \mathcal{K}_i, \quad i \in \mathcal{I}, \end{aligned} \tag{10}$$

where $\overline{R}_{ik} = \lim_{t\to\infty} \frac{1}{t} \sum_{\tau=0}^{t-1} l_k[\tau](s[\tau] R_{ik}^{\mathrm{SM}}[\tau] + (1 - s[\tau]) R_{ik}^{\mathrm{IA}}[\tau])$. The last constraint in problem (10) implies that all queues in the system should be stable. In general, it is difficult to find an optimal solution $\overline{\mathbf{R}}^*$ for this problem, since solving problem (10) requires CSI for all time slots, which is not possible in practice. However, it has been shown in previous work [23, p. 99] that near optimal dynamic scheduling is possible for problems with a structure similar to that of (10) by using a stochastic network optimization approach, which will be discussed in the following section.

III. Dynamic Scheduling Schemes

In this section, we develop a dynamic scheduling framework with transmission strategy selection based on a stochastic network optimization approach, and propose centralized and distributed scheduling schemes under perfect CSI. We also discuss the impact of imperfect CSI at the base stations and propose a rate adjustment scheme to improve the performance.

A. Centralized Dynamic Scheduling Scheme

We first consider the scenario where global CSI and queue backlog information are available at the scheduler (either a base station or a central controller). Note that problem (10) involves optimizing a concave function of time average rates by making scheduling decisions in each time slot, which has a similar structure to the problem discussed in [23, p. 99]. Therefore, we can apply a stochastic network optimization approach to the system considered in Section II. The main idea to solve problem (10) is to use a weighted sum-rate maximization algorithm which operates in each time slot with causal CSI. The weight of each user's rate is updated according to the user's actual queue backlog and the virtual queue backlog of an auxiliary variable in order to satisfy the stability and fairness criteria. Based on this approach, we obtain a dynamic scheduling framework with transmission strategy selection as follows. We first introduce an auxiliary variable $\gamma_{ik}[t]$ for each user k in cell i at time slot t, and let $W_{ik}[t]$ represent the virtual queue backlog associated with $\gamma_{ik}[t]$. The virtual queues evolve according to the following stochastic difference equation

$$\begin{aligned} W_{ik}[t+1] \quad &= \quad \max\{W_{ik}[t] - R_{ik}[t] + \gamma_{ik}[t], 0\}, \\ & \qquad \forall\, k \in \mathcal{K}_i, \ i \in \mathcal{I}. \end{aligned} \tag{11}$$

Then, at the beginning of time slot t ($t = 0, 1, \dots$), the proposed dynamic scheduling framework involves the following steps.

(i) The first step is to determine the values of auxiliary variables $\gamma_{ik}[t]$ ($k \in \mathcal{K}_i, i \in \mathcal{I}$) by solving the following problem:

$$\begin{aligned} \underset{\boldsymbol{\gamma}[t], i\in\mathcal{I}}{\text{maximize}} \quad & \beta\phi(\boldsymbol{\gamma}[t]) - \sum_{i\in\mathcal{I}}\sum_{k\in\mathcal{K}_i} \gamma_{ik}[t]W_{ik}[t] \\ \text{subject to} \quad & 0 \le \gamma_{ik}[t] \le \gamma_{\max}, \quad \forall\ k \in \mathcal{K}_i,\ i \in \mathcal{I}, \end{aligned} \tag{12}$$

where β, $\gamma_{\max} > 0$ are predetermined system parameters, $W_{ik}[t]$ is the corresponding virtual queue backlog known at the scheduler, and vector $\boldsymbol{\gamma}[t] = (\gamma_{ik}[t], k \in \mathcal{K}_i, i \in \mathcal{I})$.
(ii) The next step is to apply a weighted sum rate maximization scheduling policy to the system with actual and virtual queues. Specifically, given the queue backlog information $Q_{ik}[t]$ and $W_{ik}[t]$ for all users, we select the users $k_i[t] \in \mathcal{K}_i, \forall\ i \in \mathcal{I}$ and the corresponding transmission strategy $s[t] \in \mathcal{S}$ by solving the following optimization problem

$$\underset{k_i[t], s[t]}{\text{maximize}} \quad \textstyle\sum_{i\in\mathcal{I}} (Q_{ik_i[t]}[t] + W_{ik_i[t]}[t]) R_{ik_i[t]}[t]. \tag{13}$$

(iii) Finally, we update all the actual queues $Q_{ik}[t+1]$ and virtual queues $W_{ik}[t+1]$ according to (2) and (11), respectively.

By applying the above scheduling framework, the following results can be obtained.

Proposition 1: Assume the data arrival rate and the service rate are upper bounded by $A_{\max}$ and $R_{\max}$, respectively. For given constants β, $\gamma_{\max}$, and a concave and entry-wise non-decreasing utility function $\phi(\cdot)$, if there exists at least one feasible scheduling policy, then we have

$$\lim_{t\to\infty} \inf \phi\left(\frac{1}{t}\sum_{\tau=0}^{t-1} \mathbb{E}\{\mathbf{R}[\tau]\}\right) \ge \phi(\overline{\mathbf{R}}^*(\gamma_{\max})) - D/\beta, \tag{14}$$

where D is a constant that satisfies

$$D \ge \mathbb{E}\{\sum_{i\in\mathcal{I}}\sum_{k\in\mathcal{K}_i} \frac{1}{2}(A_{ik}[t]^2 + \gamma_{ik}[t]^2 + 2R_{ik}[t]^2)\},$$

$\mathbf{R}[\tau]$ is the vector containing the service rates for all users in time slot τ, the expectation $\mathbb{E}[\cdot]$ is with respect to the joint probability distribution of the channel matrix and scheduling decisions under the proposed scheduling scheme, and $\overline{\mathbf{R}}^*(\gamma_{\max})$ is the solution to problem (10) with the additional constraint $0 \le \overline{R}_{ik} \le \gamma_{\max}$, $\forall\ k \in \mathcal{K}_i$, $i \in \mathcal{I}$. If there is an $\epsilon \ge 0$ and a feasible scheduling policy ν that gives rates $\mathbf{R}^\nu[t] = \{R^\nu_{ik}[t], \forall\ k \in \mathcal{K}_i, i \in \mathcal{I}\}$ which satisfy $\mathbb{E}\{A_{ik}[t] - R^\nu_{ik}[t]\} \le -\epsilon$, $0 \le \mathbb{E}\{R^\nu_{ik}[t]\} \le \gamma_{\max}$, $\forall\ k \in \mathcal{K}_i, i \in \mathcal{I}$ and $\phi(\mathbb{E}\{\mathbf{R}^\nu[t]\}) = \phi_\epsilon$, then we have

$$\begin{aligned} & \lim_{t\to\infty} \sup \frac{1}{t}\sum_{\tau=0}^{t-1}\sum_{i\in\mathcal{I}}\sum_{k\in\mathcal{K}_i} \mathbb{E}\{Q_{ik}[\tau]\} \\ \le \quad & \frac{D + \beta[\phi(\overline{\mathbf{R}}^*(\gamma_{\max})) - \phi_\epsilon]}{\epsilon}. \end{aligned} \tag{15}$$

The proof of Proposition 1 follows [23, Chapter 5], and a sketch of the proof is provided in Appendix A. The result in (14) implies that, when $\gamma_{\max}$ is sufficiently large (such that $\overline{\mathbf{R}}^*(\gamma_{\max}) = \overline{\mathbf{R}}^*$), the proposed dynamic scheduling framework can achieve a utility that is arbitrarily close to the optimal value $\phi(\overline{\mathbf{R}}^*)$ by increasing β. As a tradeoff, the actual queue backlog of the system grows linearly with β, which can be seen from (15). Based on the above framework, we propose a centralized scheduling scheme as shown in Algorithm 1.

Algorithm 1 Centralized dynamic scheduling algorithm.

1: **Initialization**
2: Initialize β, $\gamma_{\max}$, and $W_{ik}[0]$, $\forall\ k \in \mathcal{K}_i,\ i \in \mathcal{I}$.
3: **repeat**
4: **if** $t \in \{0, 1, 2, \ldots\}$ **then**
5: Each BS collects the CSI from its subscribed users.
6: The scheduler obtains global CSI and queue backlog information via backhaul links.
7: The scheduler finds $\gamma_{ik}[t]$, $\forall\ k \in \mathcal{K}_i,\ i \in \mathcal{I}$ by solving (12).
8: The scheduler finds $k_i^*[t] \in \mathcal{K}_i$, $i \in \mathcal{I}$ and $s^*[t]$ by solving (13).
9: The scheduler updates $W_{ik}[t+1]$, $\forall\ k \in \mathcal{K}_i,\ i \in \mathcal{I}$ according to (11).
10: The scheduler sends out the scheduling decision to each base station.
11: Each BS updates $Q_{ik}[t+1]$, $\forall\ k \in \mathcal{K}_i,\ i \in \mathcal{I}$ according to (2) at the end of the time slot.
12: **until** system stops operation.

In Algorithm 1, the scheduler first initializes all system parameters before the scheduling process begins. The scheduler can be either one of the base stations or a central controller that connects to all base stations. Then, at the beginning of each time slot, each base station collects the CSI of all direct links (from the base station to its subscribed users) and interference links (from other base stations to these users), and passes the CSI and queue backlog information of its subscribed users to the scheduler. Next, the scheduler numerically computes the values of auxiliary variables according to (12) in Line 7 and selects the desired users and the corresponding transmission strategy by searching for the optimal solution to (13) in Line 8. Then, the scheduler updates the virtual queue backlogs and sends the scheduling decision to each base station in Lines 9 and 10, respectively. Finally, at the end of the time slot, both base stations update their actual queues according to (2). This scheduling process will be repeated until the end of the transmission session.

B. Distributed Dynamic Scheduling Scheme

The centralized dynamic scheduling scheme requires global CSI and queue backlog information at the scheduler to make scheduling decisions. However, in practical systems, the backhaul links are capacity-limited and exchanging extensive amounts of information may incur a large communication overhead. For instance, in the considered system, the ith base station needs to send information regarding MK_i channel matrices and K_i queue backlogs to the scheduler in each time slot. Therefore, it is attractive to develop distributed scheduling schemes. In this section, we propose an efficient distributed dynamic scheduling scheme which only requires limited message exchanges between the base stations. Note that designing precoding and decoding matrices for interference alignment becomes more complicated as the number of cells increases. To simplify the analysis, we focus on the design of a distributed scheduling scheme for a two-cell system.

From the discussion in Section III, it can be seen that the desired distributed scheduling scheme requires distributed solutions to (12) and (13) that can be found at each base station. We first consider solving problem (12) distributively. Intuitively, if the utility function $\phi(\cdot)$ can be decomposed at each base station independently, then problem (12) can be solved distributively. In this paper, since we adopt the proportional fair utility $\phi(\boldsymbol{\gamma}) = \sum_{k\in\mathcal{K}_1} \log(\gamma_{1k}) + \sum_{k'\in\mathcal{K}_2} \log(\gamma_{2k'})$ for a two-cell system, a distributed solution for (12) can be obtained by solving the following optimization problem at the ith base station (for simplicity, we omit the time index $[t]$ in this subsection):

$$\begin{aligned} \underset{\gamma_{ik}}{\text{maximize}} \quad & \sum_{k\in\mathcal{K}_i} \left(\beta \log(\gamma_{ik}) - W_{ik}\gamma_{ik}\right) \\ \text{subject to} \quad & 0 \le \gamma_{ik} \le \gamma_{\max}, \quad \forall\, k \in \mathcal{K}_i. \end{aligned} \tag{16}$$

The optimal solution of problem (16) is given by $\gamma_{ik} = \min\{\beta/W_{ik}, \gamma_{\max}\}, \forall\, k \in \mathcal{K}_i, i \in \mathcal{I}$.

Next, we develop a distributed algorithm to solve problem (13). The major challenge to solve the problem distributively is that the objective function is not decomposable, since the achievable rate of a user in one cell depends on the scheduling decision in the other cell. Specifically, when calculating the achievable rate for spatial multiplexing independently at a base station, the covariance matrix of the interference in (5) is not known. Moreover, the rate in (6) can only be achieved when both base stations choose to use interference alignment, and therefore, coordination is needed when determining the transmission strategy. To address the above challenges, we propose a two-step approach. In the first step, we relax the constraints in (13) and find distributed solutions to the resulting subproblems with a fixed transmission strategy. In the second step, we design a coordination scheme such that the base stations make final scheduling decisions with limited message exchange based on the results obtained in the first step.

Step 1: We introduce $\varphi_i(k_i, s) = (Q_{ik_i} + W_{ik_i})R^s_{ik_i}$, where $R^s_{ik_i}$ represents the transmission rate at the ith base station for user k_i with strategy s. Since s only takes binary values from $\mathcal{S}$, for a fixed s, (13) is reduced to the following optimization problem:

$$\underset{k_1\in\mathcal{K}_1, k_2\in\mathcal{K}_2}{\text{maximize}} \quad \varphi_1(k_1, s) + \varphi_2(k_2, s) \tag{17}$$

To solve (13) distributively, we first find the distributed solution for (17) for different values of s.

Case 1: When $s = 0$, both base stations employ the spatial multiplexing transmission strategy. Note that each base station only has local CSI (including the CSI of the desired links and the CSI of the links between the intended users and the interfering base stations) obtained via feedback from its intended users. To solve (17) distributively at each base station, we adopt the following approximation. When computing the achievable rate for the users in cell i using (5), we use the average value of the interference covariance matrix $\mathbb{E}[\mathbf{\Phi}_{SM,j}]$ instead of the instantaneous value $\mathbf{\Phi}_{SM,j}$ since the scheduling decision of the other cell is not known. Based on this approximation, the objective function in (17) can be decomposed into two independent functions with respect to different base stations, and the distributed solution is to let base station i find the user k_i^0 that satisfies $\varphi_i(k_i^0, 0) = \max_{k_i\in\mathcal{K}_i} \varphi_i(k_i, 0)$.

Case 2: When $s = 1$, the base stations use the interference alignment transmission strategy simultaneously. In this paper, for the two-cell case, we use a fixed precoding vector with equal power allocation at the base stations for interference alignment. Then, the inter-cell interference can be canceled at the users by designing decoding matrices with local CSI, and the achievable data rate can be calculated independently at each base station. Therefore, problem (17) can also be solved distributively by letting base station i select the user k_i^1 that satisfies $\varphi_i(k_i^1, 1) = \max_{k_i\in\mathcal{K}_i} \varphi_i(k_i, 1)$.

Step 2: After solving the relaxed optimization problem (17) in Step 1, each base station obtains two scheduling decisions with respect to different transmission strategies, i.e., the decisions at the ith base station are (k_i^s, s) $\forall s \in \mathcal{S}$. The next step is to design an efficient coordination scheme which finds the optimal scheduling decision that maximizes the overall system utility. Based on the distributed solution in Step 1, it can be easily verified that the optimal value of the objective function in (13) is $\max\{\sum_{i\in\mathcal{I}} \varphi_i(k_i^0, 0), \sum_{i\in\mathcal{I}} \varphi_i(k_i^1, 1)\}$. We introduce a coordination variable δ_i for the ith base station, where $\delta_i = \varphi_i(k_i^0, 0) - \varphi_i(k_i^1, 1)$. Then, after exchanging this variable with the other base station, the ith base station obtains $\sum_{i\in\mathcal{I}} \delta_i = \sum_{i\in\mathcal{I}} \varphi_i(k_i^0, 0) - \sum_{i\in\mathcal{I}} \varphi_i(k_i^1, 1)$. It can be seen that when $\sum_{i\in\mathcal{I}} \delta_i > 0$, the scheduling decision with spatial multiplexing is desired, otherwise the scheduling decision with interference alignment is preferable. Therefore, the base stations can find their scheduling decisions by exchanging only the value of the coordination variable δ_i, and the optimal decision for the ith base station is given by

$$(k_i^*, s^*) = \begin{cases} (k_i^0, 0), & \text{if } \sum_{i\in\mathcal{I}} \delta_i > 0, \\ (k_i^1, 1), & \text{if } \sum_{i\in\mathcal{I}} \delta_i \le 0. \end{cases} \tag{18}$$

Based on the above discussion, we propose the distributed scheduling scheme described in Algorithm 2. Different from Algorithm 1, in Line 7 of Algorithm 2, the base stations find their potential scheduling decisions based on local CSI and queue backlog information using the proposed the two-step approach. Then, they compute and exchange the value of the coordination variable in Line 8, and make the final scheduling decisions according to (18) in Line 9. The rest of the algorithm is similar to Algorithm 1. In Algorithm 2, the scheduling problem is solved distributively at each base station with limited information exchange (only the value of one variable is exchanged). Therefore, the communication overhead is reduced, with the trade-off that the scheduling decisions are suboptimal since an approximation is used when solving problem (17). Although Algorithm 2 is designed for a two-cell system, it can be extended to systems with more cells with proper adjustment. For example, for a three-cell system, when solving the distributed scheduling problem with $s = 1$ in Line 7 of Algorithm 2, we may use average data rate under different channel realizations as an approximation of the instantaneous data rate for each user, i.e., we simulate different global CSI at a base station and numerically compute the average data rate for its intended user assuming centralized design for interference alignment (as shown in Section II-C). Other steps remain the same as those in Algorithm 2. Note that the objective of the distributed scheduling algorithm is to determine the desired user to be served and the corresponding transmission strategy for each base station. Once these decisions are made, base stations can cooperate with each other to transmit their data, i.e., interference alignment with local CSI can be achieved by using existing distributed algorithms such as those in [25] and [26].

Algorithm 2 Distributed scheduling algorithm executed at the ith base station.

Initialization
  Initialize β, $\gamma_{\max}$, and $W_{ik}[0]$, $\forall\ k \in \mathcal{K}_i$.
repeat
  if $t \in \{0, 1, 2, \ldots\}$ **then**
    Obtain all the CSI from subscribed users.
    Find $\gamma_{ik}[t]$, $\forall\ k \in \mathcal{K}_i$ by solving(12).
    Find $(k_i^0[t], \varphi_i(k_i^0[t], 0))$ and $(k_i^1[t], \varphi_i(k_i^1, 1))$ by solving (17) with $s = 0$ and $s = 1$, respectively.
    Compute $\delta_i[t]$ and exchange it with the other base station to obtain $\sum_{i\in\mathcal{I}} \delta_i[t]$.
    Obtain the scheduling decision according to (18).
    Update $W_{ik}[t+1]$, $\forall\ k \in \mathcal{K}_i$ according to (11).
    Update $Q_{ik}[t+1]$, $\forall\ k \in \mathcal{K}_i$ according to (2) at the end of the time slot.
until system stops operation.

C. Scheduling with Imperfect CSI

The dynamic scheduling schemes proposed in the previous subsections assume perfect CSI at the base stations. However, in practice, the channel matrices at the base stations may not be perfect (due to delayed or erroneous feedback from the user terminals). Therefore, it is of great importance to analyze the impact of imperfect CSI on the performance of the proposed scheduling schemes. We adopt the CSI model for MIMO systems from [27] and [28], where we assume the CSI is perfect at the user terminals but is imperfect at the base stations. This model is realistic as the user terminal can update its channel estimate frequently exploiting the pilots sent by the base stations. On the other hand, the channel estimate at the base station may be updated less frequently to reduce the feedback and computational cost. The imperfect CSI at the ith base station (for user k) is modeled as $\widehat{\mathbf{H}}_{ik} = \mathbf{H}_{ik} + e\mathbf{\Psi}$, where $\mathbf{H}_{ik}$ is the true channel matrix and $e\mathbf{\Psi}$ is the error incurred during feedback which is statistically independent from $\mathbf{H}_{ik}$. The elements of $\mathbf{\Psi}$ are i.i.d. zero mean complex Gaussian variables with unit variance, and e (where $0 \le e \le 1$) is a scalar that characterizes how accurate the feedback is. In this scenario, since the precoding and decoding matrices are designed at the scheduler (or the base stations) based on the imperfect CSI, the achievable rates obtained from (5) and (8) are inaccurate. For user k in cell i, we denote the precoding and decoding matrices with spatial multiplexing under imperfect CSI as $\widehat{\mathbf{V}}_{ik}$ and $\widehat{\mathbf{U}}_{ik}$, respectively, and the corresponding precoding and decoding matrices with interference alignment as $\widehat{\widehat{\mathbf{V}}}_{ik}$ and $\widehat{\widehat{\mathbf{U}}}_{ik}$, respectively. We further denote $\widehat{R}_{ik}^s$ as the corresponding estimated data rate under transmission strategy s, which is calculated according to (5) with $\widehat{\mathbf{V}}_{ik}$ and $\widehat{\mathbf{U}}_{ik}$ (or (8) with $\widehat{\widehat{\mathbf{V}}}_{ik}$ and $\widehat{\widehat{\mathbf{U}}}_{ik}$), and let $\widehat{R}_{ik}^{s\dagger}$ be the corresponding actual achievable rate. Then, we have

$$\widehat{R}_{ik}^s = \begin{cases} \log_2 \det \Big(\mathbf{I}_{N_R} + (g_{ik}\widehat{\mathbf{H}}_{ik}\widehat{\mathbf{\Phi}}_{SM,i}\widehat{\mathbf{H}}_{ik}^{\mathrm{H}}) \\ \quad \cdot (\mathbf{I}_{N_R} + \sum_{j\neq i} g_{jk}\widehat{\mathbf{H}}_{jk}\widehat{\mathbf{\Phi}}_{SM,j}\widehat{\mathbf{H}}_{jk}^{\mathrm{H}})^{-1} \Big), & s = 0, \\ \log_2 \det \Big(\mathbf{I}_{d_i} + g_{ik}\mathbf{H}'_{ik}\widehat{\mathbf{\Phi}}_{IA,i}(\mathbf{H}'_{ik})^{\mathrm{H}} \Big), & s = 1, \end{cases} \tag{19}$$

and

$$\widehat{R}_{ik}^{s\dagger} = \begin{cases} \log_2 \det \Big(\mathbf{I}_{N_R} + (g_{ik}\mathbf{H}_{ik}\widehat{\mathbf{\Phi}}_{SM,i}\mathbf{H}_{ik}^{\mathrm{H}}) \\ \quad \cdot (\mathbf{I}_{N_R} + \sum_{j\neq i} g_{jk}\mathbf{H}_{jk}\widehat{\mathbf{\Phi}}_{SM,j}\mathbf{H}_{jk}^{\mathrm{H}})^{-1} \Big), & s = 0, \\ \log_2 \det \Big(\mathbf{I}_{d_i} + g_{ik}\mathbf{H}_{ik}^{\dagger}\widehat{\mathbf{\Phi}}_{IA,i}(\mathbf{H}_{ik}^{\dagger})^{\mathrm{H}} \\ \quad \cdot (\mathbf{I}_{d_i} + \sum_{j\neq i} g_{jk}\mathbf{H}_{jk}^{\dagger}\widehat{\mathbf{\Phi}}_{IA,j}(\mathbf{H}_{jk}^{\dagger})^{\mathrm{H}})^{-1} \Big), & s = 1, \end{cases} \tag{20}$$

where $\widehat{\mathbf{\Phi}}_{SM,i}$ and $\widehat{\mathbf{\Phi}}_{IA,i}$ are transmit covariance matrices designed according to the imperfect channel, $\mathbf{H}'_{ik} = \widehat{\widehat{\mathbf{U}}}_{ik}\widehat{\mathbf{H}}_{ik}\widehat{\widehat{\mathbf{V}}}_{ik}$, and $\mathbf{H}_{ik}^{\dagger} = \widehat{\widehat{\mathbf{U}}}_{ik}\mathbf{H}_{ik}\widehat{\widehat{\mathbf{V}}}_{ik}$. According to Shannon's channel coding, when $\widehat{R}_{ik}^s > \widehat{R}_{ik}^{s\dagger}$, the receiver cannot successfully decode the data and an outage event occurs. Therefore, the effective data rate with imperfect CSI for any $s \in \mathcal{S}$ is

$$R_{ik}^{s*} = \begin{cases} \widehat{R}_{ik}^s, & \text{if } \widehat{R}_{ik}^s \le \widehat{R}_{ik}^{s\dagger}, \\ 0, & \text{otherwise}. \end{cases} \tag{21}$$

We denote the corresponding transmission outage probability as $\xi_{ik}^s = \Pr\{\widehat{R}_{ik}^s > \widehat{R}_{ik}^{s\dagger}\}$. Intuitively, when ξ_{ik}^s is large, scheduling based on $\widehat{R}_{ik}^s$ is inefficient and the system performance may degrade severely. To address this problem, we extend the proposed scheduling schemes by introducing a weighting factor to adjust the transmission rate for each user. Specifically, when searching for the optimal scheduling decision, we use $p_{ik}^s\widehat{R}_{ik}^s$ instead of $\widehat{R}_{ik}^s$ as the transmission rate, where $p_{ik}^s > 0$ is a weighting factor for user k in cell i when transmission strategy s is employed. We find p_{ik}^s by running simulations over different channel realizations, and select the value such that the average outage probability with adjusted service rate is smaller than a certain value ξ_0. For example, for a particular user k, we search by gradually increasing p_{ik}^s from 0 with a step size of Δp. For each p_{ik}^s, we simulate N_s channel realizations, and count the total number of outage events N_{out} (where $p_{ik}^s\widehat{R}_{ik}^s > \widehat{R}_{ik}^{s\dagger}$). We select the largest value of p_{ik}^s such that $N_{\text{out}}/N_s < \xi_0$. By adjusting the data rate with the weighting factor, the system performance is improved since the average outage probability for a user is limited to a small value and the transmission becomes more efficient.

IV. Performance Evaluation

We evaluate the performance of the proposed dynamic scheduling schemes via simulations. We first consider a two-

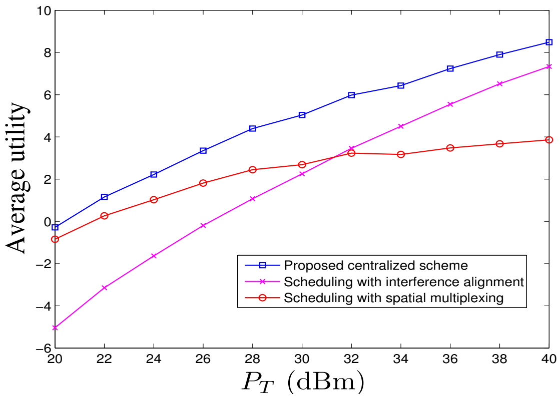


Fig. 2. Two-cell model: the average utility versus transmission power P_T with d = 1 km and N_e = 3.

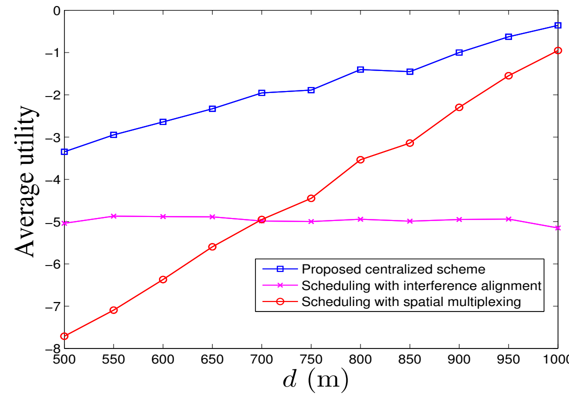


Fig. 3. Two-cell model: the average utility versus the distance d for P_T = 20 dBm and N_e = 3.

cell MIMO system, where the radius of each cell is 500 m and the distance between the two base stations is d. In each cell, 10 users are randomly deployed and at least N_e of them are located in the cell-edge region. For any position in the cell-edge region of the ith cell, the distance from this position to base station i is between 450 m and 500 m, and the angle between the direction from base station i to this position and the direction from base station i to the other base station is no more than 30°. The base stations and the users are equipped with two omni-directional antennas. All wireless links experience Rayleigh fading and path loss, and the 3GPP urban-micro path loss model is used [29]. The transmission power at a base station is P_T. The common channel has a bandwidth of 200 kHz with noise variance -130 dBm. The duration of a time slot is 100 ms. The data packet size is 8 kbits. We consider Poisson arrival processes with different average data rates for users, where the average arrival data rate for a user is randomly selected from the set $\{3, 4, 5, 6\}$ (packets per time slot). The base stations store 50 packets for each user before transmission starts. Other parameters are $R_{\max} = \gamma_{\max} = 100$ bit/s/Hz.

We first evaluate the performance of the proposed scheduling schemes for perfect CSI. We implement the proposed centralized scheduling scheme according to Algorithm 1. We compare its performance of scheduling schemes where a single transmission strategy is adopted. Fig. 2 shows the average utility obtained by different scheduling schemes under varying transmission power (P_T), where $d = 1$ km and $N_e = 3$ cell edge users. It is shown that the average utility of all the scheduling schemes increase as P_T increases, and the proposed scheduling scheme outperforms the schemes with a single transmission strategy. As P_T decreases, the performance of the proposed scheduling scheme approaches that of the scheme with spatial multiplexing. The reason is that, when the transmission power decreases, the interference power becomes insignificant and noise dominates the performance. Therefore, the spatial multiplexing transmission strategy is preferable for almost all the users. On the other hand, as the transmission power increases, the interference power becomes larger while the noise power becomes comparably insignificant, and eliminating interference becomes critical. Hence, interference alignment has superior performance for almost all the users, and the performance of the proposed scheduling scheme approaches that of the scheme with interference alignment.

Fig. 3 shows the average utility for different distances between the base stations (d), where $P_T = 20$ dBm and $N_e = 3$. It can be seen that the average utility of the scheduling scheme using interference alignment remains almost constant, while the average utility of the other scheduling schemes increase as d increases. In addition, the performance of the proposed scheduling scheme is close to that of the scheme with interference alignment when d is small and it approaches that of the scheme with spatial multiplexing as d increases. The reasons for this behavior are as follows. First, since the transmission power is fixed, the inter-cell interference becomes stronger as the base stations get closer, which degrades the performance of spatial multiplexing. However, since the performance of interference alignment only depends on the transmission power of the desired signal (but not on the interference power), the average utility of the scheduling scheme with interference alignment remains almost constant. Second, when the base stations are close to each other (d is small), the inter-cell interference dominates the performance, and the interference alignment strategy is preferable for most of the users. On the contrary, when the two base stations are far apart from each other (d is large), the impact of the inter-cell interference becomes insignificant compared to the noise, and spatial multiplexing becomes superior for most of the users in the system. The performance of the proposed scheduling scheme for different numbers of cell-edge users (N_e) is shown in Fig. 4, where P_T = 20 dBm and d = 1 km. As can be observed, the performance of all scheduling schemes degrades as N_e increases. Specifically, the performance of the proposed scheduling scheme is close to that of the scheme with spatial multiplexing when N_e is small, while it approaches the performance of the scheme with interference alignment when N_e is large. This is because on average interference alignment outperforms spatial multiplexing for users in the cell-edge region. Therefore, when there are few cell-edge users, the proposed scheduling scheme will choose to use spatial multiplexing most of the time. On the other hand, when the system is dominated by cell-edge users, the proposed scheduling scheme tends to use interference alignment.

Next, we compare the performance of the proposed schedul-

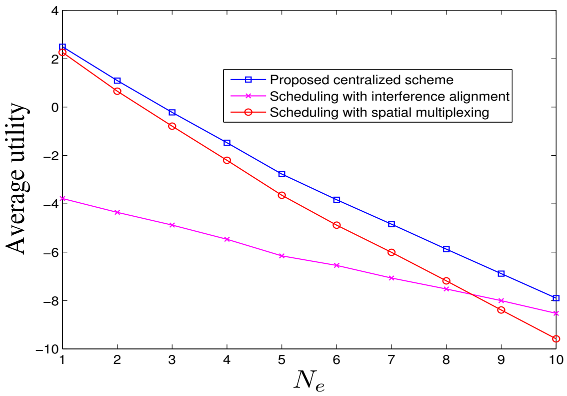


Fig. 4. Two-cell model: the average utility versus the number of cell-edge users N_e for $P_T = 20$ dBm and d = 1 km.

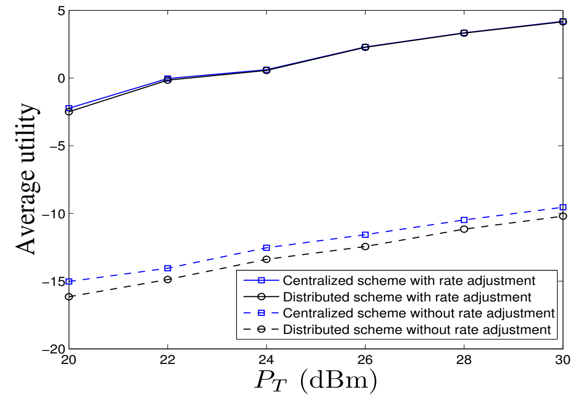


Fig. 6. Two-cell model: the average utility versus transmission power P_T for $\xi_0 = 0.05$.

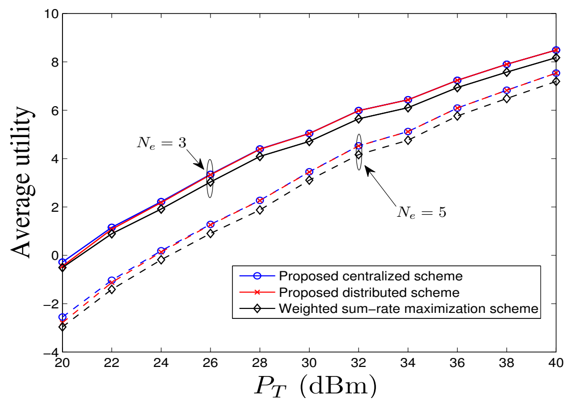


Fig. 5. Two-cell model: the average utility versus transmission power P_T for d = 1 km and $N_e = 3, 5$.

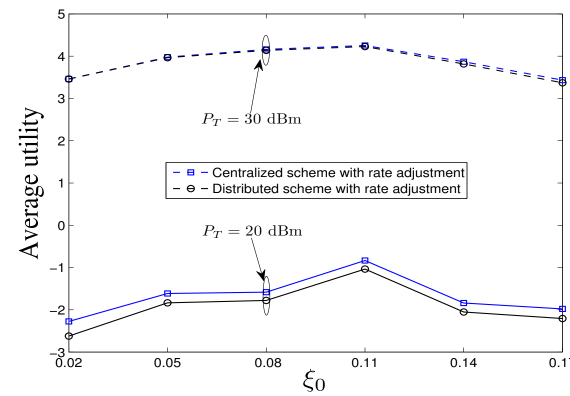


Fig. 7. Two-cell model: the average utility versus ξ_0 for $P_T = 20, 30$ dBm.

ing scheme with a weighted sum-rate maximization (WSRM) scheduling scheme. The WSRM scheduling scheme aims to maximize the weighted sum of all users' rates in each time slot, where the weight for a user is chosen as its corresponding queue backlog. It is shown in [30] that this scheduling scheme guarantees the system stability when the average data arrival rates are in the feasible region. In Fig. 5, we show the average utility for the proposed centralized and distributed scheduling schemes, as well as the WSRM scheme for which the transmission strategy selection was implemented in a centralized manner. As can be seen, the proposed distributed scheduling scheme achieves almost the same performance as the centralized scheduling scheme, which demonstrates its effectiveness. Both the proposed schemes achieve a higher utility than the WSRM scheme, which implies that the proposed schemes are superior in fairly allocating the resources to the users while stabilizing the system.

We also evaluate the performance of the proposed scheduling schemes for imperfect CSI. We adopt the imperfect CSI model in Section III-C, and set $e = 0.05$. The other simulation parameters are identical to those in Fig. 2. Fig. 6 shows the average utility of the proposed schemes with and without rate adjustment for different transmission powers (P_T), where we set $\xi_0 = 0.05$. The scheduling schemes with rate adjustment achieve significant performance improvement compared to those without rate adjustment. Fig. 7 shows the average utility of the proposed schemes with rate adjustment for different ξ_0 values. It is shown that the average utility first increases with ξ_0 and then decreases when ξ_0 exceeds some value. The reason for this behavior is as follows. According to Section III-C, a larger ξ_0 implies a larger weighting factor (p_{ik}^s), which tends to increase the effective service rate. Increasing ξ_0 may also increase the outage probability, which tends to degrade the effective service rate. When ξ_0 is small, increasing the weighting factor has a greater impact and the average effective service rate becomes larger. However, when ξ_0 exceeds some values, the impact of increasing the outage probability becomes significant and the average effective service rate starts to decrease.

Finally, we evaluate the performance of the proposed scheduling schemes for a three-cell model. The system model is shown in Fig. 1 (b), where the distance between any two base stations is 1 km and 10 users are randomly deployed in each cell. Other system parameters are identical to those of the two-cell model. The three-cell interference alignment scheme is implemented according to [9]. We evaluate the performance for both perfect and imperfect CSI. Fig. 8 shows the performance for different transmission powers at the base stations, where the proposed scheduling scheme achieves a better performance compared to schemes without transmission strategy selection. Fig. 9 shows the results for an imperfect CSI scenario with $e = 0.03$ and $\xi_0 = 0.05$, where the proposed centralized and distributed schemes with rate adjustment achieve superior performance compared to those without rate

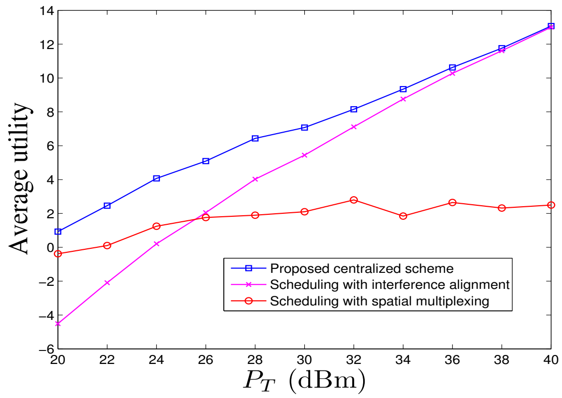


Fig. 8. Three-cell model: the average utility versus transmission power P_T for perfect CSI.

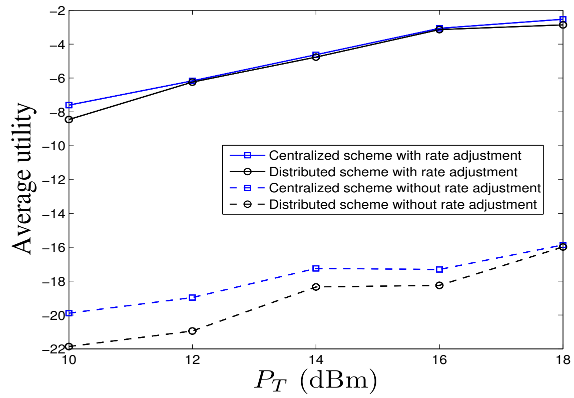


Fig. 9. Three-cell model: the average utility versus transmission power P_T for imperfect CSI for $\xi_0 = 0.05$.

adjustment. Note that the results in Figs. 8 and 9 are consistent with those for the two-cell model, which demonstrates the effectiveness of the proposed strategy.

V. Conclusion

In this paper, we designed scheduling schemes with transmission strategy selection for the downlink of MIMO systems. We employed two MIMO transmission strategies, spatial multiplexing and interference alignment, to improve the system performance. Based on a stochastic optimization technique, we proposed a centralized dynamic scheduling scheme which jointly selects a user and the corresponding transmission strategy for each base station to maximize the overall system utility while keeping the system stable. To reduce the communication overhead, we proposed a distributed scheduling algorithm which only requires limited message exchanges between the base stations. We also discussed the impact of imperfect CSI on the performance of the proposed scheduling schemes and introduced a rate adjustment approach to improve the system performance for imperfect CSI. Simulation results showed that the performance of the proposed distributed scheduling scheme is close to that of the centralized scheduling scheme, and both schemes achieved a better performance than schemes with a single transmission strategy, especially for the case where inter-cell interference dominates the performance of some users. While this work studied the multi-cell system where base stations have a common interest, it is also interesting to consider systems with selfish base stations and design energy efficient scheduling schemes. These are interesting topics for future work.

Appendix A : Proof of Proposition 1

Proof: First, with the auxiliary variables $\boldsymbol{\gamma}[t] = (\gamma_{ik}[t], k \in \mathcal{K}_i, i \in \mathcal{I})$, we introduce the following problem:

$$\begin{aligned}
&\underset{l_k[t]\in\mathcal{S}, s[t]\in\mathcal{S}}{\text{maximize}} && \overline{\phi(\boldsymbol{\gamma})} \\
&\text{subject to} && \sum_{k\in\mathcal{K}_i} l_k[t] = 1, \quad \forall\, i \in \mathcal{I},\ \ t \in \{1,2,\ldots\}, \\
&&& \overline{R}_{ik} \geq \overline{A}_{ik}, \quad \forall\, k \in \mathcal{K}_i,\ \ i \in \mathcal{I}, \\
&&& \overline{\gamma}_{ik} \leq \overline{R}_{ik}, \quad \forall\, k \in \mathcal{K}_i,\ \ i \in \mathcal{I}, \\
&&& 0 \leq \overline{\gamma}_{ik} \leq \gamma_{\max}, \quad \forall\, k \in \mathcal{K}_i.\ \ i \in \mathcal{I},
\end{aligned} \tag{22}$$

where $\overline{\phi(\boldsymbol{\gamma})} = \lim_{t\to\infty} \frac{1}{t}\sum_{\tau=0}^{t-1} \phi(\boldsymbol{\gamma})$ and $\overline{\gamma}_{ik} = \lim_{t\to\infty} \frac{1}{t}\sum_{\tau=0}^{t-1} \gamma_{ik}[\tau]$. According to [23, Chapter 5], it can be proved that designing a policy to solve problem (22) ensures all the desired constraints of the original problem are satisfied while providing a utility that is at least as good as $\phi(\overline{\mathbf{R}}^*(\gamma_{\max}))$, where $\overline{\mathbf{R}}^*(\gamma_{\max})$ is the solution to the original problem (10) with the additional constraint $0 \leq \overline{R}_{ik} \leq \gamma_{\max},\ \forall\, k \in \mathcal{K}_i,\ i \in \mathcal{I}$.

We denote $\boldsymbol{\Theta}[t] = [\mathbf{Q}[t], \mathbf{W}[t]]$, and define a Lyapunov function:

$$L(\boldsymbol{\Theta}[t]) \triangleq \frac{1}{2}\left(\sum_{i\in\mathcal{I}}\sum_{k\in\mathcal{K}_i} Q_{ik}[t]^2 + \sum_{i\in\mathcal{I}}\sum_{k\in\mathcal{K}_i} W_{ik}[t]^2\right). \tag{23}$$

Then, we have

$$\begin{aligned}
& L(\boldsymbol{\Theta}[t+1]) - L(\boldsymbol{\Theta}[t]) \\
= & \frac{1}{2}\sum_{i\in\mathcal{I}}\sum_{k\in\mathcal{K}_i}\left(Q_{ik}[t+1]^2 - Q_{ik}[t]^2\right) \\
& + \frac{1}{2}\sum_{i\in\mathcal{I}}\sum_{k\in\mathcal{K}_i}\left(W_{ik}[t+1]^2 - W_{ik}[t]^2\right) \\
= & \frac{1}{2}\sum_{i\in\mathcal{I}}\sum_{k\in\mathcal{K}_i}\left((\max[Q_{ik}[t] - R_{ik}[t], 0] + A_{ik}[t])^2\right. \\
& \left. - Q_{ik}[t]^2\right) + \frac{1}{2}\sum_{i\in\mathcal{I}}\sum_{k\in\mathcal{K}_i}\left((\max[W_{ik}[t] - R_{ik}[t], 0]\right. \\
& \left. + \gamma_{ik}[t])^2 - W_{ik}[t]^2\right) \\
\leq & \sum_{i\in\mathcal{I}}\sum_{k\in\mathcal{K}_i}\frac{1}{2}\left(A_{ik}[t]^2 + \gamma_{ik}[t]^2 + 2R_{ik}[t]^2\right) \\
& + \sum_{i\in\mathcal{I}}\sum_{k\in\mathcal{K}_i} Q_{ik}[t](A_{ik}[t] - R_{ik}[t]) \\
& + \sum_{i\in\mathcal{I}}\sum_{k\in\mathcal{K}_i} W_{ik}[t](\gamma_{ik}[t] - R_{ik}[t]).
\end{aligned} \tag{24}$$

We define a Lyapunov drift as

$$\Delta(\boldsymbol{\Theta}[t]) \triangleq \mathbb{E}\left\{L(\boldsymbol{\Theta}[t+1]) - L(\boldsymbol{\Theta}[t]) \,\middle|\, \boldsymbol{\Theta}[t]\right\}.$$

It can be shown that

$$\Delta(\boldsymbol{\Theta}[t])$$

$$\leq \mathbb{E}\left\{\sum_{i\in\mathcal{I}}\sum_{k\in\mathcal{K}_i}\frac{1}{2}\left(A_{ik}[t]^2+\gamma_{ik}[t]^2+2R_{ik}[t]^2\right)\;\middle|\;\mathbf{\Theta}[t]\right\}$$
$$+\mathbb{E}\left\{\sum_{i\in\mathcal{I}}\sum_{k\in\mathcal{K}_i}Q_{ik}[t](A_{ik}[t]-R_{ik}[t])\;\middle|\;\mathbf{\Theta}[t]\right\}$$
$$+\mathbb{E}\left\{\sum_{i\in\mathcal{I}}\sum_{k\in\mathcal{K}_i}W_{ik}[t](\gamma_{ik}[t]-R_{ik}[t])\;\middle|\;\mathbf{\Theta}[t]\right\}. \quad (25)$$

Now, we define D as a finite constant that bounds the first term on the right-hand-side of the above drift inequality, so that for all t, all possible $\mathbf{\Theta}[t]$, and all possible control actions that can be taken, we have

$$\mathbb{E}\left\{\sum_{i\in\mathcal{I}}\sum_{k\in\mathcal{K}_i}\frac{1}{2}\left(A_{ik}[t]^2+\gamma_{ik}[t]^2+2R_{ik}[t]^2\right)\;\middle|\;\mathbf{\Theta}[t]\right\}\leq D. \quad (26)$$

Assuming i.i.d. channels, from (25), we have

$$\begin{aligned}&\Delta(\mathbf{\Theta}[t])-\beta\mathbb{E}\{\phi(\boldsymbol{\gamma}[t])\mid\mathbf{\Theta}[t]\}\\ \leq\;& D-\beta\mathbb{E}\left\{\phi(\boldsymbol{\gamma}[t])\mid\mathbf{\Theta}[t]\right\}\\ &+\mathbb{E}\left\{\sum_{i\in\mathcal{I}}\sum_{k\in\mathcal{K}_i}Q_{ik}[t](A_{ik}[t]-R_{ik}[t])\;\middle|\;\mathbf{\Theta}[t]\right\}\\ &+\mathbb{E}\left\{\sum_{i\in\mathcal{I}}\sum_{k\in\mathcal{K}_i}W_{ik}[t](\gamma_{ik}[t]-R_{ik}[t])\;\middle|\;\mathbf{\Theta}[t]\right\}.\end{aligned} \quad (27)$$

The proposed stochastic optimization steps (i)-(iii) in Section III-A aim to minimize the right-hand-side of the above inequality given any realization of $\mathbf{\Theta}[t]$, which leads to

$$\begin{aligned}&\Delta(\mathbf{\Theta}[t])-\beta\mathbb{E}\{\phi(\boldsymbol{\gamma}[t])\mid\mathbf{\Theta}[t]\}\\ \leq\;& D-\beta\phi(\boldsymbol{\gamma}^*)\\ &+\mathbb{E}\left\{\sum_{i\in\mathcal{I}}\sum_{k\in\mathcal{K}_i}Q_{ik}[t](A^*_{ik}[t]-R^*_{ik}[t])\;\middle|\;\mathbf{\Theta}[t]\right\}\\ &+\mathbb{E}\left\{\sum_{i\in\mathcal{I}}\sum_{k\in\mathcal{K}_i}W_{ik}[t](\gamma^*_{ik}-R^*_{ik}[t])\;\middle|\;\mathbf{\Theta}[t]\right\},\end{aligned} \quad (28)$$

where $\boldsymbol{\gamma}^*=(\gamma^*_{ik},k\in\mathcal{K}_i,i\in\mathcal{I})$ is any vector in the feasible region, A^*_{ik} is any arrival rate, and R^*_{ik} is derived from any feasible scheduling policy. It has been shown in [23, Chapter 5] that if a feasible solution of the original problem exists, for any $\delta>0$, there is a feasible scheduling policy and a vector $\boldsymbol{\gamma}^*$ such that

$$\begin{aligned}&-\phi(\boldsymbol{\gamma}^*)\leq-\phi(\overline{\mathbf{R}}^*(\gamma_{\max}))+\delta\\ &\mathbb{E}\left\{A^*_{ik}[t]-R^*_{ik}[t]\right\}\leq\delta, \qquad \forall\, k\in\mathcal{K}_i,\; i\in\mathcal{I},\\ &\mathbb{E}\left\{(\gamma^*_{ik}[t]-R^*_{ik}[t])\right\}\leq\delta, \qquad \forall\, k\in\mathcal{K}_i.\; i\in\mathcal{I}.\end{aligned} \quad (29)$$

Taking $\delta\to0$, together with (28), we have

$$\Delta(\mathbf{\Theta}[t])-\beta\mathbb{E}\left\{\phi(\boldsymbol{\gamma}[t])\;\middle|\mathbf{\Theta}[t]\right\}\leq D-\beta\phi(\overline{\mathbf{R}}^*(\gamma_{\max})). \quad (30)$$

By applying the telescoping sums in the above inequality (where we take the value of t in (30) from 0 to $t-1$ and take the summation of both sides of all the inequalities), for all $t>0$, we have

$$\frac{1}{t}\sum_{\tau=0}^{t-1}\mathbb{E}\{\phi(\boldsymbol{\gamma}[t])\big|\mathbf{\Theta}[t]\}\geq\phi(\overline{\mathbf{R}}^*(\gamma_{\max}))-D/\beta-\frac{\mathbb{E}\{L(\mathbf{\Theta}(0))\}}{\beta t}. \quad (31)$$

According to Jensen's inequality for the concave function $\phi(\cdot)$, we have

$$\lim_{t\to\infty}\inf\phi\left(\overline{\boldsymbol{\gamma}}\right)\geq\phi(\overline{\mathbf{R}}^*(\gamma_{\max}))-D/\beta. \quad (32)$$

On the other hand, rearranging (30) yields

$$\Delta(\mathbf{\Theta}[t])\leq D+\beta\left(\mathbb{E}\left\{\phi(\boldsymbol{\gamma}[t])\;\middle|\;\mathbf{\Theta}[t]\right\}-\phi(\overline{\mathbf{R}}^*(\gamma_{\max}))\right). \quad (33)$$

According to the Lyapunov Drift Theorem in [23, Chapter 1], (33) implies that all the queues are mean rate stable, which means $\overline{\gamma}_{ik}-\overline{R}_{ik}\leq0$. Using this along with the continuity and entrywise non-decreasing properties of $\phi(\cdot)$, we have

$$\begin{aligned}&\lim_{t\to\infty}\inf\phi\left(\frac{1}{t}\sum_{\tau=0}^{t-1}\mathbb{E}[\mathbf{R}[\tau]]\right)\\ \geq\;&\lim_{t\to\infty}\inf\phi\left(\overline{\boldsymbol{\gamma}}\right)\geq\phi(\overline{\mathbf{R}}^*(\gamma_{\max}))-D/\beta.\end{aligned} \quad (34)$$

Note that we assume there exists a feasible scheduling scheme ν which leads to $0\leq\mathbb{E}\{R^\nu_{ik}[t]\}\leq\gamma_{\max}$, $\mathbb{E}\{A_{ik}[t]-R^\nu_{ik}[t]\}\leq-\epsilon$, and $\phi(\mathbb{E}\{R^\nu_{ik}[t]\})=\phi_\epsilon$. From (28), we have

$$\Delta(\mathbf{\Theta}[t])\leq D+\beta\left(\mathbb{E}\left\{\phi(\boldsymbol{\gamma}[t])\;\middle|\mathbf{\Theta}[t]\right\}-\phi_\epsilon\right)-\epsilon\sum_{i\in\mathcal{I}}\sum_{k\in\mathcal{K}_i}Q_{ik}[t]. \quad (35)$$

By rearranging the above inequality and taking iterated expectations and telescoping sums, we obtain

$$\begin{aligned}&\frac{1}{t}\sum_{\tau=0}^{t-1}\sum_{i\in\mathcal{I}}\sum_{k\in\mathcal{K}_i}\mathbb{E}\{Q_{ik}[\tau]\}\\ \leq\;&\frac{D+\beta(\frac{1}{t}\sum_{\tau=0}^{t-1}\mathbb{E}\{\phi(\boldsymbol{\gamma}[\tau])\}-\phi_\epsilon)}{\epsilon}-\frac{\mathbb{E}\{L(\mathbf{\Theta}(0))\}}{\epsilon t}.\end{aligned} \quad (36)$$

Since $\lim_{t\to\infty}\frac{1}{t}\sum_{\tau=0}^{t-1}\mathbb{E}\{\phi(\boldsymbol{\gamma}[\tau])\}\leq\phi(\overline{\mathbf{R}}^*(\gamma_{\max}))$, taking $\lim_{t\to\infty}\sup$ at both sides of (36), we have

$$\begin{aligned}&\lim_{t\to\infty}\sup\frac{1}{t}\sum_{\tau=0}^{t-1}\sum_{i\in\mathcal{I}}\sum_{k\in\mathcal{K}_i}\mathbb{E}\{Q_{ik}[\tau]\}\\ \leq\;&\frac{D+\beta(\phi(\overline{\mathbf{R}}^*(\gamma_{\max}))-\phi_\epsilon)}{\epsilon}.\end{aligned} \quad (37)$$

This completes the proof. ■

References

[1] B. Niu, V. W. S. Wong, and R. Schober, "Downlink scheduling with transmission strategy selection for two-cell MIMO networks," in *Proc. of IEEE GLOBECOM'11*, Houston, TX, Dec. 2011.

[2] 3GPP TR 36.871, "MIMO enhancement for LTE-Advanced (Release 11)." [Online]. Available: www.3gpp.org.

[3] 3GPP TR 36.819, "Coordinated multi-point operation for LTE (Release 11)." [Online]. Available: www.3gpp.org.

[4] D. Tse and P. Viswanath, *Fundamentals of Wireless Communication*. Cambridge University Press, 2005.

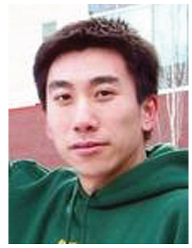
[5] J. G. Andrews, W. Choi, and R. W. Heath, "Overcoming interference in spatial multiplexing MIMO cellular networks," *IEEE Wireless Comm. Mag.*, vol. 14, no. 6, pp. 95–104, Dec. 2007.

[6] V. R. Cadambe and S. A. Jafar, "Interference alignment and degrees of freedom of the K-user interference channel," *IEEE Trans. on Information Theory*, vol. 54, no. 8, pp. 3425–3441, Aug. 2008.

[7] R. Tresch and M. Guillaud, "Cellular interference alignment with imperfect channel knowledge," in *Proc. of IEEE ICC Workshop on LTE Evolution*, Tokyo, Japan, June 2009.

[8] ——, "Clustered interference alignment in large cellular networks," in *Proc. of IEEE PIMRC*, Tokyo, Japan, Sept. 2009.

[9] C. Suh, M. Ho, and D. Tse, “Downlink interference alignment,” in *Proc. of IEEE GLOBECOM*, Miami, FL, Dec. 2010.
[10] R. Tresch, M. Guillaud, and E. Riegler, “On the achievability of interference alignment in the K-user constant MIMO interference channel,” in *Proc. of IEEE Workshop on Statistical Signal Processing*, Cardiff, UK, Sept. 2009.
[11] W. Shin, N. Lee, J. Lim, C. Shin, and K. Jang, “On the design of interference alignment scheme for two-cell MIMO interfering broadcast channels,” *IEEE Trans. on Wireless Commun.*, vol. 10, no. 2, pp. 437–442, Feb. 2011.
[12] A. Sang, N. Lee, X. Wang, M. Madihian, and R. D. Gitlin, “A flexible downlink scheduling scheme in cellular packet data systems,” *IEEE Trans. on Wireless Commun.*, vol. 5, no. 3, pp. 568–577, Mar. 2006.
[13] M. Dianati, X. Shen, and K. Naik, “Cooperative fair scheduling for the downlink of CDMA cellular networks,” *IEEE Trans. on Veh. Technol.*, vol. 56, no. 4, pp. 1749–1760, July 2007.
[14] V. Tsibonis, L. Georgiadis, and L. Tassiulas, “Exploiting wireless channel state information for throughput maximization,” *IEEE Trans. on Inf. Theory*, vol. 50, no. 11, pp. 2566–2582, Nov. 2004.
[15] A. Eryilmaz and R. Srikant, “Fair resource allocation in wireless networks using queue-length-based scheduling and congestion control,” in *Proc. of IEEE INFOCOM*, Miami, FL, Mar. 2005.
[16] V. K. N. Lau, “Proportional fair space-time scheduling for wireless communications,” *IEEE Trans. on Commun.*, vol. 53, no. 4, pp. 1353–1360, Aug. 2005.
[17] H. Shirani-Mehr, G. Caire, and M. J. Neely, “MIMO downlink scheduling with non-perfect channel state knowledge,” *IEEE Trans. on Commun.*, vol. 58, no. 7, pp. 2055–2066, July 2010.
[18] H. Zhang, L. Venturino, N. Prasad, P. Li, S. Rangarajan, and X. Wang, “Weighted sum-rate maximization in multi-cell networks via coordinated scheduling and discrete power control,” *IEEE J. Sel. Areas Commun.*, vol. 29, no. 6, pp. 1214–1224, June 2011.
[19] H. Shirani-Mehr, H. Papadopoulos, S. A. Ramprashad, and G. Caire, “Joint scheduling and hybrid-ARQ for MU-MIMO downlink in the presence of inter-cell interference,” in *Proc. of IEEE ICC*, Cape Town, South Africa, May 2010.
[20] W. Yu, T. Kwon, and C. Shin, “Multicell coordination via joint scheduling, beamforming and power spectrum adaptation,” in *Proc. of IEEE INFOCOM*, Shanghai, China, Apr. 2011.
[21] R. Tresch, C. Mehlfuhrer, and M. Guillaud, “LMMSE channel estimation for MIMO W-CDMA with out-of-cell interference mitigation,” in *Proc. of the 42nd Asilomar Conf. on Signals, Systems and Computers*, Pacific Grove, CA, Oct. 2008.
[22] A. Zanella, M. Chiani, and M. Z. Win, “MMSE reception and successive interference cancellation for MIMO systems with high spectral efficiency,” *IEEE Trans. on Wireless Commun.*, vol. 4, no. 3, pp. 1244–1253, May. 2005.
[23] M. J. Neely, *Stochastic Network Optimization with Application to Communication and Queueing Systems*. Morgan and Claypool, 2010.
[24] F. Kelly, A. Maulloo, and D. Tan, “Rate control in communication networks: Shadow prices, proportional fairness and stability,” *Journal of the Operational Research Society*, vol. 49, no. 3, pp. 237–252, Mar. 1998.
[25] K. Gomadam, V. R. Cadambe, and S. A. Jafar, “Approaching the capacity of wireless networks through distributed interference alignment,” in *Proc. of IEEE GLOBECOM’08*, New Orleans, LA, Dec. 2008.
[26] I. Santamaria, O. Gonzalez, R. W. Heath, and S. W. Peters, “Maximum sum-rate interference alignment algorithms for MIMO channels,” in *Proc. of IEEE GLOBECOM’10*, Miami, FL, Dec. 2010.
[27] C. Wang, E. K. S. Au, R. D. Murch, W. H. Mow, R. S. Cheng, and V. K. N. Lau, “On the performance of the MIMO zero-forcing receiver in the presence of channel estimation error,” *IEEE Trans. on Wireless Commun.*, vol. 6, no. 3, pp. 805–810, Mar. 2007.
[28] L. Musavian, M. R. Nakhai, M. Dohler, and A. H. Aghvami, “Effect of channel uncertainty on the mutual information of MIMO fading channels,” *IEEE Trans. on Veh. Technol.*, vol. 56, no. 5, pp. 2798–2866, Sept. 2007.
[29] 3GPP TR 25.996, “Spatial channel model for multiple input multiple output (MIMO) simulations (Release 11).” [Online]. Available: www.3gpp.org.
[30] L. Tassiulas and A. Ephremides, “Stability properties of constrained queueing systems and scheduling policies for maximum throughput in multihop radio networks,” *IEEE Trans. on Automatic Control*, vol. 37, no. 12, pp. 1936–1948, Dec. 1992.



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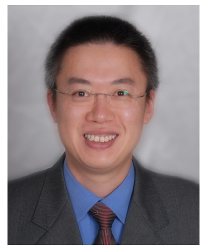

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