Joint Long-Term Admission Control and Beamforming in Downlink MISO Networks

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***Abstract*—Admission control has been widely utilized to alleviate network congestion. However, most current studies choose the admissible users based on instantaneous channel information. Due to the time-varying characteristics of wireless channels, the admissible user set changes quickly, which complicates network management and renders heavy operational costs. This motivates us to take the stability of the admissible user set into account in admission control, thus leading to a long-term admission control problem. In this paper, we consider a joint long-term admission control and beamforming problem in a downlink network consisting of one multi-antenna base station (BS) and multiple single-antenna users. To maintain a relatively stable admissible user set and minimize the power cost for the admissible users to achieve their quality-of-service levels, we jointly optimize the admissible users, the BS transmit beamformers, and the switching frequency of each user's admissible status in a given time period. To handle this challenging non-convex problem, we first design a sequential convex approximation (SCA) algorithm to iteratively compute a stationary solution. To facilitate algorithm's implementation, we further employ the alternating direction method of multipliers to come up with an efficient, semi-closed-form update of each SCA problem.**

***Index Terms*—Multi-input single-output, long-term admission control, beamforming, sequential convex approximation, alternating direction method of multipliers**

I. Introduction

As a promising solution to network congestion, admission control has attracted intensive attention in the past decades [1]. Usually, admission control works jointly with power control or beamforming to support the maximum number of users at their desired quality-of-service (QoS) levels, while using minimum transmit power [2]–[8]. Since these problems are shown to be NP-hard [2], [3], [6], various efficient approximation methods, e.g., linear programming deflation [2], [3], L_p approximation [4], difference-of-convex (DC) programming [5], second-order cone programming (SOCP) [6], semidefinite relaxation (SDR) [7], etc., have been proposed to seek some suboptimal solution with manageable complexity.

Despite the differences in problem formulation and algorithm design, all the aforementioned studies choose the admissible users based on *instantaneous* channel state information (CSI). Because of the time-varying characteristics of wireless channels, the user admissible status may change quickly with time, thereby complicating the network management and rendering heavy operational burdens in practice. For instance, as a user is allowed to access the network, some necessary yet complicated operations (e.g., handover) need to be implemented to establish the transmission link, thus yielding extra signaling and power cost [9]. As a result, frequently admitting and rejecting a user may cost more power than that in data transmission. Moreover, if the user's status keeps switching between admissible and inadmissible, it may suffer from severe service break because of the frequent interruptions in data transmission. In view of this, we are motivated to emphasize the stability of admissible user set, thus leading to a *long-term* admission control problem.

Unfortunately, few works have recognized the importance of a relatively stable admissible user set when applying admission control. There are some works considering a related problem — they properly select the active BSs in different timeslots so that stable transmission links can be achieved [10], [11]. In this paper, however, we formulate stable transmission links from the perspective of selecting users. Specifically, we address the long-term admission control problem in a network consisting of one multi-antenna BS and multiple single-antenna users. By jointly optimizing the admissible users, the BS transmit beamformers, and the switching frequency of each user's admissible status, we aim to provide qualified service to a relatively stable user set at the minimum power cost. In particular, to balance the flexibility and stability of each user's admissible status, we impose a sparse constraint onto its variation. That is, the users' statuses are allowed to change to optimize the admissible user set and reduce the power cost, while their variations should be sparse. To handle this non-convex problem, we first propose an algorithm which sequentially solves its convex approximations with stationary convergence guarantee. To facilitate algorithm implementation, we further employ the alternating direction method of multipliers (ADMM) [12] and devise an efficient algorithm, with a closed-form update in each step.

II. System Model and Problem Statement

Consider the downlink transmission in a network consisting of one N-antenna BS and M single-antenna users. We assume block fading channels here; i.e., the channels remain static in each fading block, while changing from one block to another according to channel distribution. We define each fading block as a timeslot, and consider transmission in a time period of T timeslots. Let $\mathbf{w}_m(t)$ and $\mathbf{h}_m(t) \in \mathbb{C}^{N\times 1}$ be the beamformer

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and the channel for user m at timeslot t, for $m = 1, 2, \ldots, M$, and $t = 1, 2, \ldots, T$. Let $\mathbf{W}(t) = [\mathbf{w}_1(t), \mathbf{w}_2(t), \ldots, \mathbf{w}_M(t)]$ and $\mathbf{H}(t) = [\mathbf{h}_1(t), \mathbf{h}_2(t), \ldots, \mathbf{h}_M(t)] \in \mathbb{C}^{N\times M}$ denote the beamformer and channel matrices for all the users.

Usually, the QoS can be measured by SINR. The SINR of user m at timeslot t is computed by

$$\mathrm{SINR}_m(t) = \frac{\left|\mathbf{h}_m^\dagger(t)\mathbf{w}_m(t)\right|^2}{\sigma^2+\sum_{n\neq m}\left|\mathbf{h}_m^\dagger(t)\mathbf{w}_n(t)\right|^2},\ \forall\, m, t, \tag{1}$$

where superscript † denotes Hermitian transpose, and σ^2 is the noise power.

Let γ denote the QoS threshold. Then we select users based on whether the QoS constraints, i.e., $\mathrm{SINR}_m(t) \geq \gamma$, can be satisfied. By applying SOCP reformulation [6] and introducing variables $s_m(t) \geq 0$, we recast the QoS constraints as

$$\begin{cases} \frac{\mathbf{h}_m^\dagger(t)\mathbf{w}_m(t)+s_m(t)}{\sqrt{\sigma^2+\sum_{n\neq m}\left|\mathbf{h}_m^\dagger(t)\mathbf{w}_n(t)\right|^2}} \geq \sqrt{\gamma}, \\ \mathrm{Im}\{\mathbf{h}_m^\dagger(t)\mathbf{w}_m(t)\} = 0, \quad \forall\, m, t. \end{cases} \tag{2}$$

Hence, the admission control process can be described by (2). In particular, $s_m(t) = 0$ indicates that user m is admissible at timeslot t since its QoS threshold can be achieved; $s_m(t) > 0$ means inadmissible.

To maintain the stability of transmission links, we need to limit the switching frequency of each user's admissible status. To this end, we define an indicator function $\mathcal{I}(\cdot)$ to map $s_m(t)$ to a binary $\{0, 1\}$ admissible status, i.e.,

$$\mathcal{I}(x) = \begin{cases} 0, & x = 0, \quad \text{(admissible)} \\ 1, & x > 0, \quad \text{(inadmissible)} \end{cases} \tag{3}$$

Clearly, $\mathcal{I}[s_m(t+1)] - \mathcal{I}[s_m(t)] = 0$ means that the admissible status of user m does not change from timeslot t to timeslot $(t + 1)$; otherwise, $\mathcal{I}[s_m(t + 1)] - \mathcal{I}[a_m(t)] \neq 0$ means that the admissible status changes.

Then, the joint long-term admission control and beamforming problem can be formulated as

$$\min_{\{\mathbf{W},\mathbf{s}\}} \left\{ \begin{array}{l} \sum_{t=1}^{T} \|\mathbf{W}(t)\|_F^2 + \lambda_1 \sum_{t=1}^{T}\sum_{m=1}^{M} \mathcal{I}[s_m(t)] \\ + \lambda_2 \sum_{t=1}^{T-1}\sum_{m=1}^{M} \left|\mathcal{I}[s_m(t+1)] - \mathcal{I}[s_m(t)]\right| \end{array} \right\} \tag{4a}$$

$$\text{s.t.} \quad \text{(2) is satisfied,}$$

$$\|\mathbf{W}(t)\|_F^2 \leq P,\ \forall\, t, \tag{4b}$$

$$s_m(t) \geq 0,\ \forall\, m, t, \tag{4c}$$

where $\|\cdot\|_F$ denotes Frobenius norm, and P is the BS transmit power budget; λ_1 and λ_2 are positive weighting factors, which can be interpreted as the cost of rejecting one user and the cost of one transmission link switching, respectively.

In brief, subject to some QoS and power budget constraints, we carefully select the admissible users and the corresponding transmit beamformers in the length-T time period, such that a good balance can be achieved among the transmit power, the size of admissible user set, and the stability of admissible user set.

III. Low-Complexity Algorithm for Problem (4)

A. Framework of SCA-Based Algorithm

Problem (4) is challenging due to the non-continuity of $\mathcal{I}(\cdot)$. To tackle this, we first approximate it by a continuous function,

$$\mathcal{I}(x) \simeq 1 - \tfrac{1}{1+\kappa x},\ x \geq 0, \tag{5}$$

where $\kappa > 0$ is a large positive number. Then, we have

$$\mathcal{I}[s_m(t)] \simeq 1 - \tfrac{1}{1+\kappa s_m(t)}, \tag{6}$$

$$\left|\mathcal{I}[s_m(t+1)] - \mathcal{I}[s_m(t)]\right| \simeq \left|\tfrac{1}{1+\kappa s_m(t+1)} - \tfrac{1}{1+\kappa s_m(t)}\right|. \tag{7}$$

However, the objective of problem (4) is still non-convex even after we apply the approximations of (6) and (7). As a compromise, we iteratively solve its sequential convex approximations by utilizing the method of DC programming [13]. Specifically, we further reformulate (6) and (7) as

$$\left[1 - \tfrac{1}{1+\kappa s_m(t)}\right] \simeq 1 - \tfrac{2}{1+\kappa \hat{s}_m(t)} + \tfrac{1+\kappa s_m(t)}{[1+\kappa \hat{s}_m(t)]^2}, \tag{8}$$

$$\begin{aligned} \left|\tfrac{1}{1+\kappa s_m(t+1)} - \tfrac{1}{1+\kappa s_m(t)}\right| &= \max\left\{ \begin{array}{l} \tfrac{1}{1+\kappa s_m(t+1)} - \tfrac{1}{1+\kappa s_m(t)}, \\ \tfrac{1}{1+\kappa s_m(t)} - \tfrac{1}{1+\kappa s_m(t+1)} \end{array} \right\} \\ &\simeq \max\left\{ \begin{array}{l} \tfrac{1}{1+\kappa s_m(t+1)} - \tfrac{2}{1+\kappa \hat{s}_m(t)} + \tfrac{1+\kappa s_m(t)}{[1+\kappa \hat{s}_m(t)]^2}, \\ \tfrac{1}{1+\kappa s_m(t)} - \tfrac{2}{1+\kappa \hat{s}_m(t+1)} + \tfrac{1+\kappa s_m(t+1)}{[1+\kappa \hat{s}_m(t+1)]^2} \end{array} \right\} \end{aligned} \tag{9}$$

where $\hat{s}_m(t)$ and $\hat{s}_m(t+1)$ are iterates of $s_m(t)$ and $s_m(t+1)$ in the previous iteration, respectively. Hence, in each iteration we solve problem (10) to update $\{\mathbf{W}, \mathbf{s}\}$.

$$\min_{\{\mathbf{W},\mathbf{s},\mathbf{z}\}} \left\{ \begin{array}{l} \sum_{t=1}^{T} \|\mathbf{W}(t)\|_F^2 + \lambda_1 \sum_{t=1}^{T}\sum_{m=1}^{M} \frac{\kappa s_m(t)}{[1+\kappa \hat{s}_m(t)]^2} \\ + \lambda_2 \sum_{t=1}^{T-1}\sum_{m=1}^{M} z_m(t) \end{array} \right\} \tag{10a}$$

$$\text{s.t.} \quad \text{(2), (4b) and (4c) are satisfied,}$$

$$z_m(t) \geq \tfrac{1}{1+\kappa s_m(t+1)} - \tfrac{2}{1+\kappa \hat{s}_m(t)} + \tfrac{1+\kappa s_m(t)}{[1+\kappa \hat{s}_m(t)]^2},\ \forall\, m, t, \tag{10b}$$

$$z_m(t) \geq \tfrac{1}{1+\kappa s_m(t)} - \tfrac{2}{1+\kappa \hat{s}_m(t+1)} + \tfrac{1+\kappa s_m(t+1)}{[1+\kappa \hat{s}_m(t+1)]^2},\ \forall\, m, t. \tag{10c}$$

Problem (10) is convex and can be solved by, e.g., CVX. Algorithm 1 summarizes the sequential convex approximation (SCA)-based approach to the joint long-term admission control and beamforming problem.

Algorithm 1: The SCA-Based Approach	
1.	Initialize $s_m(t), \forall\, m, t$;
2.	`repeat`
3.	$\hat{s}_m(t) = s_m(t), \forall\, m, t$;
4.	Solve problem (10) to update $\{\mathbf{w}_m(t), s_m(t)\}, \forall\, m, t$;
5.	`until` some stopping criterion is satisfied.

Remark 1. *The property of DC programming [13] has shown that every limit point of the iterates generated by Algorithm 1 is a stationary solution of problem* (4) *with* $\mathcal{I}(\cdot)$ *approximated by* (5).

$$\mathcal{L}_\rho\begin{pmatrix}\mathbf{W},\mathbf{s},\mathbf{x},\mathbf{y},\mathbf{z},\mathbf{F},\mathbf{a},\mathbf{b},\mathbf{c},\mathbf{d},\\ \boldsymbol{\Sigma},\boldsymbol{\theta},\boldsymbol{\phi},\boldsymbol{\alpha},\boldsymbol{\beta},\boldsymbol{\epsilon},\boldsymbol{\eta}\end{pmatrix} = \sum_{t=1}^T \|\mathbf{W}(t)\|_F^2 + \lambda_1 \sum_{t=1}^T \sum_{m=1}^M \frac{\kappa s_m(t)}{[1+\kappa \hat{s}_m(t)]^2} + \lambda_2 \sum_{t=1}^{T-1} \sum_{m=1}^M z_m(t)$$
$$+ \sum_{t=1}^T \left\{ \mathrm{Re}\left\{ \mathrm{Tr}\left\{ \boldsymbol{\Sigma}^\dagger(t)\big[\mathbf{F}(t) - [\mathbf{H}^\dagger(t)\mathbf{W}(t), \sigma\mathbf{1}]\big]\right\}\right\} + \frac{\rho}{2}\left\|\mathbf{F}(t) - [\mathbf{H}^\dagger(t)\mathbf{W}(t), \sigma\mathbf{1}]\right\|_F^2 \right\}$$
$$+ \sum_{t=1}^{T-1} \sum_{m=1}^M \left\{ \theta_m(t)\left[z_m(t) - x_m(t)\right] + \frac{\rho}{2}\left[z_m(t) - x_m(t)\right]^2 + \phi_m(t)\left[z_m(t) - y_m(t)\right] + \frac{\rho}{2}\left[z_m(t) - y_m(t)\right]^2 \right\}$$
$$+ \sum_{t=1}^{T-1} \sum_{m=1}^M \left\{ \alpha_m(t)\left[a_m(t) - 1 - \kappa s_m(t)\right] + \frac{\rho}{2}\left[a_m(t) - 1 - \kappa s_m(t)\right]^2 \right\}$$
$$+ \sum_{t=1}^{T-1} \sum_{m=1}^M \left\{ \beta_m(t)\left[b_m(t) - 1 - \kappa s_m(t+1)\right] + \frac{\rho}{2}\left[b_m(t) - 1 - \kappa s_m(t+1)\right]^2 \right\} \tag{13}$$
$$+ \sum_{t=1}^{T-1} \sum_{m=1}^M \left\{ \epsilon_m(t)\left[c_m(t) - \frac{1+\kappa s_m(t+1)}{[1+\kappa\hat{s}_m(t+1)]^2}\right] + \frac{\rho}{2}\left[c_m(t) - \frac{1+\kappa s_m(t+1)}{[1+\kappa\hat{s}_m(t+1)]^2}\right]^2 \right\}$$
$$+ \sum_{t=1}^{T-1} \sum_{m=1}^M \left\{ \eta_m(t)\left[d_m(t) - \frac{1+\kappa s_m(t)}{[1+\kappa\hat{s}_m(t)]^2}\right] + \frac{\rho}{2}\left[d_m(t) - \frac{1+\kappa s_m(t)}{[1+\kappa\hat{s}_m(t)]^2}\right]^2 \right\},$$

B. ADMM-Based Algorithm

The main computation of Algorithm 1 lies in solving problem (10), which may not be easy when the problem dimension is high. Hence, we are driven to pursue some low-complexity and scalable algorithms. To this end, we reformulate problem (10) such that it fits into the framework of ADMM [12], [14], [15]. Finally, an efficient algorithm is developed.

We introduce the following variables to make problem (10) separable,

$$\mathbf{F}(t) = [\mathbf{H}^\dagger(t)\mathbf{W}(t), \sigma\mathbf{1}] \in \mathbb{C}^{M\times(M+1)},\ \forall t, \tag{11a}$$
$$x_m(t) = z_m(t),\ y_m(t) = z_m(t),\ \forall m, t, \tag{11b}$$
$$a_m(t) = 1 + \kappa s_m(t),\ b_m(t) = 1 + \kappa s_m(t+1), \forall m, t \tag{11c}$$
$$c_m(t) = \frac{1+\kappa s_m(t+1)}{[1+\kappa\hat{s}_m(t+1)]^2},\ d_m(t) = \frac{1+\kappa s_m(t)}{[1+\kappa\hat{s}_m(t)]^2},\ \forall m, t. \tag{11d}$$

Then, problem (10) is equivalent to

$$\min_{\left\{\substack{\mathbf{W},\mathbf{s},\mathbf{z},\mathbf{x},\mathbf{y}\\ \mathbf{F},\mathbf{a},\mathbf{b},\mathbf{c},\mathbf{d}}\right\}} \left\{ \begin{array}{l} \sum_{t=1}^T \|\mathbf{W}(t)\|_F^2 + \lambda_2 \sum_{t=1}^{T-1}\sum_{m=1}^M z_m(t) \\ + \lambda_1 \sum_{t=1}^T \sum_{m=1}^M \frac{\kappa s_m(t)}{[1+\kappa\hat{s}_m(t)]^2} \end{array} \right\} \tag{12a}$$
$$\text{s.t. } f_m^m(t) + s_m(t) \geq \sqrt{\gamma}\|\mathbf{f}_{-m}^m(t)\|_2,\ \forall m, t, \tag{12b}$$
$$\mathrm{Im}\{f_m^m(t)\} = 0,\ \forall m, t, \tag{12c}$$
$$x_m(t) \geq \frac{1}{b_m(t)} - \frac{2}{1+\kappa\hat{s}_m(t)} + d_m(t),\ \forall m, t, \tag{12d}$$
$$y_m(t) \geq \frac{1}{a_m(t)} - \frac{2}{1+\kappa\hat{s}_m(t+1)} + c_m(t), \forall m, t, \tag{12e}$$
$$a_m(t) \geq 1,\ b_m(t) \geq 1, \forall m, t, \tag{12f}$$
$$\text{(4b) and (11a)} \sim \text{(11d) are satisfied.}$$

Notice that (12b) and (12c) correspond to the QoS constraint (2), where $\mathbf{f}^m(t)$ is the mth row of $\mathbf{F}(t)$; $f_m^m(t)$ is the mth element of $\mathbf{f}^m(t)$; $\mathbf{f}_{-m}^m(t) = [f_1^m(t), \ldots, f_{m-1}^m(t), f_{m+1}^m(t), \ldots, f_{M+1}^m(t)]$ is the subvector after removing $f_m^m(t)$ from $\mathbf{f}^m(t)$.

The partial augmented Lagrangian function of problem (12) is expressed as (13), where $\boldsymbol{\Sigma}, \boldsymbol{\theta}, \boldsymbol{\phi}, \boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{\epsilon}, \boldsymbol{\eta}$ are associated Lagrangian multipliers. Dividing $\{\mathbf{W}, \mathbf{s}, \mathbf{x}, \mathbf{y}, \mathbf{z}, \mathbf{F}, \mathbf{a}, \mathbf{b}, \mathbf{c}, \mathbf{d}\}$ into two blocks of $\{\mathbf{W}, \mathbf{x}, \mathbf{y}, \mathbf{a}, \mathbf{b}, \mathbf{c}, \mathbf{d}\}$ and $\{\mathbf{F}, \mathbf{s}, \mathbf{z}\}$, we can employ the ADMM framework to solve problem (10) or (12) iteratively (cf. Algorithm 2).

In Algorithm 2, the subproblems in each iteration can be further divided into smaller problems. All these smaller problems have closed-form solutions, thus giving the algorithm very low complexity. Next, we show the step-by-step computation.

Algorithm 2: ADMM-Based Approach for Problem (10)	
1.	Initialization;
2.	**repeat**
3.	$\{\mathbf{W}, \mathbf{x}, \mathbf{y}, \mathbf{a}, \mathbf{b}, \mathbf{c}, \mathbf{d}\} \leftarrow \mathrm{argmin}_{\{\mathbf{W},\mathbf{x},\mathbf{y},\mathbf{a},\mathbf{b},\mathbf{c},\mathbf{d}\}} \mathcal{L}_\rho(\cdot)$ s.t. (4b), (12d) $\sim$ (12f) satisfied;
4.	$\{\mathbf{F}, \mathbf{s}, \mathbf{z}\} \leftarrow \mathrm{argmin}_{\{\mathbf{F},\mathbf{s},\mathbf{z}\}} \mathcal{L}_\rho(\cdot)$ s.t. (12b), (12c) satisfied;
5.	$\boldsymbol{\Sigma}(t) \leftarrow \boldsymbol{\Sigma}(t) + \rho\left(\mathbf{F}(t) - [\mathbf{H}^\dagger(t)\mathbf{W}(t), \sigma\mathbf{1}]\right), \forall t;$ Update $\{\boldsymbol{\theta}, \boldsymbol{\phi}, \boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{\epsilon}, \boldsymbol{\eta}\}$ similarly;
6.	**until** some stopping criterion is satisfied.

1) Update $\{\mathbf{W}, \mathbf{x}, \mathbf{y}, \mathbf{a}, \mathbf{b}, \mathbf{c}, \mathbf{d}\}$*:* This problem can be separated into T subproblems of $\mathbf{W}(t)$, $M(T-1)$ subproblems of $\{x_m(t), b_m(t), d_m(t)\}$ and $M(T-1)$ subproblems of $\{y_m(t), a_m(t), c_m(t)\}$. We solve them independently.

- Let $\mathbf{F}_w(t)$ and $\boldsymbol{\Sigma}_w(t) \in \mathbb{C}^{M\times M}$ be the left sub-matrices of $\mathbf{F}(t)$ and $\boldsymbol{\Sigma}(t) \in \mathbb{C}^{M\times(M+1)}$, respectively. The subproblem of $\mathbf{W}(t)$ is expressed as

$$\min_{\mathbf{W}(t)}\ \|\mathbf{W}(t)\|_F^2 + \frac{\rho}{2}\|\mathbf{H}^\dagger(t)\mathbf{W}(t) - \frac{\rho\mathbf{F}_w(t)+\boldsymbol{\Sigma}_w(t)}{\rho}\|_F^2 \tag{14a}$$
$$\text{s.t. } \|\mathbf{W}(t)\|_F^2 \leq P, \tag{14b}$$

and can be easily solved as

$$\mathbf{W}(t) = \left[\frac{\rho\mathbf{H}(t)\mathbf{H}^\dagger(t)+2[1+\delta(t)]\mathbf{I}}{\rho}\right]^{-1}\left[\frac{\mathbf{H}(t)[\rho\mathbf{F}_w(t)+\boldsymbol{\Sigma}_w(t)]}{\rho}\right] \tag{15}$$

where $\delta(t)$ is the Lagrangian multiplier and should be properly chosen so that the KKT conditions are satisfied. This can be done via bisection.

- The subproblem of $\{x_m(t), b_m(t), d_m(t)\}$ is given by

$$\min_{\left\{\substack{x_m(t)\\ b_m(t)\\ d_m(t)}\right\}} \left\{ \begin{array}{l} \frac{\rho}{2}\left[b_m(t) - 1 - \kappa s_m(t+1) + \frac{\beta_m(t)}{\rho}\right]^2 \\ + \frac{\rho}{2}\left[d_m(t) - \frac{1+\kappa s_m(t)}{[1+\kappa\hat{s}_m(t)]^2} + \frac{\eta_m(t)}{\rho}\right]^2 \\ + \frac{\rho}{2}\left[x_m(t) - z_m(t) - \frac{\theta_m(t)}{\rho}\right]^2 \end{array} \right\} \tag{16a}$$
$$\text{s.t. } x_m(t) \geq \frac{1}{b_m(t)} - \frac{2}{1+\kappa\hat{s}_m(t)} + d_m(t), \tag{16b}$$
$$b_m(t) \geq 1. \tag{16c}$$

Utilizing the first-order optimality condition, we obtain

$$\begin{cases} x_m(t) = z_m(t) + \frac{\theta_m(t)}{\rho} + \frac{\tau_m(t)}{\rho}, \\ b_m(t) = \left[\mathrm{root}\left\{\frac{\rho[b_m(t)-1-\kappa s_m(t+1)]+\beta_m(t)}{\rho} = \frac{\tau_m(t)}{\rho b_m^2(t)}\right\}\right]_1^+ \\ d_m(t) = \frac{1+\kappa s_m(t)}{[1+\kappa\hat{s}_m(t)]^2} - \frac{\eta_m(t)}{\rho} - \frac{\tau_m(t)}{\rho}, \end{cases} \tag{17}$$

where $\mathrm{root}(\cdot)$ returns the root of the equation within brackets; $[\cdot]_1^+ = \max\{1, \cdot\}$; $\tau_m(t)$ is the Lagrangian multiplier.

To determine $\tau_m(t)$, we first check whether (16b) is satisfied at $\tau_m(t) = 0$. If the answer is positive, i.e.,

$$\begin{aligned} \Omega_m(t) &= z_m(t) + \frac{\theta_m(t)+\eta_m(t)}{\rho} + \frac{1+\kappa[2\hat{s}_m(t)-s_m(t)]}{[1+\kappa\hat{s}_m(t)]^2} \\ &\geq \frac{1}{\left[1+\kappa s_m(t+1) - \frac{\beta_m(t)}{\rho}\right]_1^+}, \end{aligned} \tag{18}$$

we have $\tau_m(t) = 0$. Otherwise, we seek some $\tau_m(t) > 0$ such that $x_m(t) = \frac{1}{b_m(t)} - \frac{2}{1+\kappa\hat{s}_m(t)} + d_m(t)$. In this case, we have

$$\frac{1}{b_m(t)} = x_m(t) + \frac{2}{1+\kappa\hat{s}_m(t)} - d_m(t) = \frac{2\tau_m(t)+\rho\Omega_m(t)}{\rho}. \tag{19}$$

By inserting (19) into (17), $b_m(t)$ can also be written as

$$b_m(t) = \left[\frac{\rho[1+\kappa s_m(t+1)]-\beta_m(t)}{\rho} + \frac{\tau_m(t)[2\tau_m(t)+\rho\Omega_m(t)]^2}{\rho^3}\right]_1^+.$$

Combining the expressions of $b_m(t)$ and $\frac{1}{b_m(t)}$, we have

$$\frac{2\tau_m(t)+\rho\Omega_m(t)}{\rho} = \frac{1}{\left[\frac{\rho[1+\kappa s_m(t+1)]-\beta_m(t)}{\rho} + \frac{\tau_m(t)[2\tau_m(t)+\rho\Omega_m(t)]^2}{\rho^3}\right]_1^+}$$

Then, $\tau_m(t)$ can be determined by performing bisection search in the range of $[\max\{0, \frac{-\rho\Omega_m(t)}{2}\}, \frac{\rho-\rho\Omega_m(t)}{2}]$.

- $\{y_m(t), a_m(t), c_m(t)\}$ can be solved similarly.

2) Update $\{\mathbf{F}, \mathbf{s}, \mathbf{z}\}$*:* This problem can be divided into MT subproblems of $\{\mathbf{f}^m(t), s_m(t)\}$ and $M(T-1)$ subproblems of $z_m(t)$. They can be solved independently.

- Let $\mathbf{G}(t) = [\mathbf{H}^\dagger(t)\mathbf{W}(t), \sigma\mathbf{1}]$. Denote $\mathbf{g}^m(t)$ and $\boldsymbol{\varepsilon}^m(t) \in \mathbb{C}^{(M+1)\times 1}$ as the mth row vectors of $\mathbf{G}(t)$ and $\boldsymbol{\Sigma}(t)$, respectively. The subproblem of $\{\mathbf{f}^m(t), s_m(t)\}$ is expressed as

$$\min_{\substack{\mathbf{f}^m(t)\\ s_m(t)}} \begin{bmatrix} \frac{\kappa\lambda_1 s_m(t)}{[1+\kappa\hat{s}_m(t)]^2} + \frac{\rho}{2}\|\mathbf{f}^m(t) - \mathbf{g}^m(t) + \frac{\boldsymbol{\varepsilon}^m(t)}{\rho}\|_2^2 \\ + \frac{\iota_a(t)\rho}{2}\left[\frac{\rho\kappa s_m(t)+\rho[1-a_m(t)]-\alpha_m(t)}{\rho}\right]^2 \\ + \frac{\iota_b(t)\rho}{2}\left[\frac{\rho\kappa s_m(t)+\rho[1-b_m(t-1)]-\beta_m(t-1)}{\rho}\right]^2 \\ + \frac{\iota_c(t)\rho}{2}\left[\frac{\kappa s_m(t)+1}{[1+\kappa\hat{s}_m(t)]^2} - \frac{\epsilon_m(t-1)+\rho c_m(t-1)}{\rho}\right]^2 \\ + \frac{\iota_d(t)\rho}{2}\left[\frac{\kappa s_m(t)+1}{[1+\kappa\hat{s}_m(t)]^2} - \frac{\eta_m(t)+\rho d_m(t)}{\rho}\right]^2 \end{bmatrix} \tag{20a}$$

$$\text{s.t.} \quad f_m^m(t) + s_m(t) \geq \sqrt{\gamma}\|\mathbf{f}_{-m}^m(t)\|_2, \tag{20b}$$

$$\mathrm{Im}\{f_m^m(t)\} = 0, \tag{20c}$$

$$\iota_a(t) = \iota_d(t) = \begin{cases} 1, & t = 1, 2, \ldots, T-1, \\ 0, & t = T, \end{cases} \tag{20d}$$

$$\iota_b(t) = \iota_c(t) = \begin{cases} 0, & t = 1, \\ 1, & t = 2, 3, \ldots, T. \end{cases} \tag{20e}$$

According to the first-order optimality conditions, we get

$$\begin{cases} s_m(t) = \frac{\chi_m(t)+\omega_m(t)}{\rho\xi_m(t)}, \\ f_m^m(t) = \frac{\mathrm{Re}\{\zeta_m^m(t)\}+\omega_m(t)}{\rho}, \\ \boldsymbol{\zeta}_{-m}^m(t) - \rho\mathbf{f}_{-m}^m(t) \in \omega_m(t)\sqrt{\gamma}\partial\|\mathbf{f}_{-m}^m(t)\|_2, \end{cases} \tag{21}$$

where $\omega_m(t)$ is the Lagrangian multiplier; $\boldsymbol{\zeta}^m(t) = \rho\mathbf{g}^m(t) - \boldsymbol{\varepsilon}^m(t)$; $\chi_m(t)$ and $\xi_m(t)$ are defined as (22) and (23), respectively (see next page). In addition, $\partial\|\cdot\|_2$ is the subgradient of the nonsmooth function $\|\cdot\|_2$, i.e.,

$$\partial\|\mathbf{v}\|_2 \triangleq \begin{cases} \frac{\mathbf{v}}{\|\mathbf{v}\|_2}, & \mathbf{v} \neq \mathbf{0}, \\ \{\mathbf{e} \mid \|\mathbf{e}\|_2 \leq 1\}, & \mathbf{v} = \mathbf{0}, \end{cases} \tag{24}$$

where $\mathbf{e}$ has the same dimension with $\mathbf{v}$.

By combining (21), (24) and the KKT conditions, we solve $\{\mathbf{f}^m(t), s_m(t)\}$ as follows.

$$\begin{cases} \texttt{if } \|\boldsymbol{\zeta}_{-m}^m(t)\|_2 \leq \frac{[-\chi_m(t)-\xi_m(t)\mathrm{Re}\{\zeta_m^m(t)\}]_0^+\cdot\sqrt{\gamma}}{1+\xi_m(t)} \\ \quad s_m(t) = \frac{\chi_m(t)+\omega_m(t)}{\rho\xi_m(t)}, \\ \quad f_m^m(t) = \frac{\mathrm{Re}\{\zeta_m^m(t)\}+\omega_m(t)}{\rho}, \\ \quad \mathbf{f}_{-m}^m(t) = \mathbf{0}, \\ \quad \omega_m(t) = \frac{[-\chi_m(t)-\xi_m(t)\mathrm{Re}\{\zeta_m^m(t)\}]_0^+}{1+\xi_m(t)}, \\ \texttt{else}, \\ \quad s_m(t) = \frac{\chi_m(t)+\omega_m(t)}{\rho\xi_m(t)}, \\ \quad f_m^m(t) = \frac{\mathrm{Re}\{\zeta_m^m(t)\}+\omega_m(t)}{\rho}, \\ \quad \mathbf{f}_{-m}^m(t) = \frac{\|\boldsymbol{\zeta}_{-m}^m(t)\|_2-\omega_m(t)\sqrt{\gamma}}{\rho}\cdot\frac{\boldsymbol{\zeta}_{-m}^m(t)}{\|\boldsymbol{\zeta}_{-m}^m(t)\|_2}, \\ \quad \omega_m(t) = \frac{\left[\xi_m(t)\left(\sqrt{\gamma}\|\boldsymbol{\zeta}_{-m}^m(t)\|_2-\mathrm{Re}\{\zeta_m^m(t)\}\right)-\chi_m(t)\right]_0^+}{1+(1+\gamma)\xi_m(t)}. \end{cases} \tag{25}$$

where $[\cdot]_0^+ = \max\{0, \cdot\}$.

- The subproblem of $z_m(t)$ is expressed as

$$\min_{z_m(t)} \left[z_m(t) - \frac{x_m(t)+y_m(t)}{2} + \frac{\lambda_2+\theta_m(t)+\phi_m(t)}{2\rho}\right]^2 \tag{26}$$

and can be easily solved as

$$z_m(t) = \frac{x_m(t)+y_m(t)}{2} - \frac{\lambda_2+\theta_m(t)+\phi_m(t)}{2\rho}. \tag{27}$$

So far, we have shown the efficient computation of each step in Algorithm 2. The convergence and complexity of Algorithm 2 are summarized below.

Remark 2. *Suppose problem* (10) *is feasible. Since the subproblems in each iterations can be uniquely solved, every limit point of the iterates generated by Algorithm 2 is an optimal solution of problem* (10) *[12].*

Remark 3. *The ADMM algorithm has very low complexity. In detail, the per-iteration complexity of Algorithm 2 is dominated by updating* $\mathbf{W}(t)$*, i.e.,* (15)*, which is* $\mathcal{O}(TMN(M+N))$*, while solving problem* (10) *directly, e.g., by interior-point (IP) method, requires the per-iteration complexity of* $\mathcal{O}((TMN)^3)$*.*

$$\chi_m(t) = \kappa\rho \left\{ \begin{array}{l} \frac{\iota_a(t)\alpha_m(t)+\iota_b(t)\beta_m(t-1)}{\rho} + \frac{\iota_c(t)\epsilon_m(t-1)+\iota_d(t)\eta_m(t)}{\rho[1+\kappa\hat{s}_m(t)]^2} - \frac{\lambda_1}{\rho[1+\kappa\hat{s}_m(t)]^2} \\ + \iota_a(t)[a_m(t)-1] + \iota_b(t)[b_m(t-1)-1] + \frac{\iota_c(t)\left[c_m(t-1)-\frac{1}{[1+\kappa\hat{s}_m(t)]^2}\right]+\iota_d(t)\left[d_m(t)-\frac{1}{[1+\kappa\hat{s}_m(t)]^2}\right]}{[1+\kappa\hat{s}_m(t)]^2} \end{array} \right\}, \quad (22)$$

$$\xi_m(t) = \kappa^2 \left\{ \iota_a(t) + \iota_b(t) + \frac{\iota_c(t)+\iota_d(t)}{[1+\kappa\hat{s}_m(t)]^4} \right\}. \quad (23)$$

IV. Simulation Results

We consider a network that consists of one 10-antenna BS and $M = 10$ single-antenna users, which are all randomly deployed in a hexagonal cell with the distance between adjacent corners being $d = 1\,\text{km}$. The BS power budget is $P = 100$, while the noise power is $\sigma^2 = 1$. The QoS requirement is $\gamma = 3$. The channels in each timeslot are assumed to be constant, while the channels in different blocks are generated according to the distribution of $\mathcal{CN}(0, \varsigma_m^2(t))$, where the variance is given by $\varsigma_m^2(t) = \varrho_m(t) \cdot [200/e_m(t)]^{3.7}$, with $\varrho_m(t)$ the shadowing parameter satisfying $10\log_{10}[\varrho_m(t)] \sim \mathcal{N}(0, 64)$, and $e_m(t)$ the distance between BS and user m at timeslot t.

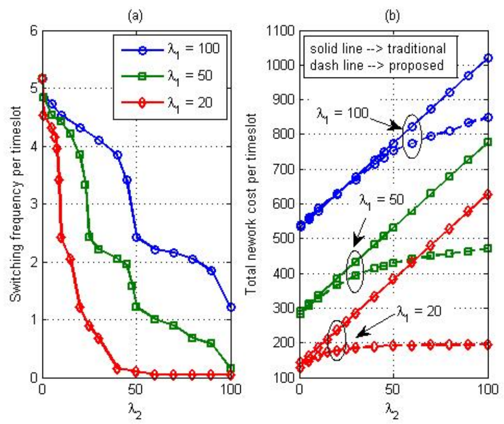

Fig. 1. Performance comparison of two algorithms: (a) switching frequency of user status; (b) total network cost.

We consider the transmission within a time period of $T = 20$ timeslots, and compare the proposed algorithm with the traditional joint admission control and beamforming algorithm; namely, we set $\lambda_2 = 0$ and optimize the admissible users and the associated beamformers in each timeslot independently. The performance comparison in terms of user status switching frequency and total network cost are shown in Fig. 1, where the switching frequency is defined as the average switching times per timeslot. In Fig. 1(a), the user status switching frequency decreases with λ_2 and thus more stable admissible user set can be achieved. In addition, as λ_2 is fixed, increasing λ_1 drives the network to emphasize more on the size of admissible user set, at the cost of the user set stability. In Fig. 1(b), we compare the total network cost (the objective of problem (4)). In the case of small λ_2, the two algorithms behave similarly because of the negligible switching cost. As λ_2 increases, the switching cost gradually dominates the total network cost. Then, the proposed algorithm shows its advantage in controlling the switching cost by performing long-term admission control.

V. Conclusions

In this paper, we take the stability of transmission links into consideration in joint admission control and beamforming, and propose a joint long-term admission control and beamforming problem. Our target is to balance the transmit power, the size of admissible user set, and the stability of admissible user set by carefully selecting the users and the beamformers in a given time period. An ADMM-based low-complexity algorithm was developed to solve this problem efficiently.

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