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Atiya, Y. S., Mobini, Z., Ngo, H. Q., & Matthaiou, M. (2024). Joint power optimization and AP selection for secure cell-free massive MIMO. In *IEEE Wireless Communications and Networking Conference (WCNC 2024): proceedings* (IEEE Wireless Communications and Networking Conference (WCNC): proceedings). Institute of Electrical and Electronics Engineers Inc.. <https://doi.org/10.1109/WCNC57260.2024.10570555>

Published in:

IEEE Wireless Communications and Networking Conference (WCNC 2024): proceedings

Document Version:

Peer reviewed version

Queen's University Belfast - Research Portal:

[Link to publication record in Queen's University Belfast Research Portal](#)

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Joint Power Optimization and AP Selection for Secure Cell-Free Massive MIMO

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Abstract—In this paper, we investigate joint power control and access point (AP) selection scheme in a cell-free massive multiple-input multiple-output (CF-mMIMO) system under an active eavesdropping attack, where an eavesdropper tries to overhear the signal sent to one of the legitimate users by contaminating the uplink channel estimation. We formulate a joint optimization problem to minimize the eavesdropping spectral efficiency (SE) while guaranteeing a given SE requirement at legitimate users. The challenging formulated problem is converted into a more tractable form and an efficient low-complexity accelerated projected gradient (APG)-based approach is proposed to solve it. Our findings reveal that the proposed joint optimization approach significantly outperforms the heuristic approaches in terms of secrecy SE (SSE). For instance, the 50% likely SSE performance of the proposed approach is 265% higher than that of equal power allocation and random AP selection scheme.

I. INTRODUCTION

CF-mMIMO has emerged as a promising wireless access technology for the next generations of wireless networks. In CF-mMIMO systems, a large number of APs are deployed over a certain area to communicate with a much smaller number of users in a user-centric scenario. Consequently, it can provide high coverage, spectral, and energy efficiency achieved by low-complexity signal processing [1]. CF-mMIMO leverages its architecture to provide efficient communication for all users in the network. However, this makes it more susceptible to eavesdropper (Eve) attacks due to the short distance between the APs and users. Therefore, the secrecy aspect of CF-mMIMO has attracted researchers' attention in recent years.

There are a few works in the context of secure CF-mMIMO systems. Specifically, in [2], a secrecy performance comparison between CF-mMIMO and co-located massive MIMO systems was performed by deriving the SSE expression under active pilot attacks. Then, using the same setup of [2], Hoang *et al.* in [3], proposed an approach for detecting the presence of the active Eve and designed power control schemes with different objectives including maximizing the achievable SE of the legitimate user who is under attack, maximizing the

SSE, and minimizing the total power at all APs subject to the constraints on the SE of the users and Eve. Later, the authors in [4] investigated the secrecy performance of CF-mMIMO utilizing non-orthogonal pilot sequences in the uplink training phase and proposed an approach for pilot transmission in the downlink phase. In addition, the authors in [5] addressed the problem of joint downlink power control and data transfer of CF-mMIMO under active eavesdropping. The effect of hardware impairments on the secrecy performance of a CF-mMIMO system was studied in [6]. Moreover, [7] studied the effect of radio frequency (RF) impairments and low-resolution analog-to-digital converters on the secrecy performance of CF-mMIMO system experiencing active eavesdropping. However, all the aforementioned works focused on power control designs, assuming that all APs serve all users.

Numerous AP selection schemes have been introduced in the literature [8]–[12] with the objective of increasing the scalability of CF-mMIMO, while simultaneously improving its SE and energy efficiency. Nevertheless, a popular assumption in the existing literature on secure CF-mMIMO systems is that each user is served by all APs in the network. In practice, APs are located at a considerable distance from users, making minimal contributions to the SE, whereas others are close to a potential Eve. Therefore, the efficient selection of APs to serve users, especially users under an eavesdropping attack, is a meaningful and important challenge. In line with this idea, in our very recent work [13], we proposed a heuristic AP selection approach to improve the SSE and showed that AP selection can provide a noticeable secrecy improvement.

In pursuit of harnessing the inherent benefits of *concurrently optimizing power allocation and AP selection*, in this paper we propose a joint optimization approach based on the APG method to minimize the overheard signal-to-interference-plus-noise ratio (SINR) at Eve while ensuring a predetermined quality of service (QoS) constraint at legitimate users. The main contributions of this paper can be summarized as follows:

- We propose a joint optimization approach for AP selection and power optimization. The formulated problem is under a transmit power constraint and individual QoS requirements of all legitimate users.
- An efficient algorithm is then proposed to solve the challenging formulated mixed-integer non-convex problem.
- Numerical results show that our joint optimization approach remarkably improves the secrecy performance of

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This work is a contribution by Project REASON, a UK Government funded project under the Future Open Networks Research Challenge (FONRC) sponsored by the Department of Science Innovation and Technology (DSIT). The work of Z. Mobini and H. Q. Ngo was supported by the U.K. Research and Innovation Future Leaders Fellowships under Grant MR/X010635/1. The work of M. Matthaiou has received funding from the European Research Council (ERC) under the European Union's Horizon 2020 research and innovation programme (grant agreement No. 101001331).

the CF-mMIMO system and outperforms the heuristic approaches.

Notation: Matrices are denoted by bold upper case letters, while bold lower case letters indicate vectors. The superscript $(\cdot)^H$ stands for the conjugate-transpose (Hermitian); we use $\mathbb{C}^{L \times N}$ to denote a $L \times N$ matrix; an $M \times M$ identity matrix is represented by \mathbf{I}_M ; $\text{tr}(\cdot)$ refers to the trace operation. The statistical expectation is denoted by $\mathbb{E}\{\cdot\}$. Finally, a zero mean circular symmetric complex Gaussian distribution with variance σ^2 is denoted by $\mathcal{CN}(0, \sigma^2)$.

II. SYSTEM MODEL

A CF-mMIMO system with L APs, K single-antenna users and time division duplex (TDD) mode is considered. Each AP $l, l \in \mathcal{L} = \{1, \dots, L\}$, is equipped with M antennas such that $LM \gg K$. There is also an active single-antenna Eve which is attempting to intercept the data destined to a specific user. Without loss of generality, let us assume that this is user 1. The $M \times 1$ channel vector from the l -th AP to the k -th user, $k \in \mathcal{K} = \{1, \dots, K\}$ and to Eve are given by

$$\mathbf{h}_{l,k} = \sqrt{\beta_{l,k}} \mathbf{g}_{l,k} \quad \text{and} \quad \mathbf{h}_{l,E} = \sqrt{\beta_{l,E}} \mathbf{g}_{l,E}, \quad (1)$$

respectively, where $\beta_{l,k}$ and $\beta_{l,E}$ denote the corresponding large-scale fading coefficients, while $\mathbf{g}_{l,k} \sim \mathcal{CN}(0, \mathbf{I}_M)$ and $\mathbf{g}_{l,E} \sim \mathcal{CN}(0, \mathbf{I}_M)$ are the complex Gaussian random vectors with covariance matrix \mathbf{I}_M which represent small-scale fading. We consider a CF-mMIMO system with an AP selection scheme in which the serving APs of each user are selected from a set of candidate APs to maximize the secrecy rate according to the system QoS requirement. In particular, we define the binary variables to indicate the AP-user association as

$$a_{l,k} \triangleq \begin{cases} 1, & \text{if user } k \text{ is served by } l\text{-th AP,} \\ 0, & \text{otherwise.} \end{cases} \quad (2)$$

The considered TDD transmission includes three main phases: uplink training phase for estimating channels, downlink data transmission, and uplink data transmission. Here, we focus on the downlink data transmission, and hence, neglect the uplink data transmission.

A. Uplink Training and Downlink Data Transmission

In the uplink training phase, we assume that all users transmit their pairwise orthogonal pilot sequences of length $\tau_p \geq K$ to all the APs in each coherence block. Denote the pilot sequence sent by the k -th user by $\phi_k \in \mathbb{C}^{\tau_p \times 1}$. Note that as discussed in [3], all pilot sequences are publicly known, and hence, Eve can transmit the same pilot as the targeted user 1 by setting $\phi_E = \phi_1$ to contaminate the channel estimates between all APs and user 1. Subsequently, Eve overhears the signals sent to user 1. By utilizing the minimum-mean-square-error (MMSE) method at the l -th AP to estimate the channel between the l -th AP and k -th user, $\hat{\mathbf{h}}_{l,k}$, we have $\hat{\mathbf{h}}_{l,k} \sim \mathcal{CN}(0, \gamma_{l,k} \mathbf{I}_M)$, where

$$\gamma_{l,k} \triangleq \begin{cases} \frac{\tau_p \rho_u \beta_{l,k}^2}{\tau_p \rho_u \beta_{l,k} + 1}, & k \neq 1, \\ \frac{\tau_p \rho_u \beta_{l,1}^2}{\tau_p \rho_u \beta_{l,1} + \tau_p \rho_E \beta_{l,E} + 1}, & k = 1, \end{cases} \quad (3)$$

where $\rho_u \triangleq P_u/N_0$ and $\rho_E \triangleq P_E/N_0$, while P_u and P_E are respectively the transmit powers of users and Eve, and N_0 is the average noise power at the APs. Let $\alpha_{l,1} = (\rho_E \beta_{l,E}^2) / (\rho_u \beta_{l,1}^2)$, then the estimated channel and the mean-square of the estimates between the l -th AP and Eve are respectively given by

$$\hat{\mathbf{h}}_{l,E} = \sqrt{\alpha_{l,1}} \hat{\mathbf{h}}_{l,1}, \quad (4)$$

$$\gamma_{l,E} = \alpha_{l,1} \gamma_{l,1}. \quad (5)$$

In the downlink data transmission phase, all APs transmit their signals to all users by exploiting the channel estimates obtained during the previous phase. Let s_k , where $\mathbb{E}\{|s_k|^2\} = 1$, denote the data symbol sent to the k -th user, the precoded data signal sent by the l -th AP to all users can be written as

$$\mathbf{x}_l = \sum_{k \in \mathcal{K}} \sqrt{\rho_d} \theta_{l,k} \mathbf{w}_{l,k} s_k, \quad (6)$$

where ρ_d is the maximum normalized transmit power of each AP, $\theta_{l,k}$ is the power control coefficient, and $\mathbf{w}_{l,k} \in \mathbb{C}^{M \times 1}$, where $\mathbb{E}\{\|\mathbf{w}_{l,k}\|^2\} = 1$, is the precoding vector associated with user k . Here, we enforce

$$\theta_{l,k} = 0, \text{ if } a_{l,k} = 0 \quad \forall l, k, \quad (7)$$

to ensure that if AP l does not serve user k , the transmit power of AP l to user k is zero. Note that AP l is required to satisfy the average normalized power constraint, which can be written as the following per-AP power constraint

$$\sum_{k \in \mathcal{K}} \theta_{l,k}^2 \leq 1, \quad \forall l. \quad (8)$$

Hence, the signals received at the k -th user and Eve are, respectively, given by

$$z_k = \sqrt{\rho_d} \sum_{l \in \mathcal{L}} \mathbf{h}_{l,k}^H \mathbf{x}_l + n_k, \quad (9)$$

$$z_E = \sqrt{\rho_d} \sum_{l \in \mathcal{L}} \mathbf{h}_{l,E}^H \mathbf{x}_l + n_E, \quad (10)$$

where $n_k \sim \mathcal{CN}(0, 1)$ and $n_E \sim \mathcal{CN}(0, 1)$.

Here, we employ the local protective partial zero-forcing (PPZF) precoding scheme due to its excellent balance between performance and complexity [14]. With PPZF, each AP mitigates the interference that causes to the subset of users, while tolerates the interference that creates to other users. For each AP l , users are split, based on the channel gains $\beta_{l,k}$, $l \in \mathcal{L}$, $k \in \mathcal{K}$, into two groups: strong group \mathcal{S}_l and weak group \mathcal{W}_l with $\mathcal{S}_l \cap \mathcal{W}_l = \emptyset$, and $|\mathcal{S}_l| + |\mathcal{W}_l| = K$. After grouping users, each AP utilizes partial ZF (PZF) and protective MRT (PMRT) schemes for precoding the signals sent to users in \mathcal{S}_l and \mathcal{W}_l , respectively. We note that, to implement PZF, the number of antenna elements must meet the requirement $M \geq |\mathcal{S}_l| + 1$. Let the collective channel estimation matrix from AP l to all users be $\hat{\mathbf{H}}_l = [\hat{\mathbf{h}}_{l,1}, \dots, \hat{\mathbf{h}}_{l,K}] \in \mathbb{C}^{M \times K}$ where \mathbf{e}_i represents the i -th column of \mathbf{I}_K , and hence $\mathbf{E}_{\mathcal{S}_l} = [\mathbf{e}_i : i \in \mathcal{S}_l] \in \mathbb{C}^{K \times |\mathcal{S}_l|}$. Also, let $\boldsymbol{\pi}_k$ be the j -th column of $\mathbf{I}_{|\mathcal{S}_l|}$ and user k corresponds to the j -th element of set \mathcal{S}_l , $j \in \{1, \dots, |\mathcal{S}_l|\}$. Then, the precoding vector in (6) is given by

$$\mathbf{w}_{l,k} = \begin{cases} \mathbf{w}_{l,k}^{\text{PZF}}, & \text{if } k \in \mathcal{S}_l, \\ \mathbf{w}_{l,k}^{\text{PMRT}}, & \text{if } k \in \mathcal{W}_l, \end{cases} \quad (11)$$

where $\mathbf{w}_{l,k}^{\text{PZF}}$ and $\mathbf{w}_{l,k}^{\text{PMRT}}$, are respectively, given by

$$\mathbf{w}_{l,k}^{\text{PZF}} = \sqrt{(M-|\mathcal{S}_l|)\gamma_{l,j}} \hat{\mathbf{H}}_l \mathbf{E}_{\mathcal{S}_l} \left(\mathbf{E}_{\mathcal{S}_l}^H \hat{\mathbf{H}}_l^H \hat{\mathbf{H}}_l \mathbf{E}_{\mathcal{S}_l} \right)^{-1} \boldsymbol{\pi}_k, \quad (12)$$

$$\mathbf{w}_{l,j}^{\text{PMRT}} = \frac{\mathbf{B}_l \hat{\mathbf{H}}_l \mathbf{e}_j}{\sqrt{(M-|\mathcal{S}_l|)\gamma_{l,j}}}, \quad (13)$$

with

$$\mathbf{B}_l = \mathbf{I}_M - \hat{\mathbf{H}}_l \mathbf{E}_{\mathcal{S}_l} \left(\mathbf{E}_{\mathcal{S}_l}^H \hat{\mathbf{H}}_l^H \hat{\mathbf{H}}_l \mathbf{E}_{\mathcal{S}_l} \right)^{-1} \mathbf{E}_{\mathcal{S}_l}^H \hat{\mathbf{H}}_l^H. \quad (14)$$

Accordingly, (6) can be expressed as

$$\mathbf{x}_l = \sum_{k \in \mathcal{S}_l} \sqrt{\rho_d} \theta_{l,k} \mathbf{w}_{l,k}^{\text{PZF}} s_k + \sum_{j \in \mathcal{W}_l} \sqrt{\rho_d} \theta_{l,j} \mathbf{w}_{l,j}^{\text{PMRT}} s_j. \quad (15)$$

B. Achievable SE at the Users and Eve

Let us denote the set of AP indices that utilize PZF and PMRT in transmission by \mathcal{Z}_k and \mathcal{M}_k , respectively,

$$\mathcal{Z}_k \triangleq \{l : k \in \mathcal{S}_l, l = 1, \dots, L\}, \quad (16)$$

$$\mathcal{M}_k \triangleq \{l : k \in \mathcal{W}_l, l = 1, \dots, L\}, \quad (17)$$

with $\mathcal{Z}_k \cap \mathcal{M}_k = \emptyset$, and $|\mathcal{Z}_k| + |\mathcal{M}_k| = L$.

Accordingly, the received signal at the k -th user in (9) can be reformulated as

$$z_k = \left(\sum_{l \in \mathcal{Z}_k} \sqrt{\rho_d} \theta_{l,k} \mathbf{h}_{l,k}^H \mathbf{w}_{l,k}^{\text{PZF}} + \sum_{p \in \mathcal{M}_k} \sqrt{\rho_d} \theta_{p,k} \mathbf{h}_{p,k}^H \mathbf{w}_{p,k}^{\text{PMRT}} \right) s_k + \sum_{\substack{t \in \mathcal{K} \\ t \neq k}} \left(\sum_{l \in \mathcal{Z}_t} \sqrt{\rho_d} \theta_{l,t} \mathbf{h}_{l,t}^H \mathbf{w}_{l,t}^{\text{PZF}} + \sum_{p \in \mathcal{M}_t} \sqrt{\rho_d} \theta_{p,t} \mathbf{h}_{p,t}^H \mathbf{w}_{p,t}^{\text{PMRT}} \right) s_t + n_k.$$

Using the use-and-then-forget bounding method [1], an achievable SE of the k -th user is expressed as $R_k = \log_2(1 + \text{SINR}_k)$, where

$$\text{SINR}_k = \frac{\left(\sum_{l \in \mathcal{L}} \sqrt{\rho_d} (M-|\mathcal{S}_l|) \gamma_{l,k} \theta_{l,k} \right)^2}{\sum_{t \in \mathcal{K}} \sum_{l \in \mathcal{L}} \rho_d \theta_{l,t}^2 (\beta_{l,k} - \delta_{l,k} \gamma_{l,k}) + 1}, \quad (18)$$

with $\delta_{l,k} \triangleq 1$ if $k \in \mathcal{S}_l$ and $\delta_{l,k} \triangleq 0$ if $k \in \mathcal{W}_l$ [15].

In addition, the received signal at Eve in (10) can be represented in the form of

$$z_E = \sum_{l \in \mathcal{L}} \sqrt{\rho_d} \theta_{l,1} \mathbf{h}_{l,E}^H \mathbf{w}_{l,1} s_1 + \sum_{\substack{t \in \mathcal{K} \\ t \neq 1}} \sum_{l \in \mathcal{L}} \sqrt{\rho_d} \theta_{l,t} \mathbf{h}_{l,E}^H \mathbf{w}_{l,t} s_t + n_E. \quad (19)$$

Following [15], the SE of Eve can be written as $R_E = \log_2(1 + \text{SINR}_E)$, where

$$\text{SINR}_E = \frac{\left(\sum_{l \in \mathcal{L}} \sqrt{\rho_d} (M-|\mathcal{S}_l|) \gamma_{l,E} \theta_{l,1} \right)^2 + \sum_{l \in \mathcal{L}} \rho_d \theta_{l,1}^2 (\beta_{l,E} - \delta_{l,1} \gamma_{l,E})}{\sum_{\substack{t \in \mathcal{K} \\ t \neq 1}} \sum_{l \in \mathcal{L}} \rho_d \theta_{l,t}^2 (\beta_{l,E} - \delta_{l,1} \gamma_{l,E}) + 1}. \quad (20)$$

Now, the SSE can be calculated as

$$\text{SSE} = [R_1 - R_E]^+ = \left[\log_2 \left(\frac{1 + \text{SINR}_1}{1 + \text{SINR}_E} \right) \right]^+, \quad (21)$$

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

III. JOINT POWER ALLOCATION AND AP SELECTION

We now seek to jointly optimize the power control coefficients $\boldsymbol{\theta} \triangleq \{\theta_{l,k}\}$ and AP selection $\mathbf{a} \triangleq \{a_{l,k}\}$ to minimize the

achievable SE at Eve under a total transmit power constraint at each AP and a QoS requirement $R_{\text{th},k}$ at each user k . The corresponding optimization problem becomes

$$\min_{\mathbf{a}, \boldsymbol{\theta}} R_E(\boldsymbol{\theta}), \quad (22a)$$

$$\text{s.t.} \quad \theta_{l,k} \geq 0, \forall l, k, \quad (22b)$$

$$\sum_{k \in \mathcal{K}} \theta_{l,k}^2 \leq 1, \forall l, \quad (22c)$$

$$R_k(\boldsymbol{\theta}) \geq R_{\text{th},k}, \quad \forall k, \quad (22d)$$

$$(\theta_{l,k}^2 = 0, \forall k, \text{ if } a_{l,k} = 0), \quad \forall l, \quad (22e)$$

$$\sum_{l \in \mathcal{L}} a_{l,k} \geq 1, \forall k, \quad (22f)$$

where the constraint in (22f) guarantees that each user is served by at least one AP. Problem (22) is a nonconvex mixed-integer optimization problem and is difficult to solve. To deal with the binary constraint in (2), we observe that $x \in \{0, 1\} \Leftrightarrow x \in [0, 1] \ \& \ x - x^2 \leq 0$ [16], and hence, we replace (2) with

$$Q(\mathbf{a}) \triangleq \sum_{k \in \mathcal{K}} \sum_{l \in \mathcal{L}} (a_{l,k} - a_{l,k}^2) \leq 0, \quad (23)$$

$$0 \leq a_{l,k}, \forall l, k, \quad (24)$$

$$a_{l,k} \leq 1, \forall l, k. \quad (25)$$

Based on (22c), (22e) can be replaced by

$$\theta_{l,k}^2 \leq a_{l,k}, \forall l, k. \quad (26)$$

To this end, problem (22) is equivalent to

$$\min_{\mathbf{x} \in \mathcal{C}} R_E(\boldsymbol{\theta}), \quad (27)$$

where $\mathbf{x} \triangleq \{\mathbf{a}, \boldsymbol{\theta}\}$, $\mathcal{C} \triangleq \{(22b), (22c), (22d), (22f), (23) - (26)\}$ is a feasible set. To solve problem (27), we propose an approach based on the APG algorithm. The APG-based method has shown to be highly effective for resource allocation in cell-free massive MIMO, as it offers very good performance, and provides much lower complexity than conventional successive convex approximation (SCA) algorithms, especially when the network size is large [17], [18].

A. APG Method

To begin, we modify the optimization problem (27) through a change in variables, enabling a more efficient computation of the function's gradient and the subsequent projection. To this end, we first introduce a new variable $z_{l,k}^2 \triangleq a_{l,k}, \forall l, k$, where

$$0 \leq z_{l,k} \leq 1, \quad (28)$$

and define new notations as follows

- $U_k(\boldsymbol{\theta}) = \left(\sum_{l \in \mathcal{L}} \sqrt{\rho_d} (M-|\mathcal{S}_l|) \gamma_{l,k} \theta_{l,k} \right)^2$,
- $V_k(\boldsymbol{\theta}) = \sum_{t \in \mathcal{K}} \sum_{l \in \mathcal{L}} \rho_d \theta_{l,t}^2 (\beta_{l,k} - \delta_{l,k} \gamma_{l,k}) + 1$,
- $U_E(\boldsymbol{\theta}) = \left(\sum_{l \in \mathcal{L}} \sqrt{\rho_d} (M-|\mathcal{S}_l|) \gamma_{l,1} \theta_{l,1} \right)^2 + \sum_{l \in \mathcal{L}} \rho_d \theta_{l,1}^2 (\beta_{l,E} - \delta_{l,1} \gamma_{l,E})$,
- $V_E(\boldsymbol{\theta}) = \sum_{\substack{t \in \mathcal{K} \\ t \neq 1}} \sum_{l \in \mathcal{L}} \rho_d \theta_{l,t}^2 (\beta_{l,E} - \delta_{l,1} \gamma_{l,E}) + 1$.

Accordingly, the objective function in Problem (27) can be rewritten as $R_E(\boldsymbol{\theta}) = \log_2 \left(1 + \frac{U_E(\boldsymbol{\theta})}{V_E(\boldsymbol{\theta})} \right)$ and the corresponding constraint (22d) can be replaced by $R_k(\boldsymbol{\theta}) = \log_2 \left(1 + \frac{U_k(\boldsymbol{\theta})}{V_k(\boldsymbol{\theta})} \right) \geq R_{\text{th}}$. Now, a key challenge in develop-

Algorithm 1 The Proposed Algorithm for Solving (30)

- 1: **Initialization:** $\varrho, \varsigma > 1, v > 0, n = 1, q^{(0)} = 0, q^{(1)} = 1, \mathbf{v}^{(0)}, \bar{\mathbf{v}}^{(0)} \in \hat{\mathcal{C}}, \alpha_{\bar{\mathbf{v}}} > 0, \alpha_{\mathbf{v}} > 0, \tilde{\mathbf{v}}^{(1)} = \mathbf{v}^{(1)} = \mathbf{v}^{(0)}, \zeta \in [0, 1), b^{(1)} = 1, c^{(1)} = f(\mathbf{v}^{(1)})$
 - 2: **repeat** (outer loop: penalty method)
 - 3: **repeat** (inner loop: APG method)
 - 4: Update $\bar{\mathbf{v}}^{(n)}$ as $\bar{\mathbf{v}}^{(n)} = \mathbf{v}^{(n)} + \frac{q^{(n-1)}}{q^{(n)}}(\tilde{\mathbf{v}}^{(n)} - \mathbf{v}^{(n)}) + \frac{q^{(n-1)-1}}{q^{(n)}}(\mathbf{v}^{(n)} - \mathbf{v}^{(n-1)})$,
 - 5: Set $\tilde{\mathbf{v}}^{(n+1)} = \mathcal{P}_{\hat{\mathcal{C}}}(\bar{\mathbf{v}}^{(n)} - \alpha_{\mathbf{v}} \nabla f(\bar{\mathbf{v}}^{(n)}))$,
 - 6: **if** $f(\tilde{\mathbf{v}}^{(n+1)}) \leq c^{(n)} - \zeta \|\tilde{\mathbf{v}}^{(n+1)} - \bar{\mathbf{v}}^{(n)}\|^2$ **then**
 - 7: $\mathbf{v}^{(n+1)} = \tilde{\mathbf{v}}^{(n+1)}$
 - 8: **else**
 - 9: Update $\hat{\mathbf{v}}^{(n+1)}$ as (49) and $\mathbf{v}^{(n+1)}$ as (50)
 - 10: **end if**
 - 11: Set $q^{(n+1)} = \frac{1 + \sqrt{4(q^{(n)})^2 + 1}}{2}$.
 - 12: Update $b^{(n+1)}$ as (48), and $c^{(n+1)}$ as (47)
 - 13: Set $n = n + 1$
 - 14: **until** $\left| \frac{f(\mathbf{v}^{(n)}) - f(\mathbf{v}^{(n-10)})}{f(\mathbf{v}^{(n)})} \right| \leq \epsilon$ or $\left| \frac{h(\boldsymbol{\theta}^{(n)}) - h(\boldsymbol{\theta}^{(n-1)})}{h(\boldsymbol{\theta}^{(n)})} \right| \leq \epsilon$
 - 15: Increase $\varrho = \varrho \times \varsigma$
 - 16: **until** Convergence.
-

ing an efficient APG algorithm for solving Problem (27) is the QoS constraint (22d) as well as the AP association constraints (22f), (23), and (26). One possible way to address this problem is to incorporate these constraints into the objective function by introducing a penalty parameter, resulting in the formulation of the penalized problem [17]. The APG technique is subsequently utilized to address the penalized problem, while this process is iterated until a predefined stopping criterion is met. To this end, for each constraint we introduce a quadratic loss function as

- $\Psi_1(\boldsymbol{\theta}) \triangleq \sum_{k \in \mathcal{K}} [\max(0, R_{\text{th},k} - R_k(\boldsymbol{\theta}))]^2$ for constraint (22d).
- $\Psi_2(\mathbf{z}) \triangleq \sum_{k \in \mathcal{K}} \sum_{l \in \mathcal{L}} (z_{l,k}^2 - z_{l,k}^4)$, where $\mathbf{z} \triangleq [\mathbf{z}_1^T, \dots, \mathbf{z}_L^T]^T$ with $\mathbf{z}_l \triangleq [z_{l,1}, \dots, z_{l,K}]^T$ for constraint (23).
- $\Psi_3(\boldsymbol{\theta}, \mathbf{z}) \triangleq \sum_{k \in \mathcal{K}} ([\max(0, 1 - \sum_{l \in \mathcal{L}} z_{l,k}^2)]^2 + \sum_{l \in \mathcal{L}} [\max(0, \theta_{l,k}^2 - z_{l,k}^2)]^2)$ for constraints (22f) and (26).

Therefore, for the given penalty coefficients μ_1, μ_2 , and μ_3 , the penalized objective function of Problem(22), denoted by \mathbf{v} , can be expressed as

$$f(\mathbf{v}) \triangleq \log_2 \left(1 + \frac{U_E(\boldsymbol{\theta})}{V_E(\boldsymbol{\theta})} \right) + \varrho [\mu_1 \Psi_1(\boldsymbol{\theta}) + \mu_2 \Psi_2(\mathbf{z}) + \mu_3 \Psi_3(\boldsymbol{\theta}, \mathbf{z})], \quad (29)$$

with $\varrho > 0$. Accordingly, at each iteration of the iterative process, the regularized optimization problem

$$\min_{\mathbf{v} \in \hat{\mathcal{C}}} f(\mathbf{v}), \quad (30)$$

for a given ϱ is solved where $\hat{\mathcal{C}}$ represents the convex feasible set of (30) (i.e., (22b), (22c), (28)) and $\mathbf{v} \triangleq [\boldsymbol{\theta}^T, \mathbf{z}^T]^T$. We summarize our proposed method to solve problem (30), which combines the penalty method and the APG method, in

Algorithm 1. We note that $\mathcal{P}_{\mathcal{C}}(\mathbf{x})$ in Algorithm 1 shows the Euclidean projection operator which is defined as

$$\mathcal{P}_{\mathcal{C}}(\mathbf{x}) = \operatorname{argmin}_{\mathbf{u} \in \mathcal{C}} \|\mathbf{x} - \mathbf{u}\|. \quad (31)$$

It is clear that the two main operations in the implementation of Algorithm 1 are the computation of the gradient of the objective function and the projections.

1) *Gradient of the objective function:* The gradients $\frac{\partial}{\partial \theta_{l,k}} f(\mathbf{v})$ and $\frac{\partial}{\partial z_{l,k}} f(\mathbf{v})$ can be calculated as

$$\frac{\partial}{\partial \theta_{l,k}} f(\mathbf{v}) = \frac{\partial}{\partial \theta_{l,k}} R_E(\mathbf{v}) + \varrho \frac{\partial}{\partial \theta_{l,k}} \tilde{\Psi}(\mathbf{v}), \quad (32)$$

$$\frac{\partial}{\partial z_{l,k}} f(\mathbf{v}) = \frac{\partial}{\partial z_{l,k}} R_E(\mathbf{v}) + \varrho \frac{\partial}{\partial z_{l,k}} \tilde{\Psi}(\mathbf{v}), \quad (33)$$

where

$$\begin{aligned} & \frac{\partial}{\partial \theta_{l,k}} R_E(\mathbf{v}) \\ &= \frac{1}{\log 2} \left[\frac{\frac{\partial}{\partial \theta_{l,k}} (U_E(\mathbf{v}) + V_E(\mathbf{v}))}{(U_E(\mathbf{v}) + V_E(\mathbf{v}))} - \frac{\frac{\partial}{\partial \theta_{l,k}} V_E(\mathbf{v})}{V_E(\mathbf{v})} \right], \quad (34) \end{aligned}$$

with

$$\frac{\partial}{\partial \theta_{l,k}} U_E(\mathbf{v}) = \begin{cases} 2 \left(\sum_{l \in \mathcal{L}} \sqrt{\rho_d (M - |\mathcal{S}_l|)} \gamma_{l,E} \theta_{l,1} \right) \\ \quad \times \sqrt{\rho_d (M - |\mathcal{S}_l|)} \gamma_{l,E} \\ \quad + 2 \rho_d \theta_{l,1} (\beta_{l,E} - \delta_{l,1} \gamma_{l,E}), & k = 1, \\ 0, & k \neq 1, \end{cases} \quad (35a)$$

$$\frac{\partial}{\partial \theta_{l,k}} V_E(\mathbf{v}) = \begin{cases} 2 \rho_d \theta_{l,t} (\beta_{l,E} - \delta_{l,1} \gamma_{l,E}), & t = k \setminus \{1\}, \\ 0, & t \neq k. \end{cases} \quad (35b)$$

In addition, $\frac{\partial}{\partial \theta_{l,k}} R_i(\mathbf{v})$ can be calculated as

$$\frac{\partial}{\partial \theta_{l,k}} R_i(\mathbf{v}) = \frac{1}{\log 2} \left[\frac{\frac{\partial}{\partial \theta_{l,k}} (U_i(\mathbf{v}) + V_i(\mathbf{v}))}{(U_i(\mathbf{v}) + V_i(\mathbf{v}))} - \frac{\frac{\partial}{\partial \theta_{l,k}} V_i(\mathbf{v})}{V_i(\mathbf{v})} \right], \quad (36)$$

where $\frac{\partial}{\partial \theta_{l,k}} U_i(\mathbf{v})$ and $\frac{\partial}{\partial \theta_{l,k}} V_i(\mathbf{v})$ are given by

$$\frac{\partial}{\partial \theta_{l,k}} U_i(\mathbf{v}) = \begin{cases} 2 \left(\sum_{l \in \mathcal{L}} \sqrt{\rho_d (M - |\mathcal{S}_l|)} \gamma_{l,k} \theta_{l,k} \right) \\ \quad \times \sqrt{\rho_d (M - |\mathcal{S}_l|)} \gamma_{l,k}, & i = k \setminus \{1\}, \\ 0, & i \neq k, \end{cases} \quad (37)$$

$$\frac{\partial}{\partial \theta_{l,k}} V_i(\mathbf{v}) = \begin{cases} 2 \rho_d \theta_{l,k} (\beta_{l,k} - \delta_{l,k} \gamma_{l,k}), & i = k \setminus \{1\}, \\ 2 \rho_d \theta_{l,k} (\beta_{l,i} - \delta_{l,i} \gamma_{l,i}), & i \neq k. \end{cases} \quad (38)$$

Thus, we obtain

$$\begin{aligned} \frac{\partial}{\partial \theta_{l,k}} \tilde{\Psi}(\mathbf{v}) &= 4 \mu_3 \max(0, \theta_{l,k}^2 - z_{l,k}^2) \theta_{l,k} \\ &\quad - \mu_2 \sum_{i \in \mathcal{K}} 2 \max(0, R_{\text{th},k} - R_i(\boldsymbol{\theta})) \frac{\partial}{\partial \theta_{l,k}} R_i(\mathbf{v}), \quad (39) \end{aligned}$$

$$\begin{aligned} \frac{\partial}{\partial z_{l,k}} \tilde{\Psi}(\mathbf{v}) &= \mu_1 (2 z_{l,k} - 4 z_{l,k}^3) - 4 \mu_3 \max(0, \theta_{l,k}^2 - z_{l,k}^2) z_{l,k} \\ &\quad - 4 \mu_3 \max \left(0, 1 - \sum_{l \in \mathcal{L}} z_{l,k}^2 \right) z_{l,k}. \quad (40) \end{aligned}$$

2) *Projection onto feasible set $\hat{\mathcal{C}}$* : The projection onto the feasible set $\hat{\mathcal{C}}$ in Algorithm 1 can be done by solving the problem

$$\begin{aligned} \mathcal{P}_{\hat{\mathcal{C}}}(\mathbf{v}) : \quad & \min_{\mathbf{v} \in \mathbb{R}^{2LK \times 1}} \|\mathbf{v} - \mathbf{r}\|^2 \\ \text{s.t.} \quad & (22\text{b}), (22\text{c}), (28), \end{aligned} \quad (41)$$

where $\mathbf{r} = [\mathbf{r}_1^T, \mathbf{r}_2^T]^T \in \mathbb{R}^{2LK \times 1}$ with $\mathbf{r}_1 \triangleq [\mathbf{r}_{1,1}^T, \dots, \mathbf{r}_{1,L}^T]^T$ and $\mathbf{r}_{1,l} \triangleq [r_{1,l,1}, \dots, r_{1,l,K}]^T$. Problem (41) can be split into two distinct subproblems as

$$\begin{aligned} \min_{\boldsymbol{\theta}_l \in \mathbb{R}^{LK \times 1}} \quad & \|\boldsymbol{\theta}_l - \mathbf{r}_{1,l}\|^2 \\ \text{s.t.} \quad & \|\boldsymbol{\theta}_l\|^2 \leq 1, \boldsymbol{\theta}_l \geq 0, \end{aligned} \quad (42)$$

and

$$\begin{aligned} \min_{\mathbf{z}_l \in \mathbb{R}^{LK \times 1}} \quad & \|\mathbf{z}_l - \mathbf{r}_{2,l}\|^2 \\ \text{s.t.} \quad & \mathbf{z}_l \geq 0, \mathbf{z}_l \leq 1, \end{aligned} \quad (43)$$

where the constraints in problems (42) and (43) adhere to the conditions outlined in (22b), (22c), and (28). Solving problem (42) involves projecting a given point onto the intersection of a Euclidean ball and the positive orthant, and this projection can be calculated using a closed-form expression [12] as

$$\boldsymbol{\theta}_l = \frac{1}{\max\left(1, \left\|[\mathbf{r}_{1,l}]_0^+\right\|\right)} [\mathbf{r}_{1,l}]_0^+, \quad (44)$$

where $[\mathbf{x}]_0^+ \triangleq [\max(0, x_1), \dots, \max(0, x_K)]^T, \forall \mathbf{x} \in \mathbb{R}^{K \times 1}$.

We note that in Algorithm 1, starting from $\bar{\mathbf{v}}^{(n)}$, we move along the gradient of the objective function using a specific step size $\alpha_{\bar{\mathbf{v}}}$. By projecting the resulting point $(\bar{\mathbf{v}} - \alpha_{\bar{\mathbf{v}}}\nabla f(\bar{\mathbf{v}}))$ onto the feasible set $\hat{\mathcal{C}}$, we obtain

$$\tilde{\mathbf{v}}^{(n+1)} = \mathcal{P}_{\hat{\mathcal{C}}}(\bar{\mathbf{v}}^{(n)} - \alpha_{\bar{\mathbf{v}}}\nabla f(\bar{\mathbf{v}}^{(n)})). \quad (45)$$

However, $f(\tilde{\mathbf{v}}^{(n+1)})$ may not improve the objective sequence because $f(\mathbf{v})$ is not convex, thus, $\mathbf{v}^{(n+1)} = \tilde{\mathbf{v}}^{(n+1)}$ is accepted if and only if the objective value $f(\tilde{\mathbf{v}}^{(n+1)})$ is below $c^{(n)}$, which represents a relaxation of $f(\mathbf{v}^{(n)})$, but relatively close to $f(\mathbf{v}^{(n)})$. Following [19], $c^{(n)}$ is computed as follows:

$$c^{(n)} = \frac{\sum_{\kappa=1}^n \zeta^{(\kappa-n)} f(\mathbf{v}^{(\kappa)})}{\sum_{\kappa=1}^n \zeta^{(\kappa-n)}}, \quad (46)$$

where $\zeta \in [0, 1)$ used to control the non-monotonicity degree. After each iteration, $c^{(n)}$ can be iteratively updated as follows:

$$c^{(n+1)} = \frac{\zeta b^{(n)} c^{(n)} + f(\mathbf{v}^{(n)})}{b^{(n+1)}}, \quad (47)$$

where $c^{(1)} = f(\mathbf{v}^{(1)})$ and $b^{(1)} = 1$, and $b^{(n+1)}$ is calculated as

$$b^{(n+1)} = \zeta b^{(n)} + 1. \quad (48)$$

In case the condition $f(\tilde{\mathbf{v}}^{(n+1)}) \leq c^{(n)} - \zeta \|\tilde{\mathbf{v}}^{(n+1)} - \bar{\mathbf{v}}^{(n)}\|^2$ is not satisfied, extra correction steps are employed to avoid this situation, where $\|\mathbf{x}\|$ denotes the Euclidean norm of vector \mathbf{x} . Specifically, an additional point is calculated with a dedicated step size $\alpha_{\mathbf{v}}$ as

$$\hat{\mathbf{v}}^{(n+1)} = \mathcal{P}_{\hat{\mathcal{C}}}(\mathbf{v}^{(n)} - \alpha_{\mathbf{v}}\nabla f(\mathbf{v}^{(n)})). \quad (49)$$

Then, $\mathbf{v}^{(n+1)}$ is updated by comparing the objective values at $\tilde{\mathbf{v}}^{(n+1)}$ and $\hat{\mathbf{v}}^{(n+1)}$ as

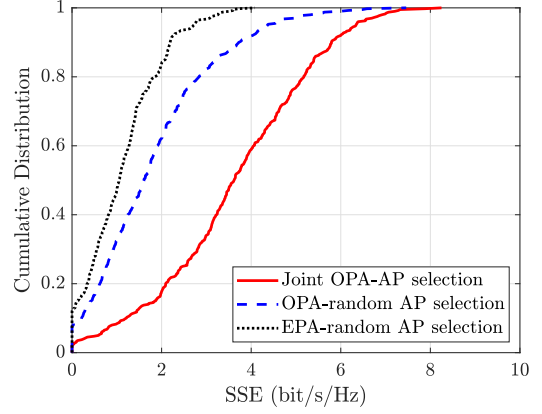


Fig. 1: CDFs of the SSE for three cases: EPA-random AP selection, OPA-random AP selection, and joint OPA-AP selection. Here, $L = 300$, $M = 4$, $K = 40$, and $r_E = 100$ m.

$$\mathbf{v}^{(n+1)} \triangleq \begin{cases} \tilde{\mathbf{v}}^{(n+1)}, & \text{if } f(\tilde{\mathbf{v}}^{(n+1)}) \leq f(\hat{\mathbf{v}}^{(n+1)}), \\ \hat{\mathbf{v}}^{(n+1)}, & \text{otherwise.} \end{cases} \quad (50)$$

Since the feasible set $\hat{\mathcal{C}}$ has bounds, it is valid to assert that $\nabla f(\mathbf{v})$ is Lipschitz continuous, with a known constant value of J , i.e.,

$$\|\nabla f(\mathbf{x}) - \nabla f(\mathbf{y})\| \leq J\|\mathbf{x} - \mathbf{y}\|, \forall \mathbf{x}, \mathbf{y} \in \hat{\mathcal{C}}. \quad (51)$$

IV. NUMERICAL RESULTS

In this section, we present numerical results to investigate the security performance of CF-mMIMO using the proposed joint power control and AP selection approach. We assume that all L APs and K users are randomly distributed within a square of 1×1 km². To avoid the boundary effects, we use a wrapped-around technique. Furthermore, Eve is randomly located inside a circle of radius r_E around the attacked user. The large-scale fading $\beta_{l,k}$ is formulated as follows:

$$\beta_{l,k} = 10^{\frac{\text{PL}_{l,k}^d}{10}} 10^{\frac{F_{l,k}}{10}}, \quad (52)$$

where $10^{\frac{\text{PL}_{l,k}^d}{10}}$ is the path loss, and $10^{\frac{F_{l,k}}{10}}$ denotes the shadowing effect with $F_{l,k} \in \mathcal{N}(0, 4^2)$ (in dB). Besides, $\text{PL}_{l,k}^d$ (in dB) can be calculated as

$$\text{PL}_{l,k}^d = -30.5 - 36.7 \log_{10}\left(\frac{d_{l,k}}{1 \text{ m}}\right), \quad (53)$$

and the correlation among the shadowing terms from the l -th AP to different k users can be given by

$$\mathbb{E}\{F_{l,k} F_{j,k'}\} \triangleq \begin{cases} 4^2 2^{-\vartheta_{k,k'}/9 \text{ m}}, & j = l, \\ 0, & \text{otherwise,} \end{cases} \quad (54)$$

where $\vartheta_{k,k'}$ is the physical distance between users k and k' [14]. In addition, we choose the bandwidth $B = 20$ MHz, a noise power equal to -92 dBm, and the maximum transmit power for each AP and each user as 1 W and 100 mW, respectively. Also, $R_{\text{th},k} = 0.2, \forall k$, and $\tau_p = K$. In Fig. 1, we investigate the effectiveness of using joint power allocation and AP selection approach provided in Algorithm 1. The cumulative distribution function of the SSE is shown for three cases: equal power allocation (EPA) with random AP

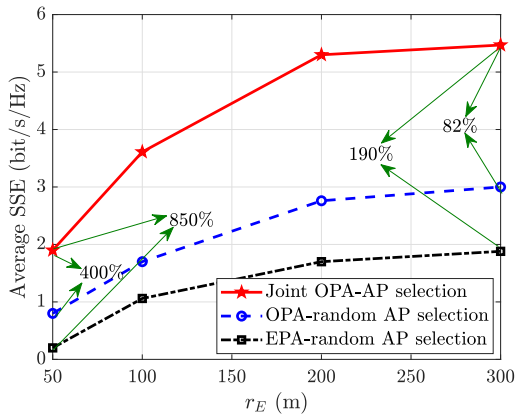


Fig. 2: Average SSE vs r_E , $L = 300$, $M = 4$, and $K = 40$.

selection, optimum power allocation (OPA) and random AP selection, and our proposed APG-based joint power allocation and AP selection scheme. We can see that optimum power control enhances the 50% likely SSE performance up to 65% compared with equal power control. Also, it is observed that the proposed joint optimization approach can provide a significant improvement in the SSE with a gain of up to 265% and 120% compared with the cases relying on random AP selection with equal power control and optimum power control, respectively. These results highlight the effectiveness of our joint optimization approach over heuristic schemes.

In Fig. 2, we investigate the impact of Eve’s position on the SSE performance. In particular, we plot the average SSE, while the average is taken over the large-scale fading realizations, versus the radius of a circle surrounding user 1, r_E , as Eve’s potential positions. We can see that SSE remarkably improves when Eve moves away from target user 1. More importantly, the performance gap between the joint optimization approach and the heuristic ones is more pronounced for more challenging scenarios when Eve is located in the closer vicinity of the target user. Specifically, when r_E changes from 200 m to 50 m, the average SSE performance gap between the joint optimization approach and EPA with random AP selection benchmark increases from 190% to 850%.

V. CONCLUSION

This paper investigated the SSE performance of a CF-mMIMO system in the presence of active eavesdropping, employing PPZF precoding with imperfect channel estimation. To this end, we proposed a joint optimization approach to minimize the SE at Eve under a transmit power constraint at the APs and QoS SE requirements at the users. We showed that our jointly optimized APG-based approach provides substantially higher SSE compared to the heuristic approaches, especially

in the scenarios where Eve is located in the close vicinity of the targeted user.

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