Minimizing Power Consumption in Age of Information Constrained Cell-Free Massive MIMO Networks

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***Abstract*—Upcoming 6G networks are expected to serve several mission-critical cyber-physical systems (CPS) applications that demand timely and fresh control updates. Different from traditional quality of service (QoS) metrics, Age of Information (AoI) measures the *freshness of information* for CPS applications. To efficiently serve such applications, cell-free massive multiple-input multiple-output (CF-mMIMO) has emerged as a better alternative to traditional cellular architectures. To the best of our knowledge, the time-average power minimization problem has not been addressed so far in AoI-constrained CF-mMIMO networks. In this context, we aim to minimize the time-average power consumed in CF-mMIMO networks with maximum tolerable average AoI constraints, along with communication QoS and per-transmitter power budget constraints. We propose a novel iterative scheduling and precoding algorithm to achieve our objective. Detailed analytical modeling and resulting simulation illustrate the performance of our algorithm as a function of a penalty parameter, which show the average AoI of all users are within constraint limits. We also show that the penalty parameter allows to dynamically prioritize between the time-averages of power consumed and AoI as per performance requirements.**

***Index Terms*—Cell-free massive MIMO, CF-mMIMO, age of information, AoI, power consumption, scheduling, precoding.**

I. Introduction

THE upcoming 6G era is expected to better serve applications such as autonomous vehicles, industrial internet of things (IIoT), etc. that rely on networked systems to integrate the physical world with a digital fabric to form cyber-physical systems (CPS). These mission critical applications demand timely and fresh control updates to operate in complex environments. Age of Information (AoI) is a receiver-centric performance metric [1] that is considered more suitable for mission critical application than traditional quality of service (QoS) parameters such latency and throughput. AoI measures the time elapsed since the last received fresh update was generated at the source. Each update contains a timestamp of when it was generated and this is used to calculate the the time elapsed since the most recently received update at the receiver. Many factors including wireless channel conditions, network load, queueing delays, scheduling decisions impact the AoI. It is therefore vital to manage available system resources carefully via intelligent scheduling and precoding to keep the AoI under a tolerable limit. To achieve this, it is imperative to have a flexible and robust communication network serving the CPS applications.

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Cell-free massive multiple-input multiple-output (CF-mMIMO) has emerged as a new wireless networking paradigm as an alternative to traditional cellular networks [2], particularly for CPS applications in 6G scenarios. Coordinated by a central processing unit (CPU), many geographically distributed multi-antenna access points (APs) cooperate to jointly serve a set of user equipments (UEs) in cell-free massive MIMO. Aligned with the ongoing push towards cloudification and open radio access networks (Open RAN), when compared to traditional cellular architectures, CF-mMIMO is capable of (i) providing higher SNR in the downlink through coherent transmission, (ii) achieving higher and more uniform signal-to-noise ratio (SNR) in the uplink, and (iii) managing interference better in the uplink [3]. These characteristics make CF-mMIMO a better choice for CPS scenarios like IIoT, smart factories, etc.

With 6G expected to satisfy stringent, personalized performance metrics of a more diverse portfolio of applications than the current 5G networks, the radio communication sector of the international telecommunication union (ITU-R) has identified the reduction of network power consumption as a key driver for future wireless networks in its IMT 2030 report [4]. It is in this context that we take a cross-layer approach with the aim to minimize the power consumption in AoI-constrained CF-mMIMO networks. We first position our work among related research before outlining our contributions in this paper.

A. Related Work

AoI has been analyzed in the context of cellular and wireless networks in recent times [5]–[8]. In [5], the authors propose low-complexity age-aware and age-and-channel-aware scheduling algorithms to minimize network-level average AoI subject to peak power constraints in downlink multi-user (MU) MIMO systems. The authors of [6] develop Markov decision process (MDP) based online and offline algorithms to minimize the average AoI in a general wireless broadcast network. Reference [7] proposes a generalized power iteration

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(GPI) precoding algorithm to minimize the AoI violation ratio which is the ratio of the time duration when AoI is higher than the AoI violation threshold to that of a sensing period during which relevant sensing data is collected. In [8], the authors propose a safety-aware two time-scale learning algorithm in the context of CF-mMIMO platooning networks to minimize the vehicle collision risk by optimizing the time to collision, velocity, and position errors. Wireless networks with AoI constraints have also garnered attention in recent works like [9]–[11]. For most of these works, minimizing the peak/average AoI has been the focus.

CF-mMIMO has been analyzed from both physical layer and power saving perspectives [12]–[16]. Reference [12] proposed scalable algorithms for CF-mMIMO, including precoding and combining. Various aspects of CF-mMIMO including channel estimation, precoding, and resource allocation have been analyzed in literature and details can be found in [13], [14] and the references therein. In [15], the authors minimize the total end-to-end power consumed in a CF-mMIMO network built on top of a virtualized cloud radio access network (V-CRAN), and this is extended to an Open RAN based architecture in [16].

B. Contributions

Different from the related work listed in Section I-A, in this work we minimize time-average power consumption in CF-mMIMO networks subject to maximum tolerable average AoI constraints in addition to communication QoS and per-AP power budget constraints. To the best of our knowledge, the time-average power minimization problem has not been explored so far in AoI-constrained CF-mMIMO networks. We achieve our objective through detailed analytical modeling to jointly optimize the scheduling and precoding decisions (cross-layer approach), which allows us to optimize the time-average objective via sequential decision making. Such a cross-layer approach, while challenging, allows us to consider the random channel realizations and application AoI requirements together to efficiently utilize limited system resources.

Remark: Scheduling decisions have to be made considering how close is the AoI of a particular UE to its violation limit, and this could mean scheduling a UE with poor channel condition by pouring in more power at certain times. Thus, the instantaneous power consumption of the network may need to be higher than the optimal minimum. This motivates the consideration of minimizing the time-average power consumption of the network.

II. System Model

We consider the downlink of a CF-mMIMO network where a set $\mathcal{K}$ of K APs with L antennas each, jointly serve a set $\mathcal{U}$ of U single-antenna UEs. All the APs are connected via fronthaul links to a central processing unit (CPU) in a C-RAN architecture, providing perfect synchronization among all APs. We assume a time-slotted system with time slots indexed by $m \in \{0, 1, 2, \dots\}$, where the duration of a time slot corresponds to the transmission time of an update packet. We follow a block-fading channel model with i.i.d. Rayleigh fading where the channel's coherence period is the same as the duration of one slot. We further assume that the CPU maintains a downlink queue for each UE, and uses the queue lengths, the channels seen by the UEs, and the AoI at the UEs to jointly make the scheduling and precoding decisions. We illustrate this setup in Fig. 1, and summarize the main notations in Table I.

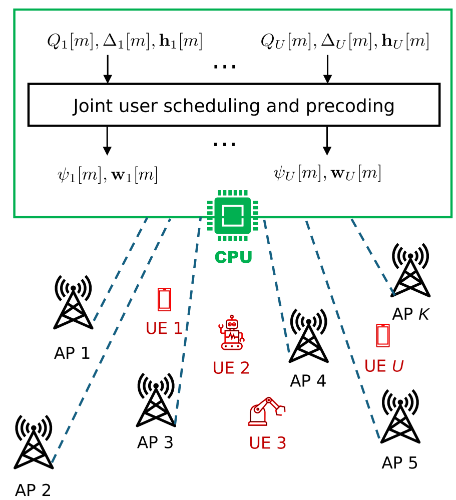


Fig. 1: Illustration of the CF-mMIMO setup. Here, $Q_i[m]$, $\Delta_i[m]$, and $\mathbf{h}_i[m]$ refer to the queue backlog, AoI, and channel from all the APs respectively, corresponding to UE i at time-slot m. Similarly, $\psi_i[m]$ and $\mathbf{w}_i[m]$ are the scheduling indicator and precoder for UE i in time slot m.

A. Data transmission model

To focus on the design of joint precoding and scheduling algorithm, we assume perfect channel state information (CSI) for all communication channels as a first step. Let $s_i[m]$ be the zero-mean, unit-power downlink communication symbol intended for UE i in time slot m. In line with [3], the transmitted signal $\mathbf{x}_k[m] \in \mathbb{C}^L$ from AP k in time slot m is given by

$$\mathbf{x}_k[m] = \sum_{i \in \mathcal{U}} \mathbf{w}_{i,k}[m]\psi_i[m]s_i[m], \quad k \in \mathcal{K}, \tag{1}$$

where $\mathbf{w}_{i,k}[m]$ is the precoder at AP k for UE i in time slot m, and $\psi_i[m]$ is an indicator random variable to denote whether UE i is scheduled in time slot m ($\psi_i[m]$ will be 1 if UE i is scheduled in time-slot m, and 0 otherwise).

The average transmit power for AP k in time slot m is then computed as[1]

$$P_k[m] = \mathbb{E}\left[\|\mathbf{x}_k[m]\|^2\right] = \sum_{i \in \mathcal{U}} \psi_i[m]\mathbb{E}\left[\|\mathbf{w}_{i,k}[m]\|^2\right], \tag{2}$$

[1] In this paper, all expectations are taken with respect to the random wireless channel realizations, and the scheduling and precoding decisions taken with respect to those channel realizations.

Note that the $P_k[m]$ are all limited by the maximum power limit at the APs, $P_{\max}$. Using (2), the time-average power consumed by all the APs in the network is calculated as

$$\bar{P} = \lim_{M\to\infty} \frac{1}{M} \sum_{m=0}^{M-1} \sum_{k\in\mathcal{K}} \sum_{i\in\mathcal{U}} \psi_i[m] \mathbb{E}\left[\|\mathbf{w}_{i,k}[m]\|^2\right]. \quad (3)$$

Let $\mathbf{h}_{i,k}^{*}[m] \in \mathbb{C}^{L\times 1}$ be the channel between AP k and UE i in time slot m. Let the channel to UE i from all the KL transmit antennas in time slot m be $\mathbf{h}_i^{*}[m] = \left[\mathbf{h}_{i,1}^{\mathrm{H}}[m], \mathbf{h}_{i,2}^{\mathrm{H}}[m], \ldots, \mathbf{h}_{i,K}^{\mathrm{H}}[m]\right]^{\mathrm{T}} \in \mathbb{C}^{KL\times 1}$, and the corresponding precoder vector be $\mathbf{w}_i[m] = \left[\mathbf{w}_{i,1}^{\mathrm{T}}[m], \mathbf{w}_{i,2}^{\mathrm{T}}[m], \ldots, \mathbf{w}_{i,K}^{\mathrm{T}}[m]\right]^{\mathrm{T}} \in \mathbb{C}^{KL\times 1}$. Then, the received signal $y_i[m]$ at UE i in time slot m is given by

$$\begin{aligned} y_i[m] &= \sum_{k\in\mathcal{K}} \mathbf{h}_{i,k}^{\mathrm{H}}[m]\mathbf{x}_k[m] + n_i[m] \\ &= \underbrace{\psi_i[m]\mathbf{h}_i^{\mathrm{H}}[m]\mathbf{w}_i[m]s_i[m]}_{\text{Desired signal}} \\ &\quad + \underbrace{\sum_{j\in\mathcal{U}\setminus\{i\}} \psi_j[m]\mathbf{h}_i^{\mathrm{H}}[m]\mathbf{w}_j[m]s_j[m]}_{\text{Interference}} + \underbrace{n_i[m]}_{\text{noise}}, \end{aligned} \quad (4)$$

where $n_i[m] \sim \mathcal{N}_{\mathbb{C}}\left(0, \sigma_n^2\right)$ is the noise. The SINR at UE i in time slot m is then given as

$$\mathsf{SINR}_i[m] = \frac{\psi_i[m]\left|\mathbf{h}_i^{\mathrm{H}}[m]\mathbf{w}_i[m]\right|^2}{\sum_{j\in\mathcal{U}\setminus\{i\}} \psi_j[m]\left|\mathbf{h}_i^{\mathrm{H}}[m]\mathbf{w}_j[m]\right|^2 + \sigma_n^2}. \quad (5)$$

For successful reception of the transmitted signal by a UE i, we stipulate that the SINR at the UE should satisfy a minimum threshold γ, i.e.,

$$\mathsf{SINR}_i[m] \geq \gamma. \quad (6)$$

Note that if only approximate CSI and channel estimates $\hat{\mathbf{h}}_{i,k}$ of $\mathbf{h}_{i,k}$ are available, then the precoding and scheduling decisions made may not satisfy (6) since those decisions will be made in the presence of channel estimation errors. In such a case, the AoI of the corresponding UEs will increase in the upcoming time slot. However, our algorithm will then prioritize these UEs in the next time slot since they will be closer to their AoI violation limits. We will consider this analysis and its implications in our future work and focus only on designing a joint precoding and scheduling algorithm in this work assuming perfect CSI is available.

B. Queueing dynamics

Let $Q_i[m]$ be the downlink queue backlog for UE i in time slot m. We assume that update packets for UE i arrive at the CPU according to a Poisson process with rate λ_i. Let $a_i[m] \geq 0$ denote the new stochastic arrivals and $b_i[m]$ denote the successful transmissions for UE i in time slot m. The discrete-time queues then evolve according to

$$Q_i[m+1] = \max\left\{Q_i[m] - b_i[m], 0\right\} + a_i[m], \quad i \in \mathcal{U}. \quad (7)$$

TABLE I: Summary of Notations

Notation	Description
m	Time-slot index
$\mathcal{K}$	Set of K APs with L antennas each
$\mathcal{U}$	Set of U single-antenna UEs
$\mathbf{h}_{i,k}[m] \in \mathbb{C}^{L\times 1}$	Channel between UE i and AP k in time-slot m
$\mathbf{w}_{i,k}[m] \in \mathbb{C}^{L\times 1}$	Precoder for UE i from AP k in time-slot m
$P_k[m]$	Transmit power consumed at AP k in time-slot m
$P_{\max}$	Max. transmit power available at each AP
$\psi_i[m] \in \{0,1\}$	Scheduling indicator for UE i in time-slot m
$Q_i[m]$	Downlink queue backlog for UE i in time-slot m
$\Delta_i[m]$	AoI at UE i in time-slot m
$\Delta_i^{\max}$	Max. tolerable time-average AoI limit for UE i
$Z_i[m]$	Virtual AoI queue backlog for UE i in time-slot m

C. Age of Information model

At time step m, the AoI $\Delta_i[m]$ corresponding to UE i is given by

$$\Delta_i[m] = m - \delta_i + 1, \quad (8)$$

where $\delta_i \leq m$ is the timestamp of the most recently received update packet at UE i. If a new update packet is successfully received by UE i in slot m, the corresponding AoI drops to 1 and continues to grow linearly with time until the next update is received. Thus, using (6), we capture the evolution of $\Delta_i[m]$ as

$$\Delta_i[m+1] = \begin{cases} 1, & \mathsf{SINR}_i \geq \gamma; \\ \Delta_i[m] + 1, & \text{otherwise.} \end{cases} \quad (9)$$

We define the average AoI of UE i as the time-average of the expected AoI given by

$$\bar{\Delta}_i = \lim_{M\to\infty} \frac{1}{M} \sum_{m=0}^{M-1} \mathbb{E}\left[\Delta_i[m]\right]. \quad (10)$$

D. Problem formulation

We aim to minimize the time-average power consumed by all the APs in the network by *jointly* optimizing the scheduling decisions $\{\psi_i[m]\}_{i\in\mathcal{U}}$, and precoding decisions $\{\mathbf{w}_{i,k}[m]\}_{i\in\mathcal{U},k\in\mathcal{K}}$, in each time slot m, subject to a power budget constraint for each AP, communication QoS constraint for each UE, and an average AoI constraint for each UE. This optimization problem is formulated as

$$\text{minimize} \quad \lim_{M\to\infty} \frac{1}{M} \sum_{m=0}^{M-1} \sum_{k\in\mathcal{K}} \sum_{i\in\mathcal{U}} \psi_i[m] \mathbb{E}\left[\|\mathbf{w}_{i,k}[m]\|^2\right] \quad (11a)$$

$$\text{subject to} \quad \lim_{M\to\infty} \frac{1}{M} \sum_{m=0}^{M-1} \mathbb{E}\left[\Delta_i[m]\right] \leq \Delta_i^{\max}, \quad \forall i \in \mathcal{U}, \quad (11b)$$

$$\mathsf{SINR}_i[m] \geq \gamma \cdot \psi_i[m], \quad \forall i \in \mathcal{U}, \quad (11c)$$

$$P_k[m] \leq P_{\max}, \quad \forall k \in \mathcal{K}, \quad (11d)$$

$$\psi_i[m] \in \{0,1\}, \quad \forall i \in \mathcal{U}, \quad (11e)$$

with variables $\{\psi_i[m]\}_{i\in\mathcal{U}}$ and $\{\mathbf{w}_{i,k}[m]\}_{i\in\mathcal{U},k\in\mathcal{K}}$ for $m \in \{0,1,2,\dots\}$. The influence of the optimization variables on (11b) will become apparent in Section III. The optimization problem in (11) is a mixed-integer non-convex problem (MINCP) because of the binary constraints in (11e). Moreover, the scheduling and precoding decisions are made in every time step m, while the objective function in (11a) depends on the decisions made across time.

III. Joint Scheduling and Precoding Algorithm Design

To deal with the challenges brought about by the time-averages in the optimization problem in (11), we resort to the *Lyapunov drift-plus-penalty* method [17]. We enforce the average AoI constraint in (11b) by transforming it into a queue stability constraint. In this regard, we introduce a virtual queue corresponding to each constraint in (11b) such that the stability of these virtual queues implies that (11b) is met.

Let $\{Z_i[m]\}_{i\in\mathcal{U}}$ be the *virtual queues* associated with (11b). We let these virtual queues evolve according to

$$Z_i[m+1] = \max\{Z_i[m] - \Delta_i^{\max}, 0\} + \Delta_i[m+1], \quad i \in \mathcal{U}, \tag{12}$$

and queue Z_i is said to be strongly stable if [17]

$$\lim_{M\to\infty} \frac{1}{M}\sum_{m=0}^{M-1} \mathbb{E}\left[Z_i[m]\right] < \infty. \tag{13}$$

Note that if $\{Z_i[m]\}_{i\in\mathcal{U}}$ are strongly stable, then it is possible to meet the constraints in (11b). Let $\mathcal{S}[m] = \{Z_i[m], \Delta_i[m]\}_{i\in\mathcal{U}}$ capture the *network state* at slot m, and let $\mathbf{Z}[m] = [Z_1[m], Z_2[m], \dots, Z_U[m]]^{\mathrm{T}}$. We now define a quadratic Lyapunov function $L(\mathbf{Z}[m])$ as

$$L(\mathbf{Z}[m]) = \frac{1}{2}\sum_{i\in\mathcal{U}} Z_i^2[m]. \tag{14}$$

The Lyapunov function in (14) gives a measure of the congestion in the virtual queues. Minimizing the expected change in the Lyapunov function from one time slot to the next, the $\{Z_i[m]\}_{i\in\mathcal{U}}$ can be stabilized [17]. To capture this expected change in $L(\mathbf{Z}[m])$ across adjacent time slots, we define the *conditional Lyapunov drift* $\alpha(\mathcal{S}[m])$ as

$$\alpha(\mathcal{S}[m]) = \mathbb{E}\left[L(\mathbf{Z}[m+1]) - L(\mathbf{Z}[m]) \mid \mathcal{S}[m]\right]. \tag{15}$$

Following the drift-plus-penalty method, a policy that minimizes the optimization problem in (11) can be obtained by solving the following optimization problem [17]:

$$\text{minimize} \quad \alpha(\mathcal{S}[m]) + V\sum_{k\in\mathcal{K}}\sum_{i\in\mathcal{U}} \psi_i[m]\mathbb{E}\left[\|\mathbf{w}_{i,k}[m]\|^2\right] \tag{16a}$$

$$\text{subject to} \quad (11c),\ (11d),\ (11e), \tag{16b}$$

with variables $\{\psi_i[m]\}_{i\in\mathcal{U}}$ and $\{\mathbf{w}_{i,k}[m]\}_{i\in\mathcal{U},k\in\mathcal{K}}$ in every time slot. The parameter $V \geq 0$ in (16a) is the penalty parameter which can be used to adjust the importance given to the objective fundtion. Thus, by varying V, we can trade-off the power consumed with the virtual queue backlogs (the $\alpha(\mathcal{S}[m])$ term). To work around the $\max\{\cdot\}$ operator which influences $\alpha(\mathcal{S}[m])$ via (12), following the standard mechanisms of drift-plus-penalty method we now derive an upper bound for (16a). Using (12), we get[2]

$$\begin{aligned} Z_i^2[m+1] \ \leq\ & Z_i^2[m] + (\Delta_i^{\max})^2 + \Delta_i^2[m+1] + \\ & 2Z_i[m]\left(\Delta_i[m+1] - \Delta_i^{\max}\right), \quad \forall i \in \mathcal{U}. \end{aligned} \tag{17}$$

Using (17), the conditional Lyapunov drift in (15) can be upper bounded as

$$\begin{aligned} \alpha(\mathcal{S}[m]) \leq & \frac{1}{2}\mathbb{E}\Bigg[\sum_{i\in\mathcal{U}}\Big((\Delta_i^{\max})^2 + \Delta_i^2[m+1] \\ & + 2Z_i[m]\left(\Delta_i[m+1] - \Delta_i^{\max}\right)\Big)\Big|\mathcal{S}[m]\Bigg] \\ = & \frac{1}{2}\sum_{i\in\mathcal{U}}\Big((\Delta_i^{\max})^2 + \mathbb{E}\left[\Delta_i^2[m+1] \mid \mathcal{S}[m]\right] + \\ & 2Z_i[m]\left(\mathbb{E}\left[\Delta_i[m+1] \mid \mathcal{S}[m]\right] - \Delta_i^{\max}\right)\Big). \end{aligned} \tag{18}$$

We now calculate the $\mathbb{E}\left[\Delta_i^2[m+1] \mid \mathcal{S}[m]\right]$ and $\mathbb{E}\left[\Delta_i[m+1] \mid \mathcal{S}[m]\right]$ terms in (18) by using (9). To do this, we assume that the CPU will schedule UE i if and only if there are enough resources to successfully guarantee (6), i.e., $\psi_i[m] = 1 \iff \mathsf{SINR}_i[m] \geq \gamma$. Thus, (9) can be concisely written as $\Delta_i[m+1] = \psi_i[m] + (1-\psi_i[m])(\Delta_i[m]+1)$. Using this to calculate $\mathbb{E}\left[\Delta_i^2[m+1] \mid \mathcal{S}[m]\right]$ and $\mathbb{E}\left[\Delta_i[m+1] \mid \mathcal{S}[m]\right]$, and substituting in (18) we get the following after simplification:

$$\begin{aligned} \alpha(\mathcal{S}[m]) \leq \frac{1}{2}\sum_{i\in\mathcal{U}}\Big[& (\Delta_i^{\max})^2 + (\Delta_i[m]+1)^2 \\ & - \Delta_i^2[m]\mathbb{E}\left[\psi_i[m] \mid \mathcal{S}[m]\right] \\ & - 2\Delta_i[m]\mathbb{E}\left[\psi_i[m] \mid \mathcal{S}[m]\right] \\ & + 2Z_i[m]\Big(\Delta_i[m] + 1 \\ & - \Delta_i[m]\mathbb{E}\left[\psi_i[m] \mid \mathcal{S}[m]\right] - \Delta_i^{\max}\Big)\Big]. \end{aligned} \tag{19}$$

Thus, the upper bound on (16a) can be written using (19) as

$$\begin{aligned} & \alpha(\mathcal{S}[m]) + V\sum_{k\in\mathcal{K}}\sum_{i\in\mathcal{U}}\psi_i[m]\mathbb{E}\left[\|\mathbf{w}_{i,k}[m]\|^2\right] \\ & \leq \mathbb{E}\Bigg[V\sum_{k\in\mathcal{K}}\sum_{i\in\mathcal{U}}\psi_i[m]\|\mathbf{w}_{i,k}[m]\|^2 \\ & - \frac{1}{2}\sum_{i\in\mathcal{U}}\psi_i[m]\left(\Delta_i^2[m] + 2\Delta_i[m] + 2Z_i[m]\Delta_i[m]\right)\Big|\mathcal{S}[m]\Bigg] \\ & + \frac{1}{2}\sum_{i\in\mathcal{U}}\Big[(\Delta_i^{\max})^2 + (\Delta_i[m]+1)^2 \\ & \qquad + 2Z_i[m](\Delta_i[m] + 1 - \Delta_i^{\max})\Big]. \end{aligned} \tag{20}$$

[2] We use the inequality $(\max\{a-b,0\}+c)^2 \leq a^2+b^2+c^2+2a(c-b)$, which holds true for any $a \geq 0, b \geq 0$, and $c \geq 0$.

Now, instead of minimizing (16a), we can minimize the upper bound in (20) with the same variables and constraints as in (16). Note that when focusing on the upper bound in (18) instead of the conditional Lyapunov drift in (15), the implications of the strong stability of the virtual queues do not change, and thus we can still meet the average AoI constraints by enforcing (13).

Moreover, since we observe $\mathcal{S}[m]$ and $\{\mathbf{h}_{i,k}[m]\}_{i\in\mathcal{U},k\in\mathcal{K}}$ every slot, we can ignore the expectations in (20), i.e., we can *opportunistically minimize the expectations*. Also, for the same reason, we can safely ignore the second term of (20) since they become constants when conditioned on $\mathcal{S}[m]$ in every slot.

We now turn our attention to the constraints in (11c), (11d), and (11e), of which only (11d) is convex. We tackle the non-convex constraints (11c) and (11e) in the following way to build an iterative algorithm for joint scheduling and precoding, based on the sequential convex programming (SCP) approach [18]. To tackle the communication QoS constraints in (11c) we introduce auxiliary optimization variables $\{\varphi_i\}_{i\in\mathcal{U}}$, using which we replace (11c) with the following two constraints:

$$\sum_{j\in\mathcal{U}\setminus\{i\}} \left|\mathbf{h}_i^{\mathrm{H}}[m]\mathbf{w}_j[m]\right|^2 \;+\; \sigma_n^2 \;\leq\; \varphi_i, \quad \forall i\in\mathcal{U}, \tag{21}$$

$$\gamma\cdot\psi_i[m] \;\leq\; \frac{\left|\mathbf{h}_i^{\mathrm{H}}[m]\mathbf{w}_i[m]\right|^2}{\varphi_i}, \quad \forall i\in\mathcal{U}. \tag{22}$$

While (21) is convex, (22) is not. Using the identity $\|\mathbf{u}\|^2 \geq 2\Re\left\{\mathbf{v}^{\mathrm{H}}\mathbf{u}\right\} - \|\mathbf{v}\|^2$ which holds for any arbitrary complex-valued vectors $\mathbf{u}$ and $\mathbf{v}$ (with equality when $\mathbf{u}=\mathbf{v}$), we rewrite (22) as the following convex constraint:

$$\begin{aligned}\gamma\cdot\psi_i[m] \;\leq\; & \frac{2\Re\left\{\left(\mathbf{w}_i^{(l)}\right)^{\mathrm{H}}\mathbf{h}_i[m]\mathbf{h}_i^{\mathrm{H}}[m]\mathbf{w}_i[m]\right\}}{\varphi_i^{(l)}} \\ & - \left(\frac{\left|\mathbf{h}_i^{\mathrm{H}}[m]\mathbf{w}_i^{(l)}\right|}{\varphi_i^{(l)}}\right)^2 \varphi_i, \quad \forall i\in\mathcal{U},\end{aligned} \tag{23}$$

where $\Re\{\cdot\}$ returns the real part of a complex valued argument, $\mathbf{w}_i^{(l)}$ and $\varphi_i^{(l)}$ represent the solutions obtained for $\mathbf{w}_i[m]$ and $\varphi_i[m]$ respectively in the l-th iteration of our joint scheduling and precoding algorithm in time-slot m.

To address the non-convexity of the constraints in (11e), we first rewrite it as $\psi_i[m]-\psi_i^2[m]\leq 0$ with $0\leq\psi_i[m]\leq 1$, and then use the second-order Taylor approximation for $\psi_i^2[m]$ to arrive at, $\forall i\in\mathcal{U}$,

$$0\leq\psi_i[m]\leq 1, \tag{24}$$

$$\psi_i[m] - \left[\left(\psi_i^{(l)}\right)^2 + 2\psi_i^{(l)}\left(\psi_i[m]-\psi_i^{(l)}\right)\right] \leq 0, \tag{25}$$

where $\psi_i^{(l)}$ represents the solution obtained for $\psi_i[m]$ in the l-th iteration of our joint scheduling and precoding algorithm in time-slot m.

We now present our iterative algorithm for joint scheduling and precoding in Algorithm 1, where we use $f_m^{(l)}$ and f_m to respectively denote the value of the objective function in the l-th iteration and final value of the objective function for time-slot m. As mentioned earlier, we follow the approach of opportunistically minimizing expectations, and thus ignore the expectations in (20) since we observe $\mathcal{S}[m]$ and $\{\mathbf{h}_{i,k}[m]\}_{i\in\mathcal{U},k\in\mathcal{K}}$ in every slot.

Algorithm 1 Joint Scheduling and Precoding Algorithm

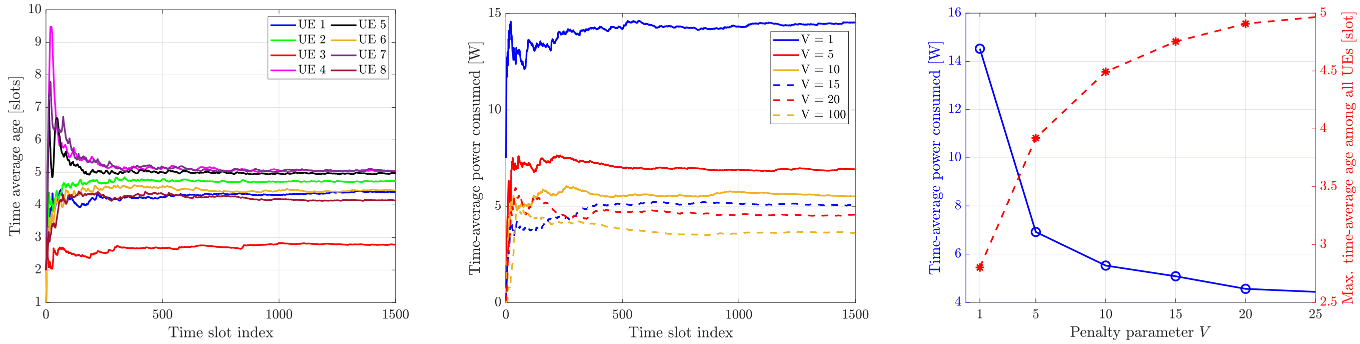
1: **Initialize:**
2: Set total time slots M, let $m=0$.
3: Set $Q_i[m]=0,\ Z_i[m]=0,\ \Delta_i[m]=1,\ \forall i\in\mathcal{U}$.
4: Set tolerance for stopping condition. $\eta=10^{-3}$.
5: Set penalty parameter value V.
6: $m\leftarrow m+1$.
7: **While** $m<M$ **do**:
8: Obtain new arrivals $a_i[m],\ \forall i\in\mathcal{U}$ according to arrival process.
9: Set $l=0$, and initialize feasible iterates for variables $\left\{\psi_i^{(0)},\mathbf{w}_{i,k}^{(0)},\varphi_i^{(0)}\right\}_{i\in\mathcal{U},k\in\mathcal{K}}$ and for objective $f_m^{(0)}$.
10: **Repeat**:
11: $l\leftarrow l+1$.
12: Obtain $\left\{\psi_i^{(l)},\mathbf{w}_{i,k}^{(l)},\varphi_i^{(l)}\right\}_{i\in\mathcal{U},k\in\mathcal{K}}$ and $f_m^{(l)}$ as the solution to the following optimization problem with variables $\{\psi_i[m],\ \mathbf{w}_{i,k}[m],\ \varphi_i\}_{i\in\mathcal{U},k\in\mathcal{K}}$:

$$\begin{aligned}\text{minimize}\quad & V\sum_{k\in\mathcal{K}}\sum_{i\in\mathcal{U}}\psi_i[m]\|\mathbf{w}_{i,k}[m]\|^2 \\ & -\frac{1}{2}\sum_{i\in\mathcal{U}}\psi_i[m]\left(\Delta_i^2[m]+2\Delta_i[m]+2Z_i[m]\Delta_i[m]\right) \\ \text{subject to}\quad & \text{(11d), (21), (23), (24), (25).}\end{aligned}$$

13: **until** $\left|f_m^{(l)}-f_m^{(l-1)}\right|\leq\eta$.
14: Set $\psi_i[m]\leftarrow\psi_i^{(l)}$ and $\mathbf{w}_{i,k}[m]\leftarrow\mathbf{w}_{i,k}^{(l)},\forall i\in\mathcal{U},k\in\mathcal{K}$.
15: Update downlink queues $\{Q_i[m]\}_{i\in\mathcal{U}}$ according to (7).
16: Update ages $\{\Delta_i[m]\}_{i\in\mathcal{U}}$ according to (9).
17: Update virtual queues $\{Z_i[m]\}_{i\in\mathcal{U}}$ according to (12).
18: $m\leftarrow m+1$.
19: **End**

IV. Simulation Results

We now proceed to illustrate the performance of our algorithm via numerical results, in terms of the time-average AoI for all the UEs and the time-average power consumed by all the APs in the cell-free massive MIMO network, as a function of the penalty parameter V. We choose our simulation parameters along the same lines as in [10]–[12]. In our simulation setup $K=16$ APs, with $L=4$ antennas each, are placed uniformly at random in a 500 m $\times$ 500 m area. There are $U=8$ UEs that are also distributed uniformly at random in the simulation area. Each AP has a maximum transmit power of $P_{\text{max}}=1$ W. The path loss of the channels between the APs and the UEs are modeled as per the 3GPP urban microcell model, and the noise variance is assumed to be -80 dBm. The communication channels follow a block fading



(a)

(b)

(c)

Fig. 2: (a) Evolution of the time-average AoI for all UEs with penalty parameter $V = 75$. (b) Evolution of the time-average power consumed by the APs, as a function of the penalty parameter V. (c) Trade-off between the time-average power consumed and the maximum time-average AoI (among all UEs), as a function of the penalty parameter V. All results were generated for $K = 16$ APs, each with $L = 4$ antennas, jointly serving $U = 8$ single-antenna UEs with maximum time-average AoI constraint of $\Delta_i^{\max} = 5$ slots $\forall i \in \mathcal{U}$.

model with i.i.d. Rayleigh fading, with the coherence time equal to one time-slot. The downlink control updates for each UE arrive according to a Poisson process with rate $\lambda_i = 0.5$ packets per time-slot, $\forall i \in \mathcal{U}$. The minimum required SINR to maintain communication QoS is set to be $\gamma = 20$ dBm.

The maximum tolerable time-average AoI for each UE is chosen as $\Delta_i^{\max} = 5$ time-slots, $\forall i \in \mathcal{U}$. In all the results, the unit of time is a time-slot. Without loss of generality, we assume that initially all the downlink queues are empty and that the initial AoI at all the UEs is 1. We also set the virtual queues to be empty at the beginning of the simulation.

In Fig. 2a, we plot the evolution of the time-average AoI for all the UEs, for a maximum time-average AoI constraint of $\Delta_i^{\max} = 5$, $\forall i \in \mathcal{U}$ and penalty parameter $V = 75$. While initially the AoI for some of the UEs are higher than the respective $\Delta_i^{\max}$, the time-average age for all the UEs eventually evolve to meet the maximum time-average AoI constraint in (11b).

In Fig. 2b, we show the evolution of the time-average power consumed by all the APs in the network as a function of the penalty parameter V. As can be seen from the objective function in (16a), V is a measure of the importance given to minimizing the time-average power consumed against that given to the time-average AoI. As V increases, more weightage is given to the time-average power consumed. This is illustrated in Fig. 2b which shows that the time-average power consumed goes down as V increases.

The trade-off between the time-average age and time-average power consumed is illustrated further in Fig. 2c. Clearly, as V increases, the time-average AoI increases before saturating close to $\Delta_i^{\max} = 5$, $\forall i \in \mathcal{U}$. This shows that Algorithm 1, using the drift-plus-penalty method, is able to meet the average AoI constraint by enforcing stability of the virtual queues associated with the AoI constraints. On the other hand, the time-average power consumed reduces with increase in V, and saturates for higher values of V. This allows for dynamic adaptation of V to prioritize power consumption or AoI, by utilizing situational awareness.

Remark: In practical scenarios like smart factory floors employing IIoT, decisions on when to place emphasis on power consumption or AoI will depend on several factors including the load on the power grid, availability of alternate/backup power sources, constraints on production/operational efficiency of the smart factory to meet seasonal demands, etc. When application demands and other parameters are well-known, the trade-off between power consumption and AoI can be studied offline by varying V, and insights gained therein can then be used to guide the dynamic adaptation of V during production time.

V. Conclusion

In this paper, we addressed the problem of minimizing the time-average power consumed in CF-mMIMO networks with maximum tolerable time-average AoI constraints. In this regard, through detailed analytical modeling we designed an iterative joint scheduling and precoding algorithm to minimize time-average power consumed in a CF-mMIMO network, while meeting a time-average AoI constraint in addition to communication QoS and per-AP power budget constraints. Through simulation results we showed that the designed algorithm minimizes power consumed while meeting the average AoI constraint limits, and also illustrated the inherent trade-off between the time-averages of power consumed and AoI, as dictated by a penalty parameter. This allows for dynamic adaptation of the penalty parameter to influence the power consumed by APs and AoI seen by UEs for efficient operation of emerging CPS applications.

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