Joint In-Band Backhauling and Interference Mitigation in 5G Heterogeneous Networks

Trung Kien Vu†, Mehdi Benni*, Sumudu Samarakoon*, Mérouane Debbah†, and Matti Latva-aho∗

†Centre for Wireless Communications, University of Oulu, Oulu, Finland, email: {v.kien, benni, sumudu, mati.latva-aho}@ee.oulu.fi

‡Mathematical and Algorithmic Sciences Lab, Huawei France R&D, Paris, France, email: merouane.debbah@huawei.fr

Abstract—In this paper, we study the problem of joint in-band backhauling and interference mitigation in 5G heterogeneous networks (HetNets) in which a massive multiple-input multiple-output (MIMO) macro cell base station equipped with a large number of antennas, overlaid with self-backhauled small cells is assumed. This problem is cast as a network utility maximization subject to wireless backhaul constraints. Due to the non-tractability of the problem, we first resort to random matrix theory to get a closed-form expression of the achievable rate and transmit power in the asymptotic regime, i.e., as the number of antennas and users grows large. Subsequently, leveraging the framework of stochastic optimization, the problem is decoupled into dynamic scheduling of macro cell users and backhaul provisioning of small cells as a function of interference and backhaul links. Via simulations, we evaluate the performance gains of our proposed framework under different network architectures and low/high frequency bands. Our proposed HetNet method achieves the achievable average UE throughput of 1.7 Gbps as well as ensures 1 Gbps cell-edge UE throughput when serving 200 UEs per km$^2$ at 28 GHz with 1 GHz bandwidth. In ultra-dense network, the UE throughput at 28 GHz achieves $62 \times$ gain as compared to 2.4 GHz.

I. INTRODUCTION

The demand for massive data traffic has grown due to the exponential increase in the number of mobile broadband subscribers such as smartphones and tablets. To handle these relentless demands, in the next generation wireless networks, a number of candidate solutions include: 1) higher frequency spectrum (centimeter and millimeter-wave (mmWave)); 2) advanced spectral-efficiency techniques (massive MIMO); and 3) ultra-dense small cell deployments [1]. Massive MIMO plays an important role in wireless networks due to an improvement in energy and spectral efficiency [2]. The basic concept of massive MIMO assumes a macro base station (MBS) equipped with a few hundreds antennas simultaneously serving tens of macro user equipments (MUEs). On the other hand, ultra dense SC deployment provides an effective solution to increase network capacity. In parallel to that, recent advances in full-duplex (FD) enables doubling spectral efficiency and lowering latency, which is another promising technique [3].

The combination of massive MIMO and ultra-dense SCs holds the promise of ensuring high capacity improvement and constitutes the main motivation of this work. Recently, SC wireless backhaul in massive MIMO was studied in [3]. Showing the efficiency of combining massive MIMO and wireless backhaul-based small cell networks focusing on minimizing power consumption. However, the key challenge of how to dynamically optimize the overall network performance taking into account the backhaul dynamics, and scheduling has not been addressed. The main contribution of this work is to study the problem of joint scheduling, interference mitigation, and in-band wireless backhauling. We design precoders to alleviate both co-tier and cross tier interference and dynamically provide wireless backhauling to SCs. An operation mode is proposed to dynamically control the interference among adjacent SCs. By invoking results from random matrix theory (RMT), we derive a closed-form expression of the signal-to-interference-plus-noise-ratio (SINR) when the numbers of MBS antennas and users grow very large. A network utility optimization problem is formulated to maximize the total network throughput subject to dynamically varying wireless backhaul. Leveraging the framework of stochastic optimization, the problem is decoupled into several subproblems. The mixed-integer non-convex subproblem is solved by applying the framework of successive convex approximation (SCA). A performance evaluation is carried out for different network deployments at low/high frequency bands.

The rest of this paper is organized as follows. Section II describes the system model and Section III formulates the problem of scheduling and interference mitigation. Section IV adopts the Lyapunov optimization framework and the SCA method used to solve the problem. In Section V, the simulation results are presented and Section VI concludes the paper.

II. SYSTEM MODEL

A. System Model

We consider the downlink (DL) transmission of a HetNet scenario as shown in Fig. 1 in which a MBS $b_0$ is underlaid with a set of uniformly deployed $S$ SCs, $\mathcal{S} = \{b_s | s \in \{1, \ldots, S\}\}$. Let $B = \{b_0\} \cup \mathcal{S}$ denote the set of all base stations (BSs), where $|B| = 1 + S$. The MBS is equipped with $N$ number of antennas and serves a set of single-antenna $M$ MUEs $M = \{1, \ldots, M\}$. Let $K = M \cup \mathcal{S}$ denote the set of $b_0$‘s associated users, where $|K| = M + S$. SCs are assumed to be FD capable with perfect self-interference cancelation (SIC) capability [4]. Each SC is equipped with two antennas: the receiving antenna is used for the wireless backhaul and the transmitting antenna to serve its single-antenna small cell user equipment (SUE) [5]. Let $\mathcal{C} = \{c_1, c_2, \ldots, c_S\}$ denote the set of SUEs, where $|\mathcal{C}| = S$. We assume closed-access policy where SCs serve their own users. Co-channel time-division duplexing (TDD) protocol is considered in which the MBS and SCs share

1The case of imperfect SIC is left for future work.
2More SUEs per SC is left for future work.
the entire bandwidth, and do the DL transmission at the same time. In this work, we consider a large number of antennas at the MBS and a dense deployment of MUEs and SCs, such that $M, N, S \gg 1$.

We denote $\mathbf{h}_{mb}(b_0) = [\mathbf{h}_{m,b_0,1}, \mathbf{h}_{m,b_0,2}, \ldots, \mathbf{h}_{m,b_0,N}]^T \in \mathbb{C}^{N \times 1}$ the propagation channels between the $m$th MUE and the antennas of the MBS $b_0$ in which $h_{m,b_0,n} \in \mathbb{C}$ is the channel between the $m$th MUE and $n$th MBS antenna. Let $\mathbf{H}_{mb}(b_0) = [\mathbf{h}_{m,b_0,1}, \mathbf{h}_{m,b_0,2}, \ldots, \mathbf{h}_{m,b_0,N}] \in \mathbb{C}^{N \times M}$ denote the channel matrix between all MUEs and the MBS antennas. Moreover, we assume imperfect channel state information (CSI) for MUEs due to mobility and we denote $\hat{\mathbf{H}}_{mb}(b_0) = [\hat{h}_{m,b_0,1}, \hat{h}_{m,b_0,2}, \ldots, \hat{h}_{m,b_0,N}] \in \mathbb{C}^{N \times M}$ as the estimate of $\mathbf{H}_{mb}(b_0)$ in which the imperfect CSI can be modeled as \[ \hat{h}_{m,b_0,n} = \sqrt{N} \mathbf{w}_{mb}(b_0) \beta_{mb} \] where $\mathbf{w}_{mb}(b_0) = \sqrt{1 - \tau_m} \mathbf{w}_{m}(b_0) + \tau_m \mathbf{z}_{m}(b_0)$ is the estimate of the small-scale fading channel matrix and $\Theta_{mb}(b_0)$ is the spatial channel correlation matrix that accounts for path loss and shadow fading. Here, $\mathbf{w}_{m}(b_0)$ and $\mathbf{z}_{m}(b_0)$ are the real channel and the channel noise, respectively, modeled as Gaussian random matrix with zero mean and variance $1/N$. The channel estimation error of MUE $m$ is denoted by $\tau_m$, in case of perfect CSI, $\tau_m = 0$. Similarly, let $\mathbf{H}(b_0) \in \mathbb{C}^{N \times S}$ and $\hat{\mathbf{H}}(b_0) \in \mathbb{C}^{N \times S}$ denote the channel matrices from the MBS antennas to SCs and SUEs, respectively. Let $\mathbf{h}_{sb}^i$ denote the channel propagation from SC $b_s$ to any receiver $i$. Let $c_s$ denote the SUE served by the SC $b_s$.

### III. Joint Access/Backhaul Scheduling and Interference Mitigation Problem Formulation

We address the problem of DL scheduling at the MBS to simultaneously provide data transmission to MUEs and wireless backhaul to SCs. We define the scheduling vector $\mathbf{l}(t) = (l_1(t), l_2(t), \ldots, l_K(t))$ to determine the subset of users served at time slot $t$, where $l_k(t) = 1$ means user $k$ is served at time slot $t$ and $l_k(t) = 0$ otherwise.

### A. Downlink Transmission Signal

The MBS serves two types of users: MUEs and SCs, let $p_{mb}(b_0), p_{s}(b_0)$, and $P_{mb}(b_0)$ denote the DL MBS transmit power assigned to MUE $m$, SC $b_s$, and the maximum transmit power at the MBS, respectively. Let $p_{c}(b_s)$ denote the DL transmit power of SC $b_s$ assigned to SUE $c_s$. Although SC exploits FD capability to double capacity, SC causes unwanted FD interference including cross-tier interference to adjacent MUEs (or other SCs) and co-tier interference to other SUEs. Moreover, inspired by [6], we invoke RMT to get closed-form expression for the user data rate as $N, K \gg 1$. In order to convert the interference channel to multiple-input single-output (MISO) channel, we design a precoder at MBS and propose an operation mode policy to control FD interference due to the SC DL transmissions such that the total FD interference at receiver is treated as noise.

### Definition 1. [Operation Mode Policy]

We define $\beta$ as the operation mode to control the SC transmission to reduce FD interference. The operation mode is expressed as $\beta(t) = \{\beta(b_s)(t) \mid \beta(b_s)(t) \in [0, 1], \forall s \in S\}$. If SC $b_s$ operates in FD mode, then $\beta(b_s)(t) = 1$. When SC $b_s$ operates in half-duplex (HD) mode, i.e., $\beta(b_s)(t) = 0$.

We assume that the MBS uses a precoding scheme, $\mathbf{V} = [v_1, v_2, \ldots, v_K] \in \mathbb{C}^{K \times K}$. We apply the technique in [7] to design the precoder $\mathbf{V} = \mathbf{U}^T$, where $\mathbf{U} \in \mathbb{C}^{N \times N}$ and $\mathbf{T} \in \mathbb{C}^{N \times K}$ are used to control cross-tier and co-tier interference, respectively. Here, $N_i$ antennas are used to mitigate the cross-tier interference with $N_i < N$, where the subscript $i$ stands for “interference”. The precoder $\mathbf{U}$ is chosen such that

\[
\mathbf{U}^\dagger \sum_{s=1}^{S} \beta(b_s) \Theta_{cs} = 0, \quad (2)
\]

where $\Theta_{cs}(b_s) \in \mathbb{C}^{N_i \times N_i}$ is the correlation matrix between MBS antennas and SUE $c_s$. Note that $\beta(b_s)$ determines that SUE $c_s$ is served or not, and $\mathbf{U}^\dagger$ denotes the Hermitian transpose of matrix $\mathbf{U}$. The precoder $\mathbf{T}$ is designed to adapt to the real time CSI based on $\hat{\mathbf{H}}^\dagger \mathbf{U} \in \mathbb{C}^{K \times N_i}$, where $\hat{\mathbf{H}} = [\hat{h}_{mb}(b_0)]_{1 \leq k \leq K \leq K}$. In this paper, we consider the regularized zero-forcing (RZF) precoding given by $\mathbf{T} = (\mathbf{U}^\dagger \hat{\mathbf{H}}^\dagger \mathbf{H} + N_0 \mathbf{I}_{N_i})^{-1} \mathbf{U}^\dagger \hat{\mathbf{H}}$, where the regularization parameter $\alpha > 0$ is scaled by $N$ to ensure that the matrix $\mathbf{U}^\dagger \hat{\mathbf{H}}^\dagger \mathbf{H} + N_0 \mathbf{I}_{N_i}$ is well conditioned as $N \rightarrow \infty$. The precoder $\mathbf{T}$ is chosen to satisfy the power constraint $\mathrm{Tr}(\mathbf{P}(\mathbf{T}^\dagger \mathbf{T}) \leq P_{mb}(b_0))$, where $\mathbf{P} = \text{diag}(p_{mb}(b_0), p_{mb}(b_1), \ldots, p_{mb}(b_K))$. MBS antennas are partly utilized to serve its MUEs and SCs, while the remaining antennas are used to mitigate interference to SUEs. Hence, we have the antenna constraint for scheduling and operation mode such that $\sum_{s=1}^{K} l_k(t) + \sum_{s=1}^{S} \beta(b_s)(t) \leq N$. For notational simplicity, we remove the time dependency from the symbols throughout the discussion. The received signal $y(b_0)$ at each MUE $m \in M$ at time instant $t$ is given

\[ y(b_0) = \sum_{k=1}^{K} \mathbf{h}_{mb}^k \mathbf{c}_k(t) + \sum_{s=1}^{S} \beta(b_s) \mathbf{h}_{mb}^s \mathbf{c}_s(t) + n(t), \]

where $n(t)$ is the additive white Gaussian noise (AWGN) with zero mean and variance $N_0$.
by
\[
y_m^{(b)} = l_m \sqrt{p_m^{(b)} | h_m^{(b)} |^2} v_m x_m^{(b)} + \sum_{s=1}^{S} \frac{\beta(s)^{(b)} \sqrt{p_c^{(b)} | h_m^{(b)} |^2} x_s^{(b)}}{\sum_{s^t \neq s} | \beta(s)^{(b)} |^2 + 1} + n_m,
\]
where \(x_m^{(b)}\) is the signal symbol from the MBS to the MUE \(m\), \(n_m = \mathcal{C} \mathcal{N}(0,1)\) is the thermal noise at MUE \(m\), and \(v_m\) is the precoding vectors of MUE \(m\). \(x_m^{(b)}\) is the transmit signal symbol from SC \(b_s\) to SUE \(c_s\).

At time instant \(t\), the received signal \(y_s^{(b)}\) at each SC \(b_s \in S\) suffers from self-interference, cross-tier interference, and co-tier interference which is given by
\[
y_s^{(b)} = l_s \sqrt{p_s^{(b)} | h_s^{(b)} |^2} v_s x_s^{(b)} + \beta(s)^{(b)} \sqrt{p_c^{(b)} | h_s^{(b)} |^2} x_s^{(b)} + n_s,
\]
where \(n_s \sim \mathcal{C} \mathcal{N}(0,1)\) is the thermal noise of the SC \(b_s\). In this work, the FD capability is leveraged at SCs.

The received signal at SUE \(c_s\) from its serving SC \(b_s\) is interfered by the DL signals from other SCs and the MBS. At time instant \(t\), it is given by
\[
y_c^{(b)} = \beta(s)^{(b)} \sqrt{p_c^{(b)} | h_s^{(b)} |^2} x_s^{(b)} + \sum_{s^t = 1}^{S} \frac{\beta(s)^{(b)} \sqrt{p_c^{(b)} | h_s^{(b)} |^2} x_s^{(b)}}{\sum_{s^t \neq s} | \beta(s)^{(b)} |^2 + 1} + n_c,
\]
where \(n_c \sim \mathcal{C} \mathcal{N}(0,1)\) is the thermal noise in the SC \(b_s\) to its own SUE \(c_s\) and \(n_c \sim \mathcal{C} \mathcal{N}(0,1)\) is the SUE thermal noise.

According to (3-5), the SINRs of MUE \(m \in M\), SC \(b_s \in S\), and SUE \(c_s\) are given by:
\[
\gamma_m^{(b)} = \frac{l_m p_m^{(b)} | h_m^{(b)} |^2 | v_m |^2}{\sum_{k \neq m} l_k p_k^{(b)} | h_m^{(b)} |^2 | v_k |^2 + \sum_{s} \beta(s)^{(b)} | h_m^{(b)} |^2 | v_s |^2 + 1},
\]
\[
\gamma_s^{(b)} = \frac{l_s p_s^{(b)} | h_s^{(b)} |^2 | v_s |^2}{\sum_{k \neq s} l_k p_k^{(b)} | h_s^{(b)} |^2 | v_k |^2 + \sum_{s^t \neq s} \beta(s^t)^{(b)} | h_s^{(b)} |^2 | v_s^t |^2 + 1}.
\]

B. Downlink Scheduling Problem

We consider a joint optimization of scheduling I, operation mode \(\beta\), interference mitigation \(U\), and transmit power allocation \(p = (p_1^{(b)} (b_1), p_2^{(b)} (b_2), \ldots, p_K^{(b)} (b_K))\) that satisfies the transmit power budget of MBS, i.e., \(\text{Tr}(P \text{T}^T) \leq P^{(b)}\). We define \(c_i^{(b)} = \rho_0^{(b)} | h_i^{(b)} |^2 \gamma^{(b)} \) and \(c_s\) as the FD interference to noise ratio (INR) from SC \(b_s\) to any scheduled receiver \(i\), and the allowed FD INR threshold, respectively. The FD INR threshold is defined such that \(\sum_{i=1}^{K} c_i^{(b)} \leq c_o\) in which the total FD interference is considered as noise. Under the operation mode policy, we schedule the receiver \(i\) and enable the transmission of SC \(b_s\) as long as \(\sum_{i=1}^{K} l_i^{(b)} c_i^{(b)} \leq c_o\). Let \(\Lambda = \{1, \beta\}\) be a composite control variable of scheduling and operation mode. We define \(\Lambda = \{A, \Upsilon, P\}\) as a composite control variable, which adapts to the spatial channel correlation matrix \(\Theta\). For a given \(\Lambda\) that satisfies \(\Upsilon\) and operation mode policy, the respective Ergodic data rates of MUE, SC, and SUE are \(r_m(\Lambda, \Theta) = E[\log (1 + r_m^{(b)}(\Lambda, \Theta))], r_s(\Lambda, \Theta) = E[\log (1 + r_s^{(b)}(\Lambda, \Theta))], r_c(\Lambda, \Theta) = E[\log (1 + r_c^{(b)}(\Lambda, \Theta))]\).

Definition 2. For any vector \(x(t) = (x_1(t), \ldots, x_K(t))\), let \(\bar{x} = (\bar{x}_1, \ldots, \bar{x}_K)\) denote the time average expectation of \(x(t)\), where \(\bar{x} \triangleq \lim_{t \to \infty} \frac{1}{t-\tau+1} \sum_{\tau=0}^{t-\tau} E[x(\tau)]\). Similarly, \(\bar{r} \triangleq \lim_{t \to \infty} \frac{1}{t-\tau+1} \sum_{\tau=0}^{t-\tau} E[r(\tau)]\) denotes the time average expectation of the Ergodic data rate.

For a given composite control variable \(\Lambda\) that adapts to the spatial channel correlation matrix \(\Theta\), the average data rate region is defined as the convex hull of the average data rate of users, which is expressed as:
\[
R = \{ r(\Lambda, \Theta) \in R^K | 1 \in \{0,1\}^K, \beta \in \{0,1\}^S, \sum_{i=1}^{K} l_i^{(b)} + \sum_{s=1}^{S} \beta(s)^{(b)} \leq N, \sum_{i=1}^{K} l_i^{(b)} + \sum_{s=1}^{S} \beta(s)^{(b)} c_s^{(b)} \leq c_o, \text{Tr}(P \text{T}^T) \leq P^{(b)} \},
\]
where \(r(\Lambda, \Theta) = (r_1(\Lambda, \Theta), \ldots, r_K(\Lambda, \Theta))^T\). Following the results from \(\Upsilon\), the boundary points of the rate region with total power constraint and no self-interference are Pareto-optimal. Moreover, according to \(\Theta\) Proposition 1], if the INR covariance matrices approach the identity matrix, the Pareto rate region of the MIMO interference system is convex. Hence, the rate region is Pareto-optimal, and thus, convex under above constraints.

Let us assume that SCs act as relays to forward data to the SUEs. If the MBS transmits data to SC \(b_s\), but the transmission of SC \(b_s\) is disabled, it cannot serve its SUE. Hence, we define \(D(t) = (D_1(t), D_2(t), \ldots, D_K(t))\) as a data queue at SCs,

The Pareto optimal is the set of user rates at which it is impossible to improve any of the rates without simultaneously decreasing at least one of the others.
where at each time slot $t$, the wireless backhaul queue at SC $b_k$ is
\[
D_k(t+1) = \max[D_k(t) + r_k(t) - r_{c_k}(t), 0].
\] (9)

We define the network utility function $f(\cdot)$ to be non-decreasing, concave over the convex region $\mathcal{R}$ for a given $\Theta$. The objective is to maximize the network utility under wireless backhaul queue constraints and imperfect CSI. Thus, the network utility maximization (NUM) problem is given by,
\[
\begin{align*}
\max_{\bar{r}} & \quad f(\bar{r}) \quad (10a) \\
\text{subject to} & \quad \bar{r} \in \mathcal{R}, \quad (10b) \\
& \quad \bar{D} < \infty. \quad (10c)
\end{align*}
\]
where $f(\bar{r}) = \sum_{k=1}^K \omega_k(t)f(\bar{r}_k)$, and $\omega_k(t) \geq 0$ is the weight of user $k$, $f(\cdot)$ is assumed to be twice differentiable, concave, and increasing $L$-Lipschitz function for all $\bar{r} \geq 0$. Solving (10) is non-trivial since the average rate region $\mathcal{R}$ does not have a tractable form. To overcome this challenge, we need to find closed-form expressions of the data rate and the average transmit power.

C. Closed-Form Expression via Deterministic Equivalent

We invoke recent results from RMT in order to get the deterministic equivalent. As $K,N \to \infty$, by applying the techniques in [6], for small $\alpha$ the deterministic equivalent of the asymptotic SINR of UEs (7) is
\[
\begin{align*}
\gamma_m^{(b_0)}(A|\Theta) \xrightarrow{a.s.} \frac{l_m p_m^{(b_0)}(1 - 2^{\beta_m})}{1 + \sum_{s=1}^S \beta_s (b_s^{(\gamma)} - b_s^{(\nu)})}, \quad (b) \\
\gamma_k^{(b_0)}(A|\Theta) \xrightarrow{a.s.} \frac{l_k p_k^{(b_0)}(1 - 2^{\beta_k})}{1 + \sum_{s'=1}^S \beta_{s'}(b_{s'}^{(\gamma)} - b_{s'}^{(\nu)})}, \quad (c)
\end{align*}
\]
where $a.s.$ denotes the almost sure convergence. The precoder $T$ is designed to satisfy a total transmit power constraint and takes into account the scheduling $l$ and $U$, and thus, we obtain $\frac{1}{N} \sum_{k=1}^K p_k^{(b_0)} \leq P(\bar{r}_k) \leq 0$. Here, $\Omega_k = \frac{1}{N} \text{Tr}(\bar{\Theta}_k G)$ forms the unique positive solution of which is the Stieltjes transform of nonnegative finite measure [6]. The Lyapunov function can be written as
\[
L(\Sigma(t)) = \frac{1}{2} \sum_{k=1}^K \left[ \sum_{s=1}^S \gamma_k^{(s)}(A|\Theta) \right] + \sum_{s'=1}^S \beta_{s'}(b_{s'}^{(\gamma)} - b_{s'}^{(\nu)}) \leq 0.
\]
For each time slot $t$, $\Delta(\Sigma(t))$ denotes the Lyapunov drift given by $\Delta(\Sigma(t)) = \text{E}[L(\Sigma(t+1)) - L(\Sigma(t))].$

Noting that $\max[a,0]^2 \leq a^2$ and $(a+b)^2 \leq a^2 + 2ab + b^2$ for any real positive number $a,b$, and thus, by neglecting the index $t$ we have, $\max[Q_k - r_k,0]^2 + a_k^2 - Q_k^2 \leq 2Q_k a_k - r_k + a_k - r_k^2$, $\max[Q_k + r_k - r_k,0]^2 - Y^2 \leq 2Y(\varphi_k - r_k + \varphi_k - r_k^2)$, $\max[Q_k + r_k - r_k,0]^2 - D_k^2 \leq 2D_k(\varphi_k - r_k + \varphi_k - r_k^2)$. Assume that $\varphi_k \in \mathcal{R}$ and a feasible $l$ for all $t$ and all possible $\Sigma(t)$, we have
\[
\Delta(\Sigma(t)) \leq \Psi + \sum_{k=1}^K \left[ Q_k(t) \text{E}[\varphi_k(t) - r_k(t) | \Sigma(t)] \right] + \sum_{s'=1}^S \beta_{s'}(b_{s'}^{(\gamma)} - b_{s'}^{(\nu)}) \leq 0.
\]
Here $\Delta(\Sigma(t)) \leq \Pi$, where $\Pi$ represents the R.H.S of (15), and $\Psi$ is a finite constant that satisfies $\Psi \geq \frac{1}{N} \sum_{k=1}^K \text{E}[\Psi(\varphi_k(t)) | \Sigma(t)] + \frac{1}{N} \sum_{k=1}^K \text{E}[\varphi_k(t) | \Sigma(t)] + \frac{1}{N} \sum_{s'=1}^S \beta_{s'}(b_{s'}^{(\gamma)} - b_{s'}^{(\nu)}) | \Sigma(t)]$ for all $t$ and all possible $\Sigma(t)$. We apply the Lyapunov drift-plus-penalty technique, where the solution of (13) is obtained by minimizing the Lyapunov drift and the objective function, i.e.,
\[
\min \quad \Pi \quad - v f(\varphi(t)),
\]
where the parameter $v$ is chosen as a non-negative constant to control optimality and queue backlogs. Since $\Psi$ is finite, the problem becomes minimizing (16), which is decoupled over scheduling and operation mode variables (1*), auxiliary variables (2*), and precoder and power allocation variables (3*), respectively. Hence, the respective variables can be found independently by minimizing the individual term at each time. Fig. 2 summarizes the relationship among subproblems.
A. Step 1: Joint Scheduling and Operation Mode

The joint scheduling and operation mode problem is a mixed-integer program with a non-convex objective function and non-convex interference constraints. To solve this problem, we first relax the integer constraints to linear constraints as continuous values. Secondly, to deal with non-convex interference constraint, we apply the SCA method [11] Lemma 3.5], where at each iteration $i$ the non-convex constraints are approximated by upper convex approximations. Hence, we solve iteratively the problem by updating the variables until convergence to obtain a Karush-Kuhn-Tucker (KKT) point. The interference constraint is replaced by $\sum_{i=1}^{K} \sum_{s=1}^{S} \left( \frac{\lambda_{i,s}(t)}{2} + \frac{(\beta_{i,s}(t))^2}{2\lambda_{i,s}(t)} \right) - \epsilon_0 \leq 0$, for every fixed positive value $\lambda_{i,s}$. Finally, instead of minimizing the non-convex objective function ($\star$), we minimize its upper bound by replacing the denominators, i.e., $1 + \sum_{s=1}^{S} \beta_{i,s}(t)$ with the largest bound, i.e., $1 + \epsilon_0$. This upper bound is obtained due to interference constraint $\sum_{i=1}^{K} \sum_{s=1}^{S} \beta_{i,s}(t) \leq \epsilon_0$ and we assume the feasibility of problem exists such that the total FD interference at each receiver is less than the total FD interference threshold $\epsilon_0$. Hence, we obtain the upper bound as below and the optimal value of $A^*$ is given by

$$\min_{b,\beta} \left[ -\sum_{k=1}^{K} D_k(t) \log \left( 1 + \frac{(\beta_{i,k}(t))^2}{2\lambda_{i,k}(t)} \right) \right]$$
subject to
$$-\sum_{k=1}^{K} A_k(t) \log \left( 1 + \frac{1}{1+\epsilon_0} \right) \leq N, \quad \text{(17a)}$$
$$\sum_{k=1}^{K} r_k(l_k(t), \beta_{i,k}(t)) \leq N, \quad \text{(17b)}$$
$$\sum_{k=1}^{K} r_k(l_k(t), \beta_{i,k}(t)) \leq \epsilon_0, \quad \text{(17c)}$$
$$r_k(l_k(t), \beta_{i,k}(t)) \in \mathcal{R}, \quad \text{(17d)}$$

where $A_k(t) = Q_k(t) + Y_k(t)$. At each time slot $t$, the joint scheduling and operation mode is outlined as Algorithm 1. We numerically observe that the SCA-based Algorithm 1 converges quickly after few iterations and yields a solution of many scheduling and operation variables close or equal to binary. Hence, we apply a binary search algorithm in order to obtain a low-complexity search algorithm to convert the continuous relaxation solution to the integer solution [12]. To ensure that all users will be served, each user is set to have the same transmit power to find the best scheduled users. Moreover, the scheduling will be performed in a short-term period, while the power allocation problem is executed in a long-term period.

Algorithm 1 Joint Scheduling and Operation Mode

1. Initialization $i = 0$, $\lambda_{i,s}^{(0)} = \text{randomly positive}$.
2. repeat
   3. Solve (17) with $\lambda_{i,s}^{(i)}$ to get optimal value $A^{*,i}$.
   4. Update $A^{(i+1)} = A^{*,i}$ and $\lambda_{i,s}^{(i+1)} = \beta_{i,s}(t) / \lambda_{i,s}^{(i)}$; $i := i + 1$.
3. until Convergence

B. Step 2: Selection of Auxiliary Variable

The optimal auxiliary variables are computed by

$$\min_{\varphi(t)} \sum_{k=1}^{K} Y_k(t) \varphi_k(t) + \sum_{s=1}^{S} D_s(t) \varphi_s(t) - \nu f(\varphi(t)),$$
subject to $\varphi(t) \leq r_{\text{max}}(t)$.

Since the above optimization problem is convex, let $\varphi^*_k(t)$ be the optimal solution obtained by the first order derivative of the objective function of (18). With a logarithmic utility function, we have:

$$\varphi^*_k(t) = \frac{y_k(t)}{\nu} \frac{\nu \varphi_{\text{max}}(t)}{\varphi_{\text{max}}(t) + D_k(t)} \quad \text{if } k \leq M,$$
$$\varphi^*_k(t) = \frac{y_k(t)}{\nu} \frac{\nu \varphi_{\text{max}}(t)}{\varphi_{\text{max}}(t) + D_k(t)} \quad \text{otherwise}.$$ 

The optimal auxiliary variable is $\min \{ \varphi^*_k(t), \varphi_{\text{max}}^*(t) \}$.

C. Step 3: Interference Mitigation and Power Allocation

For given scheduled users in Step 1, the precoder $U$ is found by solving (19). Finally, problem (13) is decomposed to find the transmit power $p_{k}^{(b)}(t)$ as follows:

$$\min_{p(t)} \sum_{k=1}^{K} A_k(t) r_k(p(t)),$$
subject to $\frac{1}{N} \sum_{k=1}^{K} p_{k}^{(b)}(t) - P_{\text{max}} \leq 0$, $\varphi^*_k(t) \geq 0$, $\forall k \in \mathcal{K}$. (19c)
The objective function (19) is rewritten as
\[ n(p(t)) = -\sum_{k=1}^{K} A_k(t) \log \left(1 + \frac{p_{k}^{(b_0)}(t)n_k(t)}{\beta_{k}(t)1^{-\tau_2}}\right). \]
The objective function is strictly convex for \( p_{k}^{(b_0)}(t) \geq 0, \forall k \in K \), and the constraints are compact. Hence, the optimal solution of \( p^*(t) \) exists, the Lagrangian function is written as 
\[ L(p(t), \mu_0) = n(p(t)) + \mu_0 g(p(t)), \]
where \( \mu_0 \geq 0 \) is the KKT multiplier. The KKT conditions are
\[ \nabla n(p(t))^T + \mu_0 \frac{1}{N} \sum_{k=1}^{K} \frac{1}{\beta_{k}(t)} = 0. \]
\[ \mu_0 \left( \frac{1}{N} \sum_{k=1}^{K} \frac{p_{k}^{(b_0)}(t)}{\beta_{k}(t)} - P(b_0) \right) = 0. \]
\[ \frac{1}{N} \sum_{k=1}^{K} \frac{p_{k}^{(b_0)}(t)}{\beta_{k}(t)} - P(b_0) \leq 0. \]
\[ -p(t) \leq 0, \mu_0 \geq 0. \]
Here, \( \nabla n(p(t))^T = (n'_1(p_{1}^{(b_0)}(t)), \ldots, n'_K(p_{K}^{(b_0)}(t))) \) where \( n'_k(p_{k}^{(b_0)}(t)) = \frac{A_k(t)n_k(t)}{1 + p_{k}^{(b_0)}(t)n_k(t)} \). Since \( \mu_0 \neq 0 \), from (20), we have
\[ p_{k}^{(b_0)}(t) = \max\left\{ \frac{A_k N n_k}{\mu_0}, \frac{1}{n_k(t)} \right\} = 0, \]
then, from (21) and (24) we derive
\[ \mu_0 = \frac{1}{NP(b_0)} \left( N \sum_{k=1}^{K} A_k(t) + \sum_{k=1}^{K} \frac{1}{n_k(t)} \right). \]
Finally, the optimal value of \( p_k(t)^{(b_0)} \) is obtained with (24) and (25).

D. Queue Update

Update the virtual queues \( Y_k(t) \) and \( D_k(t) \) according to (14) and (12), and the actual queue \( Q_k(t) \) in (11).

V. NUMERICAL RESULTS

We consider a HetNet scenario, where a MBS is located at the center of the cell. The path loss is modeled as a distance-based path loss with line-of-sight (LOS) model for urban environments at 28 GHz, 10 GHz, and 2.4 GHz [13]. We denote our proposed algorithms for HetNet (resp. Homogeneous network) as HetNet-Hybrid (resp. HomNet). Here, HomNet refers to when the MBS serves both MUEs and SUEs without SCs. The data arrivals follow the Poisson distribution with the mean rate of 1 Gbps, 100 Mbps, and 20 Mbps for 28 GHz, 10 GHz, and 2.4 GHz, respectively. We consider the proportional fairness utility function, i.e., \( f(r_k) = \log r_k \) [14]. The parameter settings are summarized in Table I.

Fig. 3 and 4 report the achievable average UE throughput, cell-edge UE throughput, and average network queue length as a function of network density at different frequency bands. The number of SCs \( S \) increases from 16 to 900, reflecting the inter-site distance (ISD) between SCs decreasing from 250 m to 33 m. On the other hand, the number of UEs \( K \) increases from 32 UEs to 1500 UEs per km². Moreover, the number of antennas \( N \) at the MBS is twice the number of UEs \( K \).

Table I: Parameter Settings

| Parameter | Value | Units |
|-----------|-------|-------|
| Path Loss Model [13] | LOS @ 2.4 GHz | 17 + 37.6 log(d) | dBm |
| | LOS @ 10 GHz | 55.25 + 18.5 log(d) | 20 |
| | LOS @ 28 GHz | 61.4 + 20 log(d) | 1000 |

With the increase in the number of SCs \( S \) and MUEs \( M \), the per UE/SC transmit power is reduced by a factor of \( K \) and the cross-tier interference becomes dominant. Hence, the achievable average UE throughput gradually decreases, while the network queue traffic becomes more congested. Moreover, the UE throughput at 28 GHz achieves 56× and 62× gain as compared to 2.4 GHz due to 50× larger bandwidth and smart beamforming, when the ISD is 250 m and 80 m, respectively. In ultra-dense deployment, the UE throughput at 2.4 GHz is below 10 Mbps, whereas 473 Mbps per UE is achieved by using 28 GHz for 33 m of ISD.

By taking advantage of mmWave frequency bands, we observe that at 28 GHz when the number of UEs per km² is increased to 200 UEs, the average UE throughput reaches 1.73 Gbps and 1.39 Gbps in case of HetNet-Hybrid and HomNet, respectively. Whereas the cell-edge UE throughput reaches 1 Gbps and 0.73 Gbps in case of HetNet-Hybrid and
HetNet-Hybrid, respectively. When the ISD is less than 50 m, the network queue size dramatically increases, and the network becomes congested. To handle this problem, the arrival traffic needs to be adjusted by reducing the admitting data or the UE throughput should increase by increasing the maximum BS transmit power and number of antennas.

The performance of NUM based on Lyapunov framework is analyzed in [10]. There exists an $O(1/\nu), O(1)$ utility-queue backlog tradeoff, which leads to an utility-delay tradeoff. We show the impact of the Lyapunov parameter $\nu$ on the achievable average network utility and queue backlog as seen in Fig. 5 when $K = 16, N = 64$, and $P(b_0) = 38$ dBm. By varying the value of $\nu$, the network utility is increasing with $O(1/\nu)$, while the network backlog linearly increases with $O(\nu)$.

![Impact of $\nu$ on the Utility and Network Backlogs at 28 GHz when $K = 16, N = 64$.](image)

Fig. 5: Impact of $\nu$ on the Utility and Network Backlogs at 28 GHz when $K = 16, N = 64$.

VI. CONCLUSION

In this paper, we have studied the problem of joint in-band backhaul scheduling and interference mitigation in 5G HetNets. The goal is to maximize a network utility function of the total time-average data rates subject to the wireless backhaul constraint in the presence of imperfect CSI. At mmWave 28 GHz with 1 GHz of BW, we observe that 1.7 Gbps of the achievable average UE throughput and 1 Gbps of the cell-edge UE throughput can be reached for 200 UE per km$^2$ in HetNet. When the network gets dense, harnessing mmWave yields 62× gain of UE throughput as compared to conventional cellular frequency.

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