Flexible Multiple Base Station Association and Activation for Downlink Heterogeneous Networks

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Abstract

This work proposes a joint base station (BS) association and power control scheme that encourages the turning-off of the BSs at the off-peak time.

Our contributions include:

- A novel flexible BS association and activation paradigm;
- An efficient algorithm based on the gradient projection method and the proximal gradient method.

Introduction

The traditional max-SINR association is suboptimal in HetNet because it does not account for *load balancing* between large cells and small cells.

A common solution used in practice is *cell-range expansion* that can be interpreted as a dual optimization; see [1] and [2].

But this scheme is based on the assumption that each user is associated with only one BS and all BSs transmit at flat power spectral density (PSD).

We propose a *flexible* framework for joint BS association and power control by assuming that

1. users can be associated with possibly multiple BSs over multiple frequency bands;
2. BSs can transmit at varying PSDs across the frequencies;
3. BSs can be deactivated for the power saving purpose.

Resource Allocation Model

Consider a downlink HetNet with K users and L BSs. The total frequency band W is divided into N equal bands. Use (ℓ, n) to index the band resources, for $\ell = [1:L]$ and $n = [1:N]$. The spectral efficiency of user k in band (ℓ, n) is

$$r_{k\ell}^n = \frac{W}{N}\log\left(1 + \frac{g_{k\ell}^n p_\ell^n}{\sigma^2 + \sum_{\ell' \neq \ell} g_{k\ell'}^n p_{\ell'}^n}\right) \tag{1}$$

where $g_{k\ell}^n$ is the channel magnitude, p_ℓ^n is the transmit power, and σ^2 is the background noise power.

Each user k can be associated with an arbitrary set of (ℓ, n)'s. Multiple users associated with the same (ℓ, n) are served via time-division multiplexing. Then, the total transmission rate of user k is

$$R_k = \sum_{\ell=1}^{L}\sum_{n=1}^{N} x_{k\ell}^n r_{k\ell}^n \tag{2}$$

where $0 \le x_{k\ell}^n \le 1$ represents the fraction of (ℓ, n) allocated to user k.

Joint BS Association and Activation

There are two types of power consumption:

- Transmit power p_ℓ^n;
- On-power ψ_ℓ.

The total power consumption at BS ℓ is

$$Q_\ell(\mathbf{p}_\ell) = \mathbf{e}_N^T\mathbf{p}_\ell + \psi_\ell \|\mathbf{p}_\ell\|_0 \tag{3}$$

where $\mathbf{p}_\ell = [p_\ell^1, \ldots, p_\ell^N]^T$.

The objective is to maximize a network utility, chosen here as a trade-off between the power consumption and the proportionally fair utility:

$$\begin{aligned} \max_{\mathbf{X},\mathbf{P}} \quad & \sum_{k=1}^{K}\log(R_k) - \lambda\sum_{\ell=1}^{L}Q_\ell(\mathbf{p}_\ell) && \text{(4a)}\\ \text{s.t.} \quad & \mathbf{0} \le \mathbf{p}_\ell \le \bar{\mathbf{p}}_\ell,\ \forall \ell && \text{(4b)}\\ & \mathbf{X}^n\mathbf{e}_L \le \mathbf{e}_K,\ \forall n && \text{(4c)}\\ & (\mathbf{X}^n)^T\mathbf{e}_K \le \mathbf{e}_L,\ \forall n && \text{(4d)}\\ & \mathbf{X}^n \ge \mathbf{0},\ \forall n && \text{(4e)} \end{aligned}$$

where $\lambda \ge 0$ is a given trade-off factor and $\mathbf{X}^n$ is the set $\{x_{k\ell}^n\}_{(k,\ell)}$ for $n = 1, 2, \ldots, N$.

Iterative Reweighting

The ℓ_0-norm term in $Q_\ell(\mathbf{p}_\ell)$ is numerically difficult to deal with. We propose to approximate the original problem by the following weighted ℓ_2/ℓ_1 problem:

$$\begin{aligned} \max_{\mathbf{X},\mathbf{P}} \quad & f(\mathbf{X},\mathbf{P}) - \lambda\sum_{\ell=1}^{L}\psi_\ell w_\ell \|\mathbf{p}_\ell\|_2 && \text{(5a)}\\ \text{s.t.} \quad & \text{(4b)–(4e)} && \text{(5b)} \end{aligned}$$

where

$$f(\mathbf{X},\mathbf{P}) = \sum_{k=1}^{K}\log(R_k) - \lambda\mathbf{e}_L^T\mathbf{P}\mathbf{e}_N \tag{6}$$

and $\{w_\ell\}$ are some iteratively updated weights. This leads to the following algorithm:

Algorithm 1: An Iteratively Reweighting Algorithm for Solving Problem (4)

Step 1. Choose a positive sequence $\{\tau(t)\}$. Set $t = 0$ and $w_\ell(0) = 1$ for all $\ell = 1, 2, \ldots, L$.

Step 2. Solve problem (5) with $w_\ell = w_\ell(t)$, $\ell = 1, 2, \ldots, L$ for its solution $\mathbf{P}(t)$ and $\mathbf{X}(t)$.

Step 3. Update the weights by

$$w_\ell(t+1) = \frac{1}{\|\mathbf{p}_\ell(t)\|_2 + \tau(t)},\ \ell = 1, 2, \ldots, L, \tag{7}$$

set $t = t + 1$, and go to **Step 2.**

Remark: We approximate $\|\mathbf{p}_\ell\|_0$ by $\|\mathbf{p}_\ell\|_2$ rather than $\|\mathbf{p}_\ell\|_1$ in the new problem (5) in order to induce *group sparsity*. The intuition is that ℓ_2 encourages setting the entire vector $\mathbf{p}_\ell$ to zero (i.e., turning off BS ℓ), whereas ℓ_1 encourages setting a subset of entries to zero.

Gradient Projection for Optimizing X

To solve problem (5), we first consider optimizing $\mathbf{X}$ assuming that $\mathbf{P}$ is fixed to $\mathbf{P}(s)$. This is a convex problem with linear constraints. Apply the gradient update:

$$\tilde{\mathbf{X}}^n(s) = \mathbf{X}^n(s) + \alpha^n(s)\nabla_{\mathbf{X}^n} f(\mathbf{X}(s), \mathbf{P}(s)) \tag{8}$$

where $\alpha^n(s)$ is some appropriately chosen step size. Then, the optimal $\mathbf{X}$ can be obtained from projection:

$$\begin{aligned} \min_{\mathbf{X}} \quad & \frac{1}{2}\|\mathbf{X}^n - \tilde{\mathbf{X}}^n(s)\|_F^2 && \text{(9a)}\\ \text{s.t.} \quad & \text{(4c)–(4e)}. && \text{(9b)} \end{aligned}$$

We propose an efficient approach by extending the dualBB algorithm in [3]. The Lagrangian dual of (9) is

$$\begin{aligned} \min_{\mathbf{y}^n,\mathbf{z}^n} \quad & \frac{1}{2}\|\Theta_s(\mathbf{y}^n,\mathbf{z}^n)\|_F^2 + \mathbf{e}_K^T\mathbf{y}^n + \mathbf{e}_L^T\mathbf{z}^n && \text{(10a)}\\ \text{s.t.} \quad & \mathbf{y}^n \le \mathbf{0},\ \mathbf{z}^n \le \mathbf{0} && \text{(10b)} \end{aligned}$$

where $\Theta_s(\mathbf{y}^n,\mathbf{z}^n) = \max\{\tilde{\mathbf{X}}^n(s) + \mathbf{y}^n\mathbf{e}_L^T + \mathbf{e}_K(\mathbf{z}^n)^T, \mathbf{0}\}$. The new problem can be efficiently solved through the projection onto the nonpositive orthant. After solving (10), we recover

$$\mathbf{X}^n(s+1) = \Theta_s(\mathbf{y}^n,\mathbf{z}^n). \tag{11}$$

Proximal Gradient for Optimizing P

We further consider optimizing $\mathbf{P}$ with $\mathbf{X}$ fixed to $\mathbf{X}(s+1)$, updated by the above gradient projection method. Because $\|\mathbf{p}_\ell\|_0$ is nonsmooth, the gradient method does not work. In this paper, we propose to use the proximal gradient method [4]. First, compute the gradient update:

$$\tilde{\mathbf{p}}_\ell(s+1) = \mathbf{p}_\ell(s) + \beta_\ell(s+1)\nabla_{\mathbf{p}_\ell} f(\mathbf{X}(s+1), \mathbf{P}(s)) \tag{12}$$

where $\beta_\ell(s+1)$ is some appropriately chosen step size.

The proximal gradient method further updates $\mathbf{p}_\ell$ by solving

$$\min_{\mathbf{p}_\ell} \quad \frac{1}{2}\|\mathbf{p}_\ell - \tilde{\mathbf{p}}_\ell(s+1)\|_2^2 + t_\ell(s+1)\|\mathbf{p}_\ell\|_2 \tag{13}$$

where

$$t_\ell(s+1) = \lambda\psi_\ell w_\ell \beta_\ell(s+1). \tag{14}$$

This problem has a closed-form solution:

$$\hat{\mathbf{p}}_\ell(s+1) = \max\left\{1 - \frac{t_\ell(s+1)}{\|\tilde{\mathbf{p}}_\ell(s+1)\|_2}, 0\right\}\tilde{\mathbf{p}}_\ell(s+1). \tag{15}$$

Block Coordinate Ascent on X and P

Algorithm 2: A Block Coordinate Gradient Ascent Algorithm for Solving Problem (5)

Step 1. Choose an initial point $(\mathbf{X}(0), \mathbf{P}(0))$. Set $s = 0$.

Step 2. Use the gradient projection method as in (8)–(11) to optimize $\mathbf{X}$ for fixed $\mathbf{P}$.

Step 3. Use the proximal gradient method as in (12)–(15) to optimize $\mathbf{P}$ for fixed $\mathbf{X}$. Set $s = s + 1$ and go to **Step 2.**

Simulation Results

Network topology	7 cells; 9 users, 1 macro-BS, and 3 pico-BS per cell
Channel bandwidth	10MHz divided into 16 equal bands
Max transmit PSD	-27dBm/Hz (macro-BS); -47dBm/Hz (pico-BS)
On-power	1450W (macro-BS); 21.32W (pico-BS)

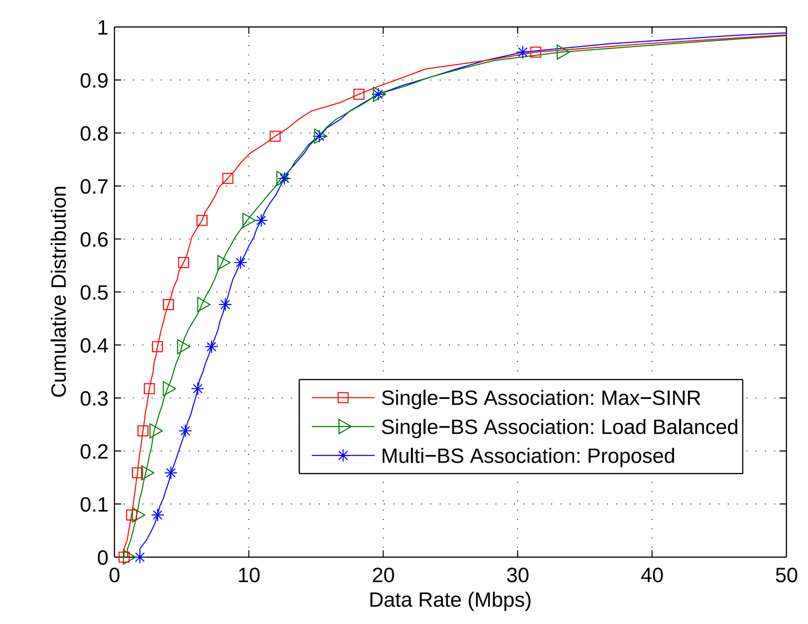

Figure 1: Rate CDFs when $\lambda = 0$.

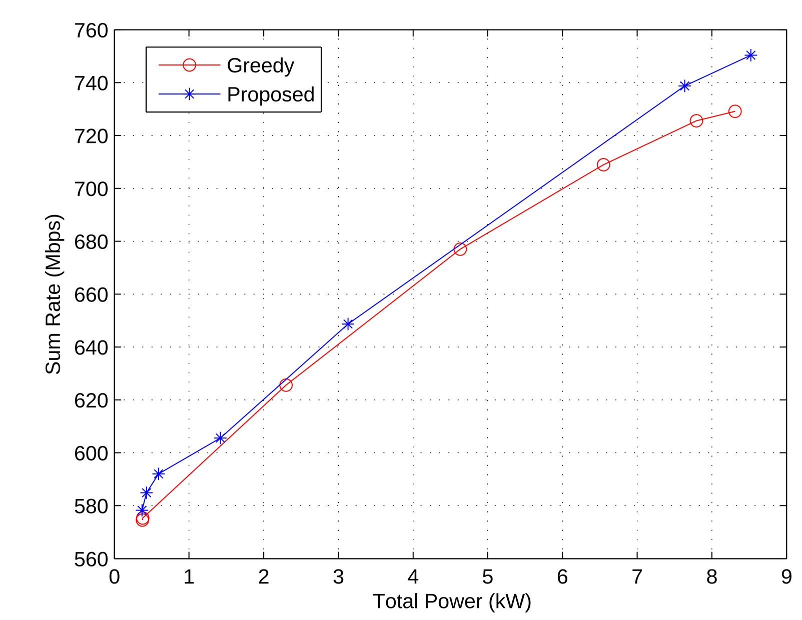

Figure 2: Greedy vs. Algorithm 1 for BS turning-off.

Conclusion

- Flexibilities of varying PSD across frequencies and multiple-BS association benefit the low-rate users.
- The proposed algorithm enables effective balancing between throughput and power consumption.

Reference:

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[2] K. Shen and W. Yu, "Distributed pricing-based user association for downlink heterogeneous cellular networks", *IEEE J. Sel. Areas Commun.*, vol. 32, no. 6, pp. 1100-1113, June 2014.

[3] B. Jiang, Y.-F. Liu, and Z. Wen, "L_p-norm regularization algorithms for optimization over permutation matrices", *SIAM J. Optim.*, vol. 26, no. 4, pp. 2284-2313, 2016.

[4] N. Parikh and S. P. Boyd, "Proximal algorithms", *Found. Trends Optim.*, vol. 1, no. 3, pp. 127-239, Jan. 2014.