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Randomized User-Centric Clustering for Cloud Radio Access Network with PHY Caching

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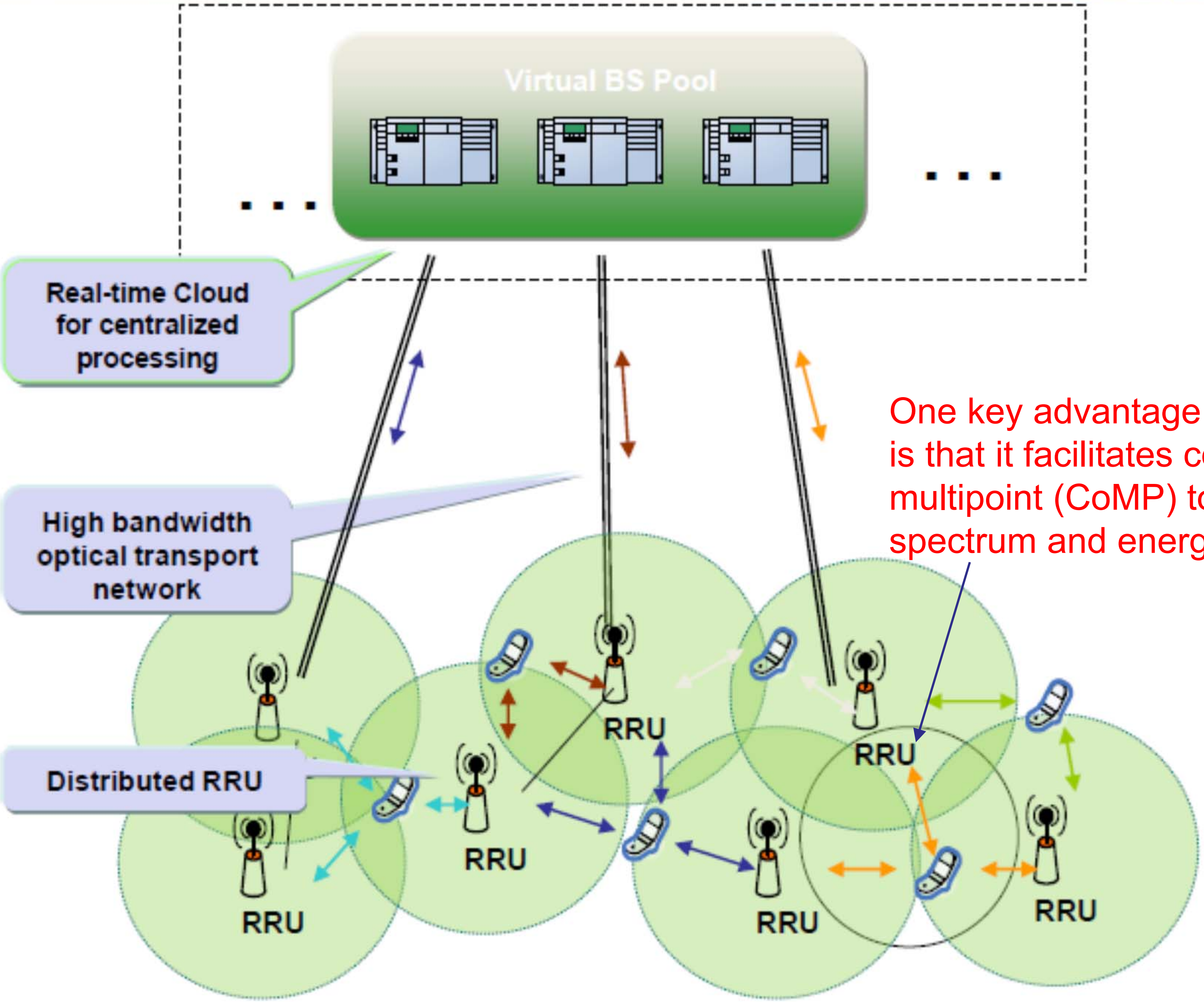
Background

Cloud Radio Access Networks (C-RAN)



One key advantage of C-RAN is that it facilitates coordinated multipoint (CoMP) to improve spectrum and energy efficiency

Issue 1: Joint Clustering and Interference Mitigation (Precoding)

- In C-RAN, as the number of RRHs increases, the overhead of full CoMP among all RRHs increases dramatically
  - The amount of feedback needed from the users increases
  - The CSI feedback and other processing delay increases which may cause further performance degradation
- Scalable Solution → clustering techniques are required
  - Network centric clustering (NCC)
    - The CRAN is divided into a set of non-overlapping RRH clusters (virtual BSs (VBSs))
    - The performance of the UEs at the boundary of the clusters will be compromised
  - User-centric clustering (UCC)
    - Each UE chooses a small number of RRHs as serving VBS
    - There can be overlap among VBSs to avoid cell edge effect. Hence UCC usually outperforms NCC.
    - However, User-centric clustering is challenging since the clusters are chosen in a dynamic way and may overlap
- One side effect of RRH clustering is the inter-cluster interferences among different VBSs
  - Efficient joint clustering and precoding is essential for practical deployment of C-RAN

Drawbacks of the Exiting Joint Clustering and Precoding Schemes

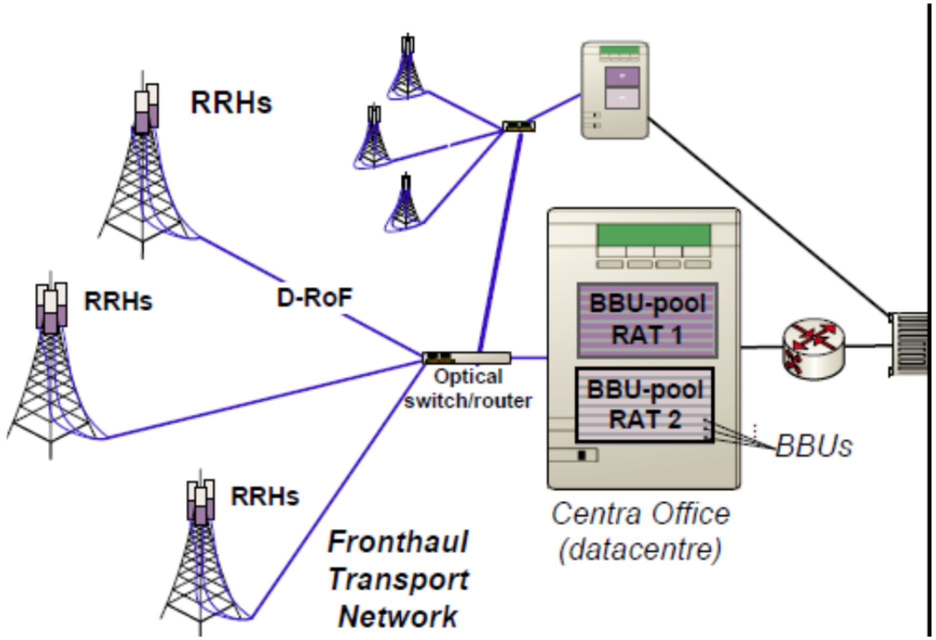
- One-timescale Centralized UCC (e.g., group sparse beamforming [1])
  - Requires real-time global CSIT -> huge CSI signaling overhead + sensitive to signaling latency
  - Large computation complexity
  - Not scalable to large network
- Heuristic two-timescale schemes (e.g., [2])
  - The RRH clustering is updated at slower timescale based on channel statistics
  - The precoder is updated at each time slot based on instantaneous CSI from the active RRHs to the users
  - Lower computational complexity and CSI signaling overhead
  - The RRH clustering and precoding solutions are obtained in a heuristic manner (i.e., the solution is not derived from a single joint optimization problem
  - The performance gap w.r.t. the optimal solution can be large.

[1] B. Dai and W. Yu, "Sparse beamforming and user-centric clustering for downlink cloud radio access network," IEEE Access, vol. 2, pp. 1326–1339, 2014.
[2] A. Liu and V. Lau, "Joint power and antenna selection optimization in large cloud radio access networks," IEEE Trans. Signal Processing, vol. 62, no. 5, pp. 1319–1328, March 2014.

Issue 2: Fronthaul Issues

- Fronthaul transport network (between BBUs and RRHs):
  - Digital Radio over Fibre (D-RoF).
  - Using typically the Common Public Radio Interface (CPRI) standard.
- Digitation requires high bit-rate CPRI links:
  - Site with 3 RRHs (LTE, 20MHz) requires 7.4 Gbit/s link.
  - Site with 15 RRHs (LTE-A (2 bands), 3G (2 bands), 2G (1 band)) requires up to 20Gbit/s link.

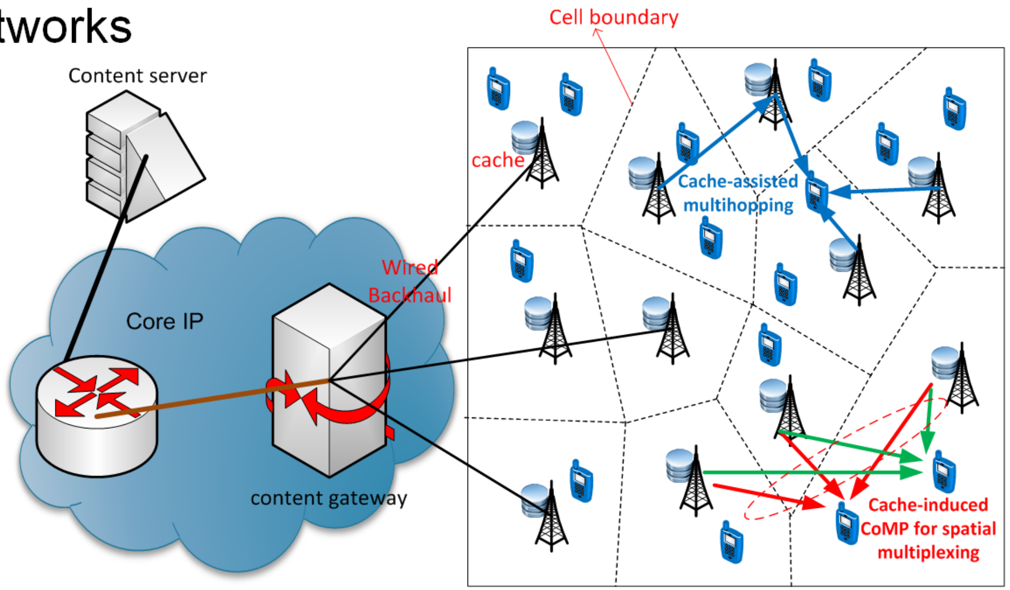
- Low latency: Maximum round trip delay of 150µs (~15km optical fiber).
- Jitter and synchronization:
  - Stringent requirements for frequency and phase synchronization.



Q: How to reduce the required fronthaul loading to reduce the cost and energy consumption of franthaul?

Can we exploit caching to reduce fronthaul loading?

- Motivation:
  - More than 50% of the wireless traffic comes from content delivery applications such as video streaming
  - Content are cachable at BS, e.g., the popular content cached at the BS is likely to be requested by many users later
  - Wireless caching: Cache the popular content at the BS during off-hours to improve the end-to-end performance and reduce backhaul/fronthaul loading at peak-hours
- PHY caching has been proposed to reduce backhaul cost and enhance capacity in dense wireless networks
  - ➢ Each BS has a cache
  - ➢ Only a small fraction of BSs have payload backhauls -> reduced backhaul cost
  - ➢ The role of backhaul is replaced by cheap cache without sacrificing order of capacity

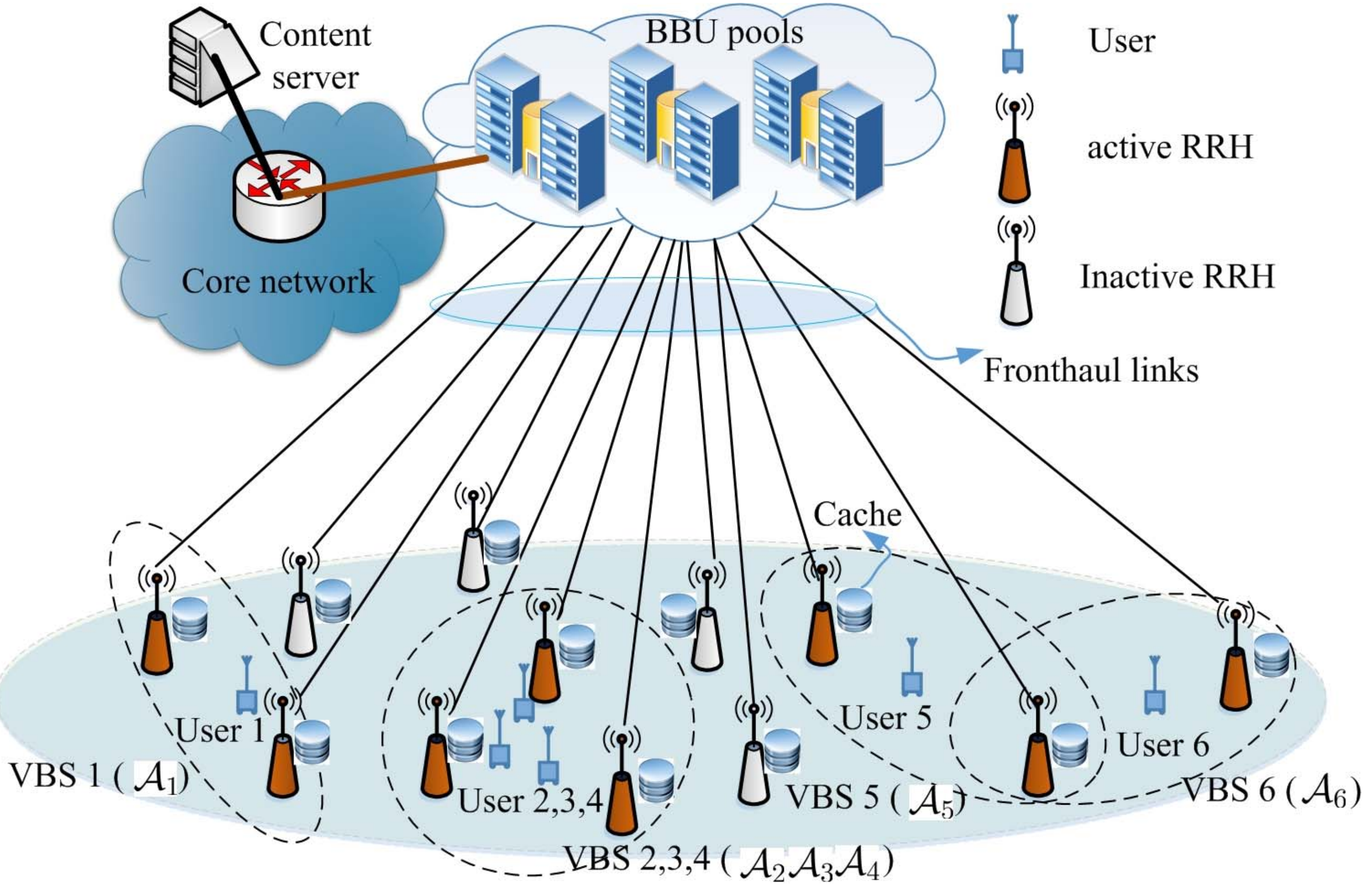


Q: Can we reduce the fronthaul loading by caching some popular content at the RRHs?

Mutli-timescale Optimization Framework & Challenges

- We propose a mutli-timescale optimization framework to address the above two issues of C-RAN, which contain the following key components
  - Radio Interference Processing
    - User-centric RRH Clustering: medium-term control adaptive to the channel statistics
    - Precoding: Short-term control adaptive to the instantaneous CSI from the active RRHs to the users at each time slot
  - PHY caching at RRH: long-term control adaptive to content popularity
    - PHY caching at the RRH is used to further reduce the fronthaul loading
- Challenges
  - Non-convex Stochastic Optimization of Precoding and RRH Clustering: In the mixed timescale optimization, the objective function (average WSR) involves the optimal short-term precoding solutions, which do not have closed form expressions. Moreover, the UCC RRH clustering belongs to combinatorial optimization
  - PHY Caching at RRH with Limited Processing Capability and Cache Capacity: In C-RAN where most baseband processing such as channel coding is implemented in the BBU, the RRH can no longer directly cache the original content packets.
  - Efficiency of PHY Caching in C-RAN: In addition to algorithm designs, it is very important to have a fundamental understanding of the tradeoff between the PHY cache capacity and the fronthaul loading in C-RAN as well as how such tradeoffs are affected by various key system parameters such as the total content size and content popularity distribution.

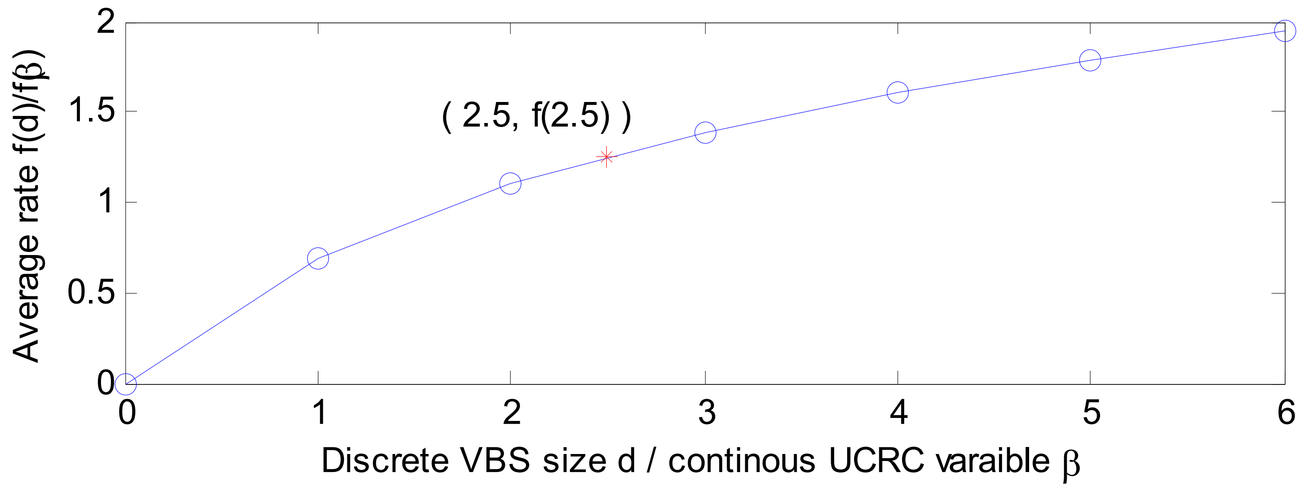
System Model



- A BBU connected with M RRHs serving K single-antenna users
- Each RRH has N_T antennas and a cache of size B_C
- Each user communicates with the nearest d_k RRHs, denoted by $\mathcal{A}_k(d_k)$ (VBS k)

Randomized User-centric RRH Clustering (UCRC)

- Let $\mathbf{d} \triangleq [d_1, ..., d_K]^T$ denote the VBS size vector
- The optimization of **d** belongs to discrete optimization, which is NP-hard
- Solution: propose a randomized UCRC with parameter $\boldsymbol{\beta} = [\beta_1, ..., \beta_K]^T$ (real vector) to make the problem continuous
- Toy example with K = 1



  - For given β , e.g., β = 2.5, the VBS size d is randomly generated from 2 candidate VBS sizes {2,3} according to the PMF [0.5,0.5]
  - In other words, if we observe the realizations of the VBS size d for 100 time slots, there are about 50 time slots with VBS size size d = 2 and 50 time slots with VBS size size d = 3
  - The average achievable rate is f(2.5) = 0.5*f(2) + 0.5*f(3)

Randomized User-centric RRH Clustering (UCRC)

- For general cases with arbitrary number of users K
  - For given $\boldsymbol{\beta}$, the VBS size d is randomly generated from K+ 1 candidate VBS size vectors $\{\mathbf{d}_1(\boldsymbol{\beta}), ..., \mathbf{d}_{K+1}(\boldsymbol{\beta})\}$ according to the PMF $\boldsymbol{\rho}(\boldsymbol{\beta}) = [\rho_1(\boldsymbol{\beta}), ..., \rho_{K+1}(\boldsymbol{\beta})]^T$
  - The candidate VBS size vectors and the PMF can be calculated using Algorithm 1
  - The candidate VBS size vectors is the coordinates of the K + 1 vertices of the simplex sub-region that contains $\boldsymbol{\beta}$, as illustrated in Figure 2.
  - The average achievable rate is $\hat{f}(\boldsymbol{\beta}) = \sum_{n=1}^{K+1} \rho_n(\boldsymbol{\beta}) f(\mathbf{d}_n(\boldsymbol{\beta}))$

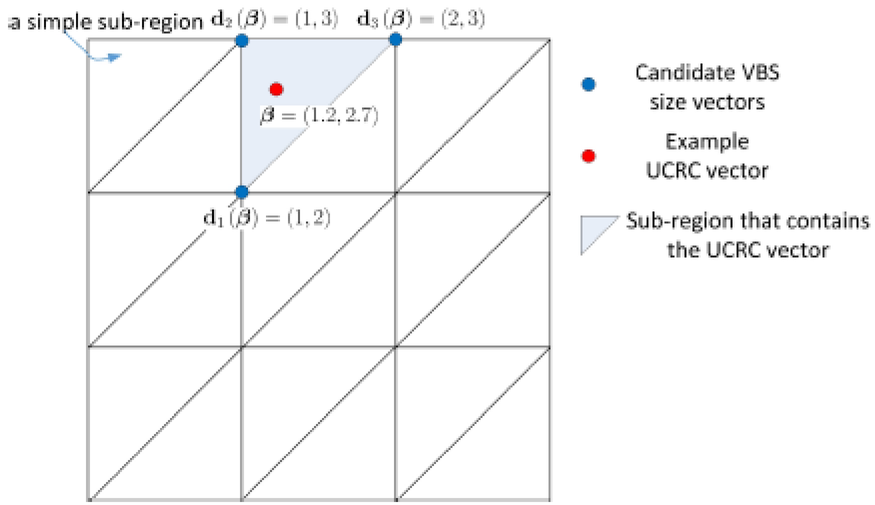


Figure 2: An illustration of randomized user-centric RRH clustering and the simplex sub-regions. Under UCRC vector $\boldsymbol{\beta} = [1.2, 2.7]^T$, the candidate VBS size vectors are $\left\{[1,2]^T, [1,3]^T, [2,3]^T\right\}$ and the PMF vector is $[0.3, 0.5, 0.2]^T$, i.e., at each time slot, the VBS size vector $\mathbf{d}$ is randomly generated from $\left\{[1,2]^T, [1,3]^T, [2,3]^T\right\}$ according to the PMF $[0.3, 0.5, 0.2]^T$.

Algorithm 1 Generate $\{\mathbf{d}_1(\boldsymbol{\beta}), ..., \mathbf{d}_{K+1}(\boldsymbol{\beta})\}$ and $\boldsymbol{\rho}(\boldsymbol{\beta})$

Step 1: Let $\tilde{\boldsymbol{\beta}} = \boldsymbol{\beta} - \lfloor \boldsymbol{\beta} \rfloor$.
Step 2: Sort the component of $\tilde{\boldsymbol{\beta}}$ to obtain $\tilde{\beta}_{\kappa(\boldsymbol{\beta},1)} \geq \tilde{\beta}_{\kappa(\boldsymbol{\beta},2)} \geq ... \geq \tilde{\beta}_{\kappa(\boldsymbol{\beta},K)}$, where $\{\kappa(\boldsymbol{\beta},1), ..., \kappa(\boldsymbol{\beta},K)\}$ is a permutation of $\{1, ..., K\}$ and it depends on $\boldsymbol{\beta}$. Let $\mathbf{d}_1(\boldsymbol{\beta}) = \lfloor \boldsymbol{\beta} \rfloor$, $\mathbf{d}_n(\boldsymbol{\beta}) = \mathbf{d}_{n-1}(\boldsymbol{\beta}) + \mathbf{e}_{n-1}, n = 2, ..., K+1$, where $\mathbf{e}_{n-1}$ is the unit vector with the $\kappa(\boldsymbol{\beta}, n-1)$-th element equal to 1.
Step 3: Let $\rho_n(\boldsymbol{\beta}) = \tilde{\beta}_{\kappa(\boldsymbol{\beta},n-1)} - \tilde{\beta}_{\kappa(\boldsymbol{\beta},n)}, n = 1, ..., K+1$, where $\tilde{\beta}_{\kappa(\boldsymbol{\beta},0)} = 1$ and $\tilde{\beta}_{\kappa(\boldsymbol{\beta},K+1)} = 0$.

Simplex-interpolation algorithm

Problem Formulation for Radio Interference Processing

- Medium-term UCRC policy:

Channel statistics

Total VBS size constraint

$$\Omega_\beta = \{\beta(\Psi) \in \mathcal{D}_\beta : \forall \Psi\} \quad \mathcal{D}_\beta = \left\{\beta : \beta_k \in [0, M], \forall k \text{ and } \sum_{k=1}^{K} \beta_k \le \beta_T\right\}.$$

- Short-term precoding policy:

Instantaneous CSI from the active RRHs to the users

$$\Omega_v = \{\mathbf{V}(\mathbf{d}, \mathbf{h}_\mathcal{A}) \in \mathcal{D}_v(\mathbf{d}) : \forall (\mathbf{d} \in \mathcal{D}_d, \mathbf{h}_\mathcal{A})\}$$

$$\mathcal{D}_d = \{\mathbf{d} : d_k \in \mathbb{Z}_+, d_k \le M, \forall k\}.$$

$$\mathcal{D}_v(\mathbf{d}) = \left\{\mathbf{V} : \mathbf{v}_k \in \mathbb{C}^{N_T d_k}, \forall k \text{ and } \sum_{k=1}^{K}\sum_{j=1}^{d_k} \|\mathbf{v}_{k,j}\|^2 \mathbb{I}(m = \mathcal{A}_{k,j}) \le P, \forall m\right\}$$

Per RRH power constraint

- Joint UCRC and precoding optimization formulation

$$\mathcal{P} : U(\Omega_\beta, \Omega_v) \triangleq \max_{\Omega_\beta, \Omega_v} \mathbb{E}\left[\sum_{k=1}^{K} \mu_k \overline{r}_k(\beta(\Psi), \Omega_v)\right]$$

Conditional average rate for given UCRC and precoding policies

Problem Decomposition Radio Interference Processing

- Using primal decomposition, P is equivalent to the following families of subproblems

Timescale $\mathbb{T}_S$ subproblem (Short-term Precoding for given $(\mathbf{d} \in \mathcal{D}_d, \mathbf{h}_\mathcal{A})$):

$$\mathcal{P}_S(\mathbf{d}, \mathbf{h}_\mathcal{A}) = \max_{\mathbf{V} \in \mathcal{D}_v(\mathbf{d})} \sum_{k=1}^{K} \mu_k r_k(\mathbf{d}, \mathbf{V}, \mathbf{h}_\mathcal{A}).$$

Timescale $\mathbb{T}_M$ subproblem (Medium-term Clustering for given Ψ):

$$\mathcal{P}_M(\Psi) = \max_{\beta \in \mathcal{D}_\beta} \sum_{k=1}^{K} \mu_k \overline{r}_k(\beta, \Omega_v^\star),$$

where $\Omega_v^\star = \{\mathbf{V}^\star(\mathbf{d}, \mathbf{h}_\mathcal{A}) : \forall (\mathbf{d} \in \mathcal{D}_d, \mathbf{h}_\mathcal{A})\}$ is the optimal precoding policy

$\boxed{\text{optimal solution of } \mathcal{P}_S(\mathbf{d}, \mathbf{h}_\mathcal{A})}$

The optimal UCRC policy is given by: $\Omega_\beta^\star = \{\beta^\star(\Psi) : \forall \Psi\}$

$\boxed{\text{optimal solution of } \mathcal{P}_M(\Psi)}$

Outline of the Solution for Radio Interference Processing

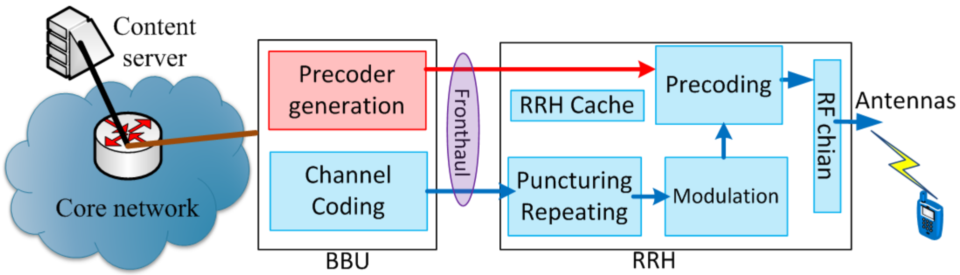
- $\mathcal{P}_S(\mathbf{d}, \mathbf{h}_{\mathcal{A}})$ can be solved using the WMMSE approach [3]
  - Since the problem is non-convex, WMMSE only finds a stationary point which may not be the global optimal solution
- For given stationary pre-coding policy $\Omega_v^* = \{\mathbf{V}^*(\mathbf{d}, \mathbf{h}_{\mathcal{A}}) : \forall (\mathbf{d} \in \mathcal{D}_d, \mathbf{h}_{\mathcal{A}})\}$, the objective (average WSR) of $\mathcal{P}_M(\boldsymbol{\Psi})$ is piece-wise linear

  $\boxed{\textit{stationary point of } \mathcal{P}_S(\mathbf{d}, \mathbf{h}_{\mathcal{A}})}$ found by WMMSE

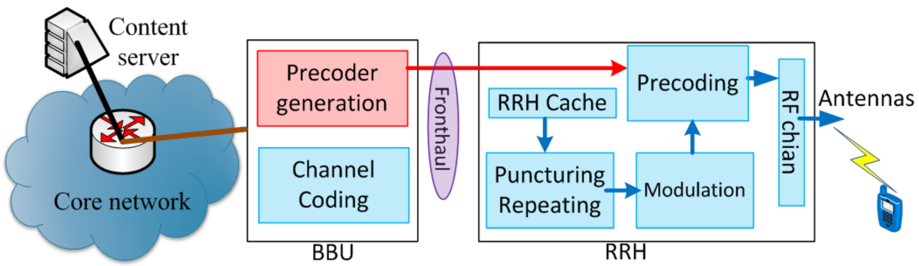
- We propose a gradient-projection-like (GP-like) algorithm to solve it
  - Again, the problem is non-convex and GP-like algorithm cannot ensure global convergence
  - Moreover, GP-like algorithm requires knowledge of channel statistics to calculate the average WSR for given UCRC vector
- Q: Can we design an online self-learning algorithm which ensures global convergence without explicit knowledge of channel statistics?
- The above question will be addressed in the journal version
  - A local stochastic cutting plane algorithm (SCPA) is proposed to solve $\mathcal{P}_M(\boldsymbol{\Psi})$
  - We can establish the global convergence of the local SCPA, i.e., the local SCPA converges to a solution whose gap from the global optimal solution can be bounded
  - In the week interference regime where the distance between users is large, it can be shown the local SCPA converges to the global optimal solution of $\mathcal{P}_M(\boldsymbol{\Psi})$

Systematic Channel Coded PHY Caching at RRH

- Consider content delivery application
  - there are L files on the content server, the size of the l-th file is F_l bits
  - each user independently accesses the l-th file with probability p_l
- Caching at RRH can be used to reduce the fronthaul loading
  - Since RRH can only perform simple baseband processing, the RRH cannot cache the original content files
- We propose a systematic channel coded PHY caching scheme
  - Each file is divided into packets of size N_S bits at the content server
  - For each packet, a systematic channel codeword with length N_S/c and coding rate c is generated
  - During off-peak hours, each RRH caches the systematic channel codewords of randomly chosen $p_l^* F_l/N_S$ packets of the l-th file for all l
  - In the online payload transmission phase, if the systematic channel codeword of the packet requested by user k is in the cache of the serving RRHs, the serving RRHs directly transmit the systematic channel codeword (after puncturing or repeating) to user k



(a) If the codeword of the packet requested by user k is not in the RRH cache, the serving RRHs will obtain it from the BBU via franthaul and transmit it to user k



(b) Otherwise, the serving RRHs directly obtains the corresponding codeword from the local caches without consuming the fronthaul and transmit it to user k

Problem Formulation for PHY Caching

- The cache content placement vector $\mathbf{q} = [q_1, \ldots q_L]^T$ determines the relative priority of caching the L files
  - It must be carefully chosen to minimize the fronthaul loading under the cache capacity constraint at each RRH
- For given UCRC and precoding policy at PHY, the total average fronthaul loading is

$$R_F(\mathbf{q}) = R_S \left(1 - \sum_{l=1}^{L} p_l q_l\right)$$

Average sum rate under given UCRC and precoding policy

- The cache optimization is formulated as a fronthaul loading minimization:

Long-term Caching Problem: $\mathcal{P}_L \ : \min_{\mathbf{q} \in \mathcal{D}_q} 1 - \sum_{l=1}^{L} p_l q_l$

cache capacity constraint

$$\mathcal{D}_q = \left\{ \mathbf{q} : \ q_l \in [0,1], \forall l \text{ and } \sum_{l=1}^{L} q_l F_l \leq c B_C \right\}$$

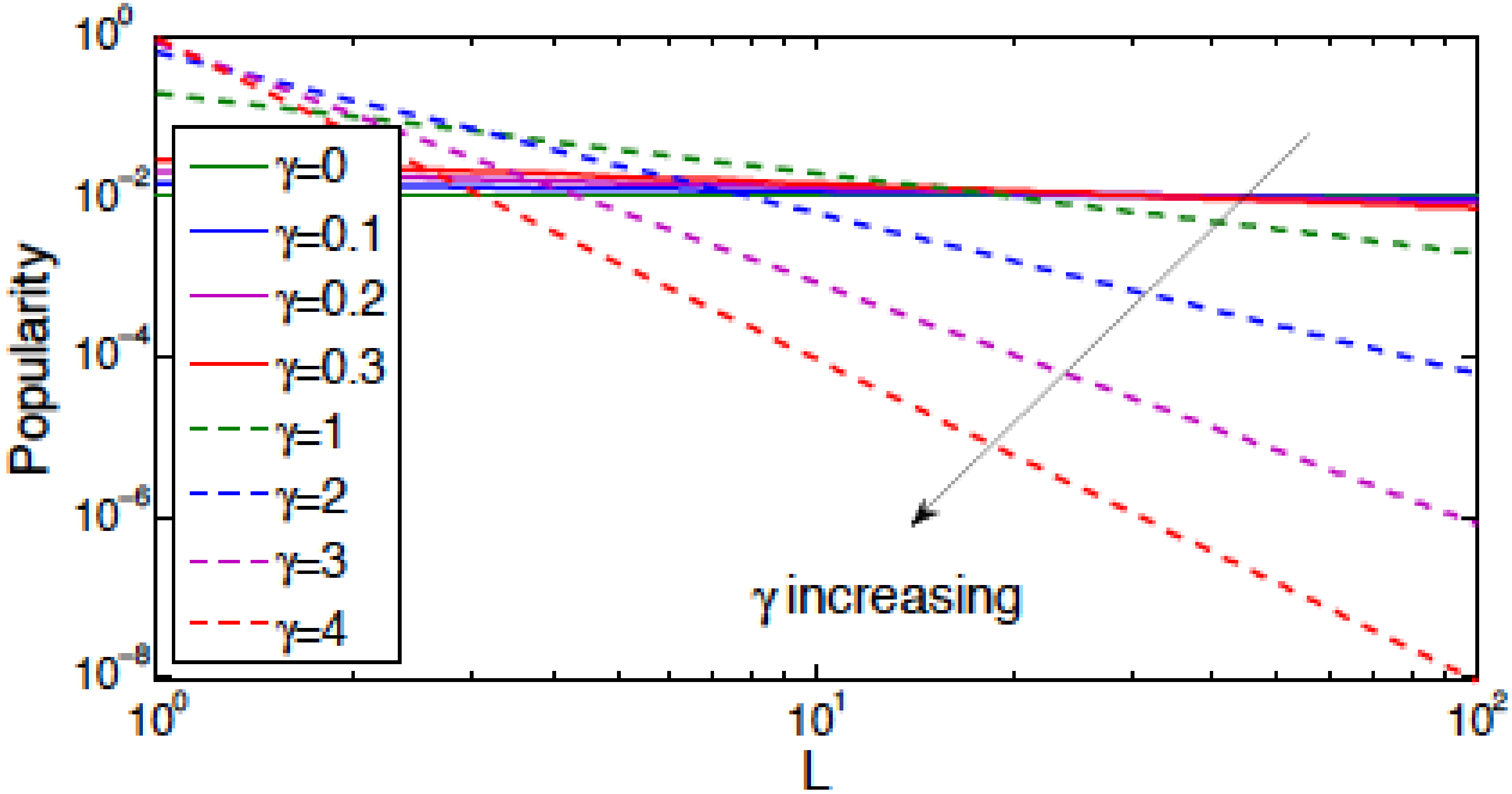
Solution for PHY Caching

- If the popularity distribution p is known, the optimal solution of the LP problem P_L can be easily obtained using numerical method.
- If p is unknown, P_L is a stochastic LP problem and the optimal solution can be solved using a stochastic subgradient algorithm
- We focus on analyzing the tradeoff between cache capacity B_C and the fronthaul loading $R_F(q)$ under the Zipf popularity distribution

Popularity skewness

Normalization factor $$p_l = \frac{1}{Z_\gamma(L)} l^{-\gamma}, l = 1, 2, \ldots, L$$

- The Zip distribution is widely used to model the Internet traffic
  - On the Internet, Zipf's law appears to be the rule rather than the exception
  - A larger popularity skewness τ implies that the user requests concentrate more on a few popular files
  - Large popularity skewness τ is usually observed in wireless applications



(a) Zipf popularity under large γ on a log-log scale. The user requests concentrate more on a few content files as γ is increasing.

Cache-fronthaul Tradeoff Analysis under Zipf Popularity Distribution

- Under Zipf Law, the optimal cache content placement vector is to cache the most popular files, i.e.,

$$q_l^\star = \begin{cases} 1, & l \le \lfloor b_C \rfloor \\ b_C - \lfloor b_C \rfloor, & l = \lfloor b_C \rfloor + 1 \\ 0, & \text{otherwise} \end{cases}$$

$$b_C = \frac{cB_C}{F}$$

normalized cache capacity

- The minimum fronthaul loading for given normalized cache capacity is

$$R_F^\star = \left(1 - \frac{\sum_{l=1}^{\lfloor b_C \rfloor} l^{-\gamma} + (b_C - \lfloor b_C \rfloor)(\lfloor b_C \rfloor + 1)^{-\gamma}}{Z_\gamma(L)}\right) R_S$$

- Define the *fronthaul gain* over the case without caching as

$$\triangle r_F^\star = \frac{R_s - R_F^\star}{R_s} = \frac{\sum_{l=1}^{\lfloor b_C \rfloor} l^{-\gamma} + (b_C - \lfloor b_C \rfloor)(\lfloor b_C \rfloor + 1)^{-\gamma}}{Z_\gamma(L)}$$

The fraction of the reduced fronthaul loading due to PHY caching

Cache-fronthaul Tradeoff Analysis under Zipf Popularity Distribution

- Impact of key system parameters on cache-fronthaul tradeoff
  - **Impact of the normalized cache capacity** b_C**:** As the normalized cache capacity b_C increases from 0 to L, the fronthaul loading decreases to 0, and the fronthaul gain increases from 0 to 1.
  - **Impact of the number of content files L:** The fronthaul loading increases as L increases. When L= Θ (1) , the fronthaul gain is Θ (1). When L → ∞, the fronthaul gain depends heavily on the popularity skewness γ .
  - **The impact of the popularity skewness** γ is summarized in the following Theorem.

Theorem 5 (Asymptotic fronthaul gain for large L). *When $L \to \infty$ and $b_C = \Theta(1)$, the asymptotic scaling laws of $\triangle r_F^\star$ are summarized below:*

- **Sub-critical:** If $\gamma < 1$, then $\triangle r_F^\star = \Theta\left(L^{-(1-\gamma)}\right)$.
- **Critical:** If $\gamma = 1$, then $\triangle r_F^\star = \Theta\left(1/\ln(L)\right)$.
- **Super-critical:** If $\gamma > 1$, then $\triangle r_F^\star = \Theta(1)$.

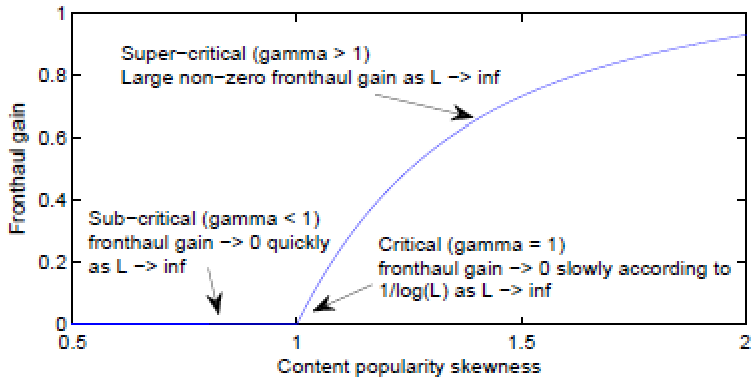
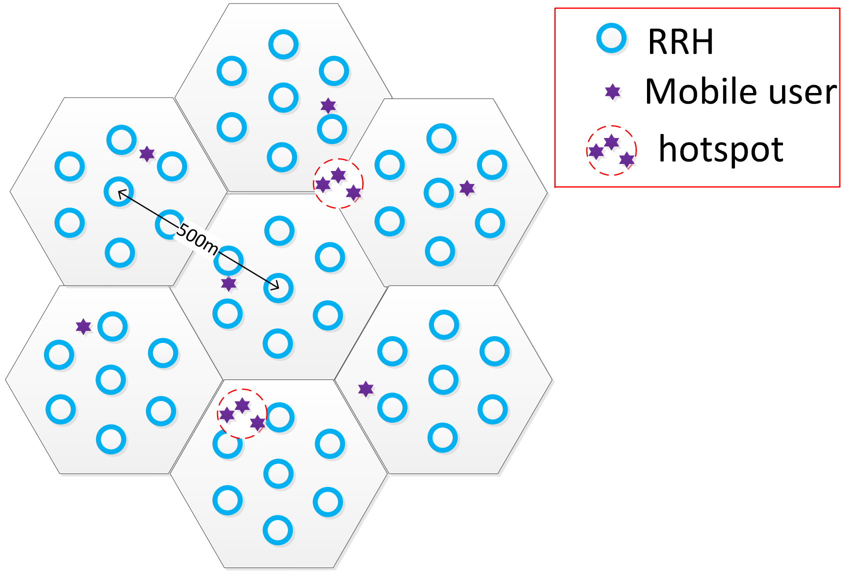


Figure 4: Phase transition behavior of asymptotic fronthaul gain for large L with $b_C = 10$.

In practice, the popularity skewness γ can be large, especially for mobile applications. In this case, it is still possible to achieve a large fronthaul gain, even when the cache capacity B_C is relatively small compared to the total content size L*F .

Simulation Configuration



- A C-RAN with 49 RRHs
- 7 regular hexagon cells
- 12 randomly distributed users
- Each RRH has two antennas
- There are L=50 content files
- The size of each file is 1GB
- Zipf popularity distribution with γ =1.5
- **Baseline 1 - One-timescale GSBF** in [1] with total fronthaul loading constraint
- **Baseline 2 - Static RRH Clustering**: A fixed number of the nearest d RRHs are chosen to serve each user. The short-term precoding is the same as the proposed scheme.
- **Baseline 3 -** Proposed user-centric RRH clustering without caching.

Simulation Results

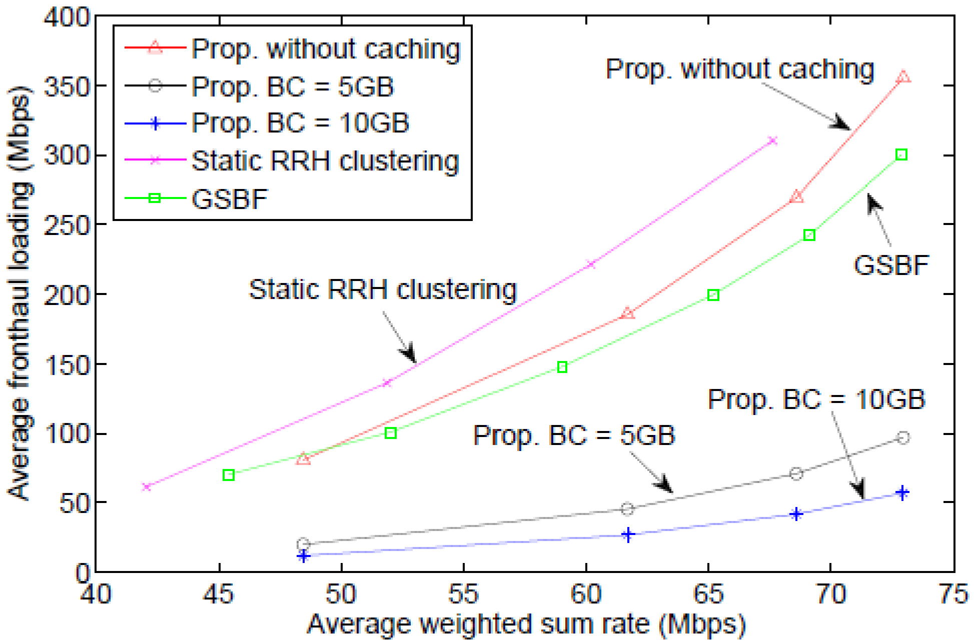


Figure 9: Average fronthaul loading versus average WSR.

- Proposed scheme without caching
  - achieve a tradeoff performance close to the one-timescale GSBF
  - better than the static RRH clustering
- Proposed With RRH-level caching
  - significantly outperforms the one-timescale GSBF
  - performance gain increases as the cache capacity increases
  - less CSI signaling overhead and lower computational complexity than the one-timescale GSBF

Conclusion

- We propose a mutli-timescale optimization framework to optimize the tradeoff performance in C-RAN
  - The mixed-timescale radio interference processing is formulated as a joint UCRC and precoding optimization problem
    - A WMMSE-based algorithm to find a stationary point for the short-term precoding
    - a self-learning local SCPA (in the journal version) to solve the medium-term UCRC subproblem with a provable performance bound.
    - The proposed solution is asymptotically optimal for the joint problem in the weak interference regime
  - The long-timescale PHY caching is formulated as a fronthaul loading minimization problem
    - The optimal cache replacement can be obtained by solving a LP
    - There is a phase transition behavior in the cache-franthaul tradeoff
      - As the total content size goes to infinity with fixed cache capacity, a large caching gain is still achievable when the popularity skewness is larger than one
      - but the caching gain is zero otherwise