Optimal Stochastic Power Control with Compressive CSI Acquisition for Cloud-RAN

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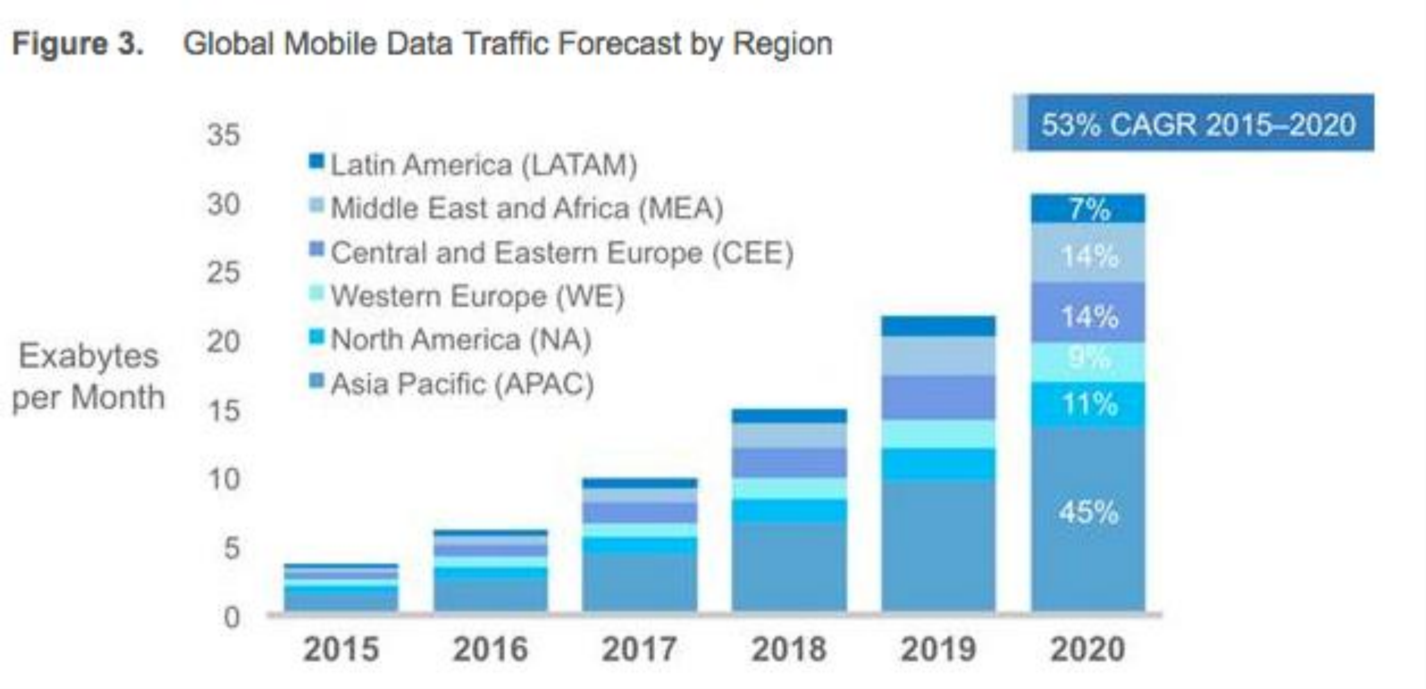
Roadmap

- Introduction
- Problem Formulation
- Solution
- Experimental Results
- Conclusion

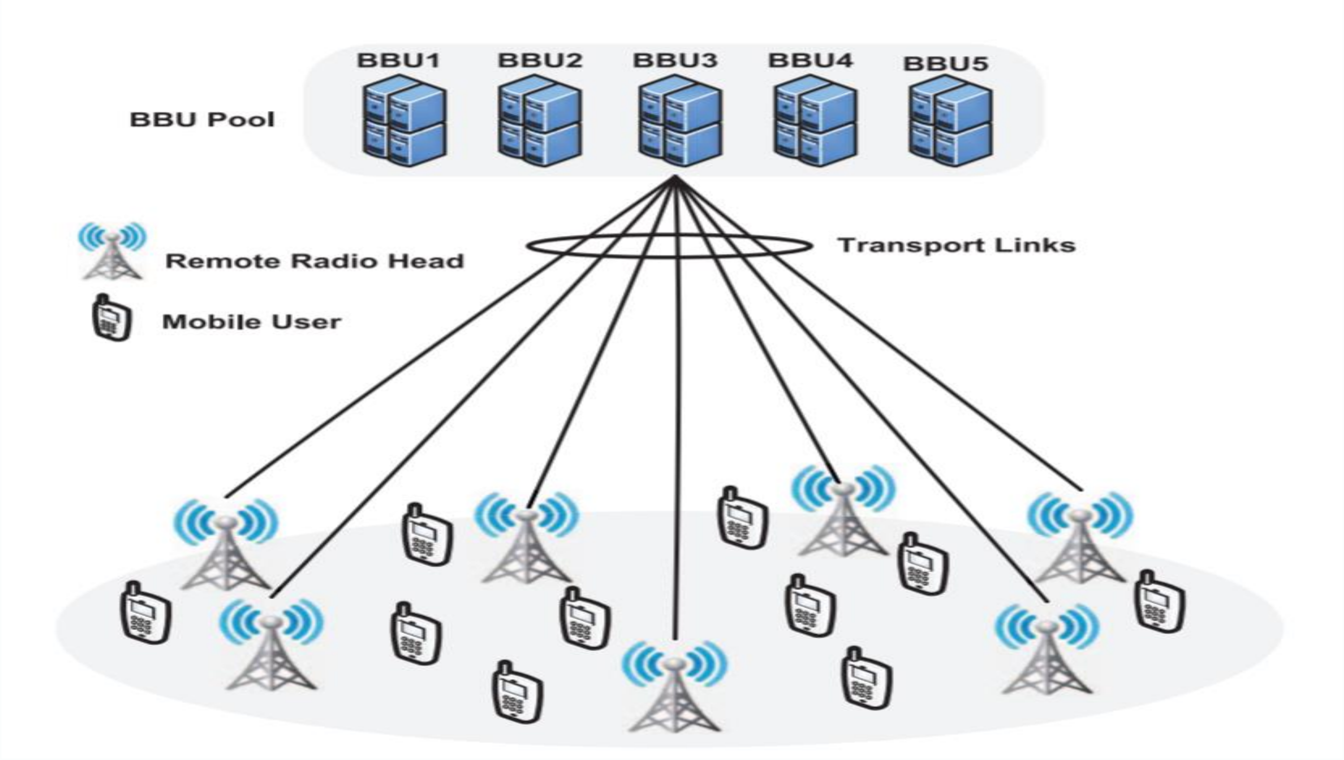
Mobile Data Explosion



Ref: Cisco Visual Networking Index: Global Mobile Data Traffic Forecast Update, 2015–2020 White Paper

Cloud-RAN Architecture

- Cloud-Radio Access Network is a promising



Ref: Y Shi, J Zhang, KB Letaief, "CSI Overhead Reduction with Stochastic Beamforming for Cloud Radio Access Networks", ICC 2014

Motivation

- To fully exploit cooperative gain in C-RAN, full channel state information (CSI) is required.
  - Challenging to obtain full CSI in large and dense networks
- Power minimization problem with probabilistic Quality-of-Service (QoS) requirements:
  - Practical but hard to obtain optimal solutions

Contributions

Challenges	Solution
(1) Challenging to obtain full CSI	(1) Compressive CSI acquisition to exploit sparsity of large-scale fading coefficients
(2) Hard to provide good approximation to the probabilistic QoS constraints?	(2) DC approximation to the probabilistic constraints, which provides optimality guarantee.

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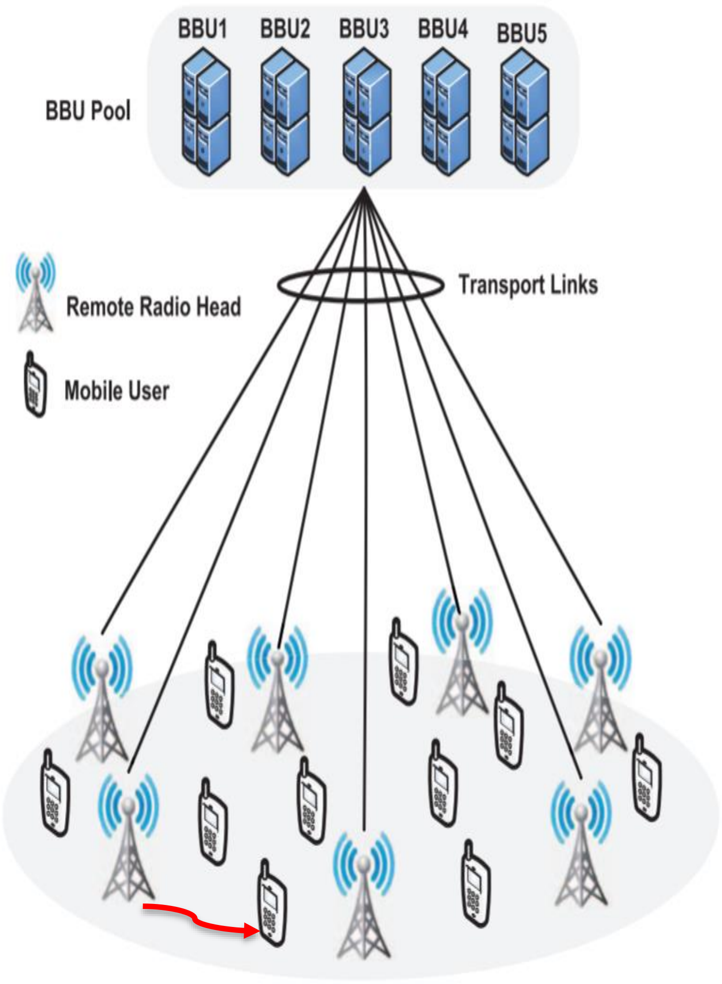
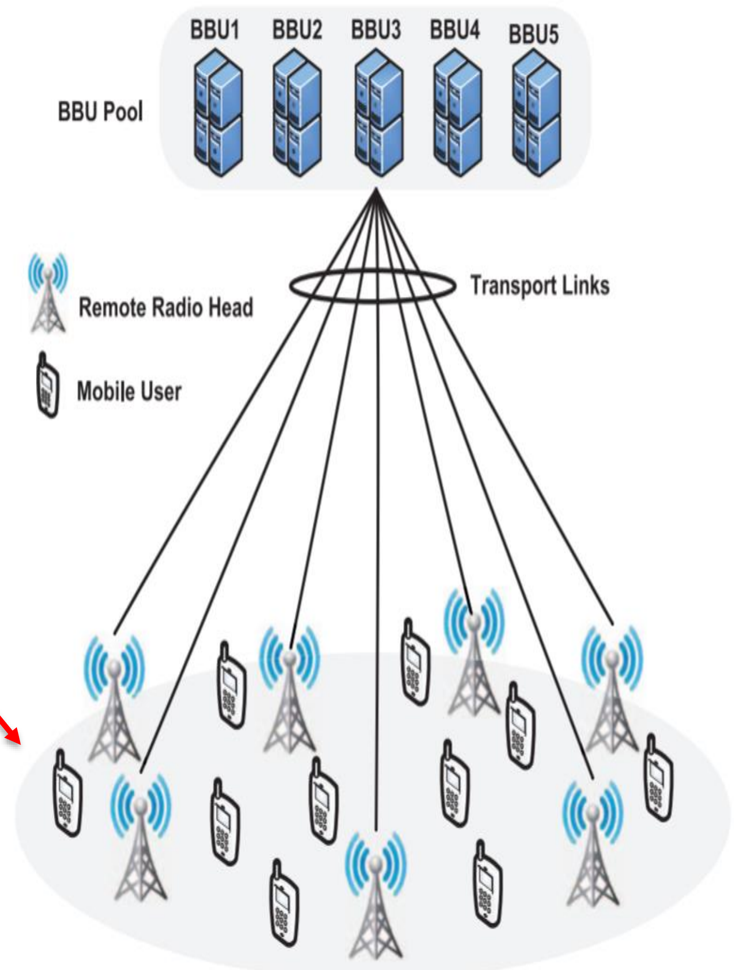
Notations

- K single-antenna mobile users (MUs).
- L multi-antenna remote radio heads (RRHs).
- l-th RRH is equipped with N_l antennas.
- l-th RRH to k-th MU:
  - h_{kl}: channel gain; v_{lk}: beamforming vector.



Notations

- For MU k:
  - n_k: additive Gaussian, s_k: encoded data symbol.
  - $\boldsymbol{h}_k = [\boldsymbol{h}_{k1}^T, \boldsymbol{h}_{k2}^T, \ldots, \boldsymbol{h}_{kL}^T]^T$, $\boldsymbol{v}_k = [\boldsymbol{v}_{k1}^T, \boldsymbol{v}_{k2}^T, \ldots, \boldsymbol{v}_{kL}^T]^T$
  - $\boldsymbol{v}_k = \sqrt{p_k}\boldsymbol{u}_k$, $\boldsymbol{u}_k$ direction, p_k power, $\boldsymbol{u}_k$ determined in advance: zero-force beamforming.



Transmit Power Minimization

Probabilistic QoS constraints: $\Pr\{\Gamma_k(\mathbf{p}, \boldsymbol{\xi}) \geq \gamma_k, \forall k\} \geq 1 - \epsilon$

SINR formula:

$$\Gamma_k(\mathbf{p}, \boldsymbol{\xi}) = \frac{|\mathbf{h}_k^{\mathsf{H}} \mathbf{v}_k|^2}{\sum_{i \neq k} |\mathbf{h}_k^{\mathsf{H}} \mathbf{v}_i|^2 + \sigma_k^2} = \frac{p_k \xi_{kk}}{\sum_{i \neq k} p_i \xi_{ki} + \sigma_k^2}, \forall k,$$

Power minimization problem:

$$\begin{aligned} &\underset{\mathbf{p} \in \mathcal{C}}{\text{minimize}} \ \mathbf{1}^T \mathbf{p} \\ &\text{subject to} \ \Pr\{\Gamma_k(\mathbf{p}, \boldsymbol{\xi}) \geq \gamma_k, \forall k\} \geq 1 - \epsilon \end{aligned}$$

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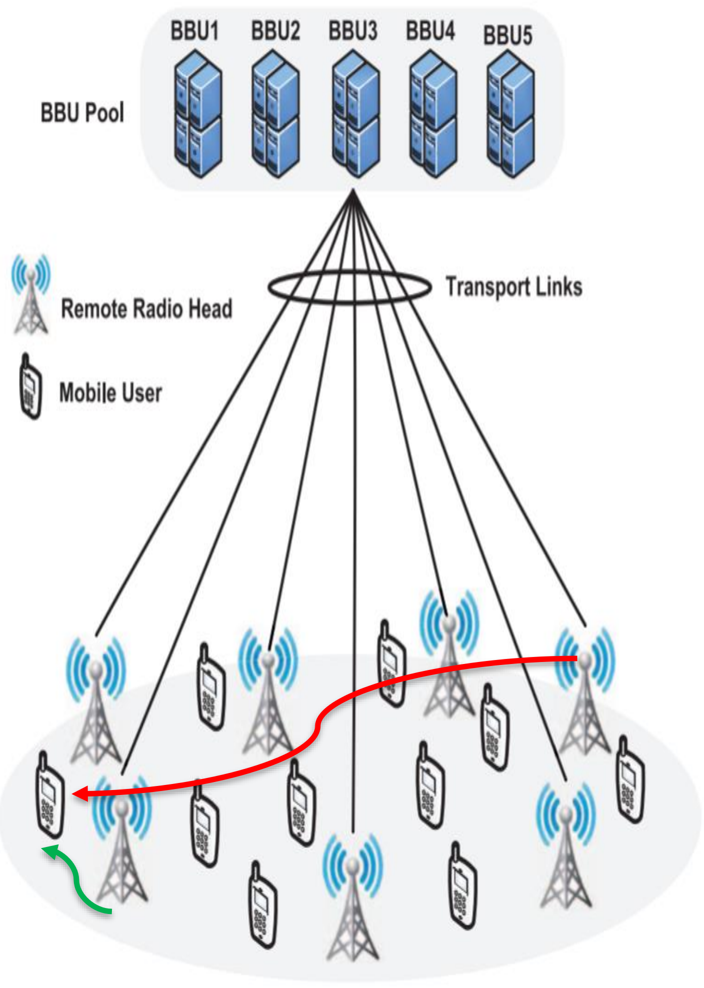
Compressive CSI Scheme

- Observation: channel links of RRH and MU that are far away have very minor contribution on system performance.
- Only select channel links that have greater contribution.



Compressive CSI Scheme

- Assumption:
  - Statistical information for all channel links are available
  - Can accurately track large scale fading coefficient D_k.

- For MU k, select Ω_k channel links to obtain their instantaneous values, These are our "relevant" links.

- Sort D_k in descending order of magnitude, select $|\Omega_k|$ largest entry indices and place them into Ω_k. Others only have statistical information.

Form Transformation

$$\Gamma_k(\mathbf{p}, \boldsymbol{\xi}) \geq \gamma_k$$

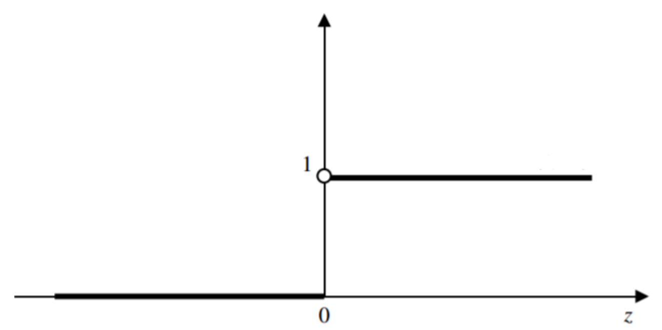
$$\pi_k(\mathbf{p}, \boldsymbol{\xi}) \triangleq \sum_{i \neq k} p_i \xi_{ki} + \sigma_k^2 - p_k \xi_{kk} / \gamma_k \leq 0, \forall k$$

$$\Pr\{\Gamma_k(\mathbf{p}, \boldsymbol{\xi}) \geq \gamma_k, \forall k\} \geq 1 - \epsilon$$

$$f(\mathbf{p}) \leq \epsilon$$

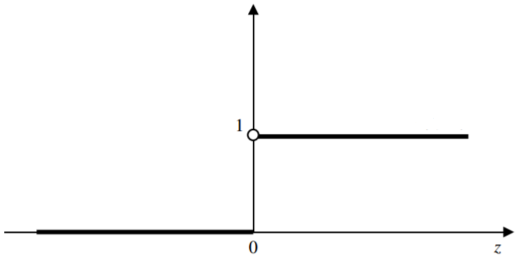
$$f(\mathbf{p}) = 1 - \Pr\{\Gamma_k(\mathbf{p}, \boldsymbol{\xi}) \geq \gamma_k, \forall k\} = \mathbb{E}\left[1_{(0,+\infty)}\left(\max_{1 \leq k \leq K} \pi_k(\mathbf{p}, \boldsymbol{\xi})\right)\right]$$

Indicator function $1_{(0,+\infty)} z$:
1 if z>0, Else 0



DC Approximation

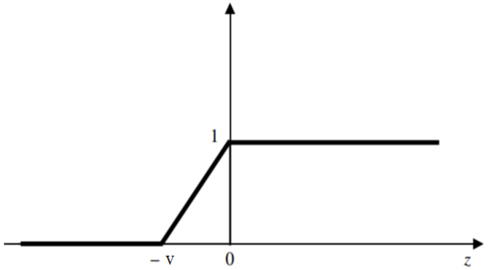
$$1_{(0,+\infty)}(z)$$



$$\phi(z,v) \geq 1_{(0,+\infty)}(z)$$

Upper bound the indicator function

$$\phi(z,v) = \frac{1}{v}[(v+z)^+ - z^+], v > 0$$



DC Approximation

$$f(P) \le \epsilon$$

$$\tilde{f}(P, v) \le \epsilon$$

$$\begin{aligned}\tilde{f}(\mathbf{p}, v) &= \mathbb{E}\left[\phi\left(\max_{1\le k\le K} \pi_k(\mathbf{p}, \boldsymbol{\xi}), v\right)\right] \\ &= \frac{1}{v}[\psi(\mathbf{p}, v) - \psi(\mathbf{p}, 0)], v > 0\end{aligned}$$

$$\psi(\mathbf{p}, v) = \mathbb{E}\left[\left(v + \max_{1\le k\le K} \pi_k(\mathbf{p}, \boldsymbol{\xi})\right)^+\right]$$

$$\begin{aligned}&\underset{\mathbf{p}\in\mathcal{C},\mu\ge 0}{\text{minimize}} \ \mathbf{1}^T\mathbf{p} \\ &\text{subject to} \ \underbrace{[\psi(\mathbf{p}, \mu) - \mu\epsilon]}_{\varphi(\mathbf{p},\mu)} - \underbrace{\psi(\mathbf{p}, 0)}_{\varphi(\mathbf{p},0)} \le 0\end{aligned}$$

Successive Convex Approximation

- **Non-convex?**

$$\varphi(\mathbf{p},\mu)-\varphi(\mathbf{p},0)$$

Convexify

→

Upper Bound

$$g_n(\mathbf{p},\mu)=\varphi(\mathbf{p},\mu)-\varphi(\mathbf{p}^{[n-1]},0)-\nabla\varphi(\mathbf{p}^{[n-1]},0)^T(\mathbf{p}-\mathbf{p}^{[n-1]})$$

- **Still Challenging?**
  - Monto Carlo Method: approximate by generating J number of realizations

$$\bar{g}_n(\mathbf{p},\mu)=\bar{\varphi}(\mathbf{p},\mu)-\bar{\varphi}(\mathbf{p}^{[n-1]},0)-\bar{\nabla}\varphi(\mathbf{p}^{[n-1]},0)^T(\mathbf{p}-\mathbf{p}^{[n-1]})$$

$$\bar{\nabla}\varphi(\mathbf{p},0)=\frac{1}{J}\sum_{j=1}^{J}\left[\nabla_{\mathbf{p}}\pi_{k^\star}((\mathbf{p},\boldsymbol{\xi}^j))\cdot\left(\left(\max_{1\le k\le K}\pi_k(\mathbf{p},\boldsymbol{\xi}^j)\right)^+\right)'\right]$$

$$\bar{\varphi}(\mathbf{p},\mu)=\frac{1}{J}\sum_{j=1}^{J}\left[\left(\mu+\max_{1\le k\le K}\pi_k(\mathbf{p},\boldsymbol{\xi}^j)\right)^+\right]-\mu\epsilon$$

Final Power Minimization

Convex optimization problem:

$$\begin{aligned}
\underset{\mathbf{p}\in\mathcal{C},\mu\geq 0}{\text{minimize}} \quad & \mathbf{1}^T\mathbf{p} \\
\text{subject to} \quad & \frac{1}{J}\sum_{j=1}^{J} z_j - \bar{\varphi}(\mathbf{p}^{[n-1]},0) - \\
& \bar{\nabla}\varphi(\mathbf{p}^{[n-1]},0)^T(\mathbf{p}-\mathbf{p}^{[n-1]}) - \mu\epsilon \leq 0, \\
& \mu + \pi_k(\mathbf{p},\boldsymbol{\xi}^j) \leq z_j,\, z_j \geq 0, \forall k, j,
\end{aligned}$$

Algorithm

- Input: initial $\boldsymbol{P}^{[0]}, \mu^{[0]}$
- Iterative Step till Convergence
  - Calculate the upper bound g_n of DC constraint $\varphi(\boldsymbol{p}, \mu) - \varphi(\boldsymbol{p}, 0)$ near $(\boldsymbol{P}^{[n-1]}, \mu^{[n-1]})$
  - Update the value $(\boldsymbol{P}^{[n]}, \mu^{[n]})$ by solving the final convex optimization problem
- Output: $\boldsymbol{P}^{[Final]}, \mu^{[Final]}$

Theorems

- DC approximation problem is equivalent to solving the original problem.

- If the original problem is convex, it can finally converge to optimal point. If the original problem is non-convex, it will converge to local optimal point.

Ref: LJ Hong, Y Yang, L Zhang, "Sequential Convex Approximations to Joint Chance Constrained Programs: A Monte Carlo Approach", Operations Research, 2011

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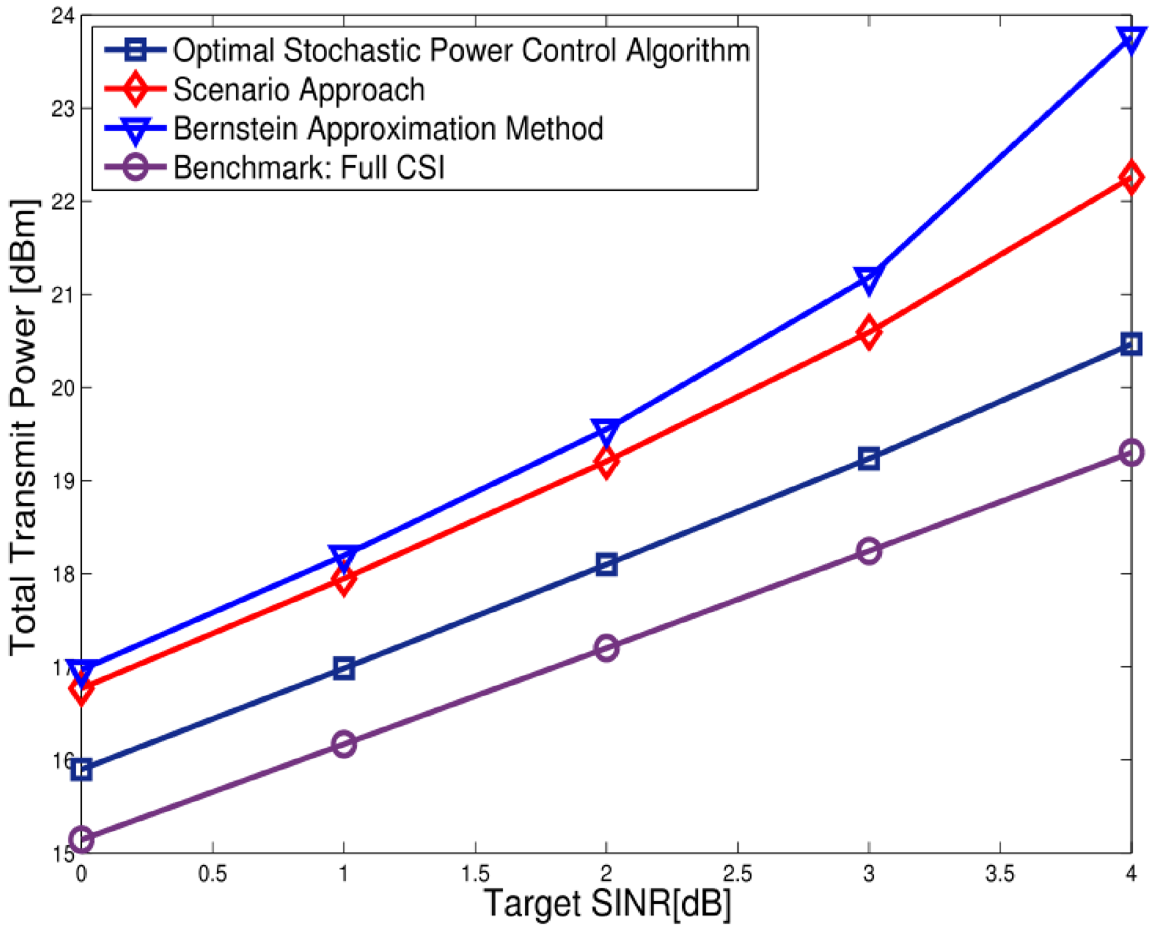
Experimental Setup

- **Channel Link Model:** $\mathbf{h}_{kl} = D_{kl}(\sqrt{1-\tau_{kl}^2}\hat{\mathbf{c}}_{kl} + \tau_{kl}\mathbf{e}_{kl})$
  - $\tau_{kl} =\ (0 \leq \tau_{kl} \leq 1)$: estimation quality.
  - $\hat{\boldsymbol{c}}_{\boldsymbol{kl}}$: estimated imperfect small-scale fading coefficient.
  - e_{kl}: estimation error.
  - D_kl large-scale fading coefficient: $10^{-L(d_{kl})/20}\sqrt{\varphi_{kl}s_{kl}}$

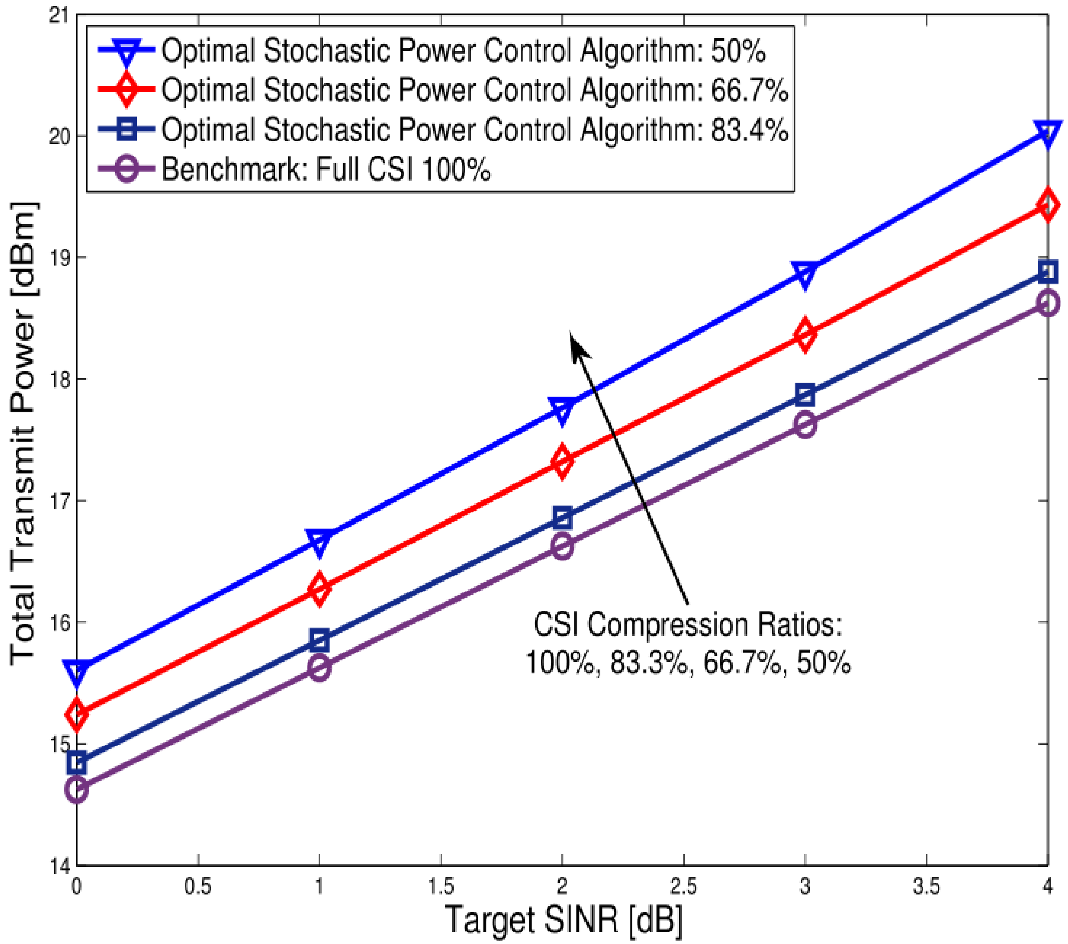
- **Comparison method:**
  - **Scenario Approach**: approximate the probabilistic constraint by multiple “sampling” constraints using Monte Carlo simulation.
  - **Bernstein Approximation**: bound the indicator function constraint with a closed-form convex function $\exp(z)$.

Total Transmit Power VS Target SINR Requirements



- $L = 10$, $N_l = 1, K = 6$.
- MUs distributed: [-500,500]×[-500,500] meters.
- 60% of the CSI are obtained.
- Result averaged over 100 times.

Total Transmit Power VS CSI Compression Ratios



- $L = 12$, $N_l = 1, K = 8$.
- MUs distributed : [-600,600]×[-600,600] meters.
- Result averaged over 60 times.

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Conclusion

- Framework:
  - Compressive CSI acquisition to reduce CSI signaling overhead.
  - DC approximation method to estimate the probabilistic constraint with optimality guarantee.

- Experiments:
  - DC Approximation + Compressive CSI: achieve performance close to full CSI case while significantly reducing CSI overhead.
  - Our method outperforms state-of-the-art methods.

Thank you!

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Questions?