Comparison of Downlink Transmission Strategies for Cloud Radio Access Networks

Pratik Patil, Binbin Dai, Wei Yu

Department of Electrical and Computer Engineering

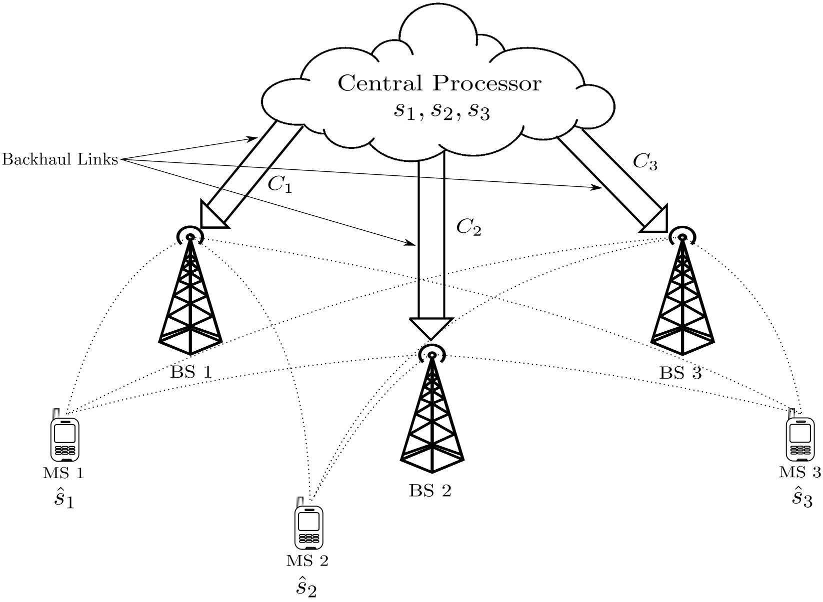
University of Toronto, Canada

EUSIPCO 2015

Future Cellular Wireless: Dense, Massive, and Cooperative

- Bottlenecks for cellular networks:
  - Path-loss, fading, and interference
- Emerging useful ideas:
  - Dense
    - Heterogeneous network
  - Massive
    - Large-scale MIMO in each base station (BS)
  - Cooperative
    - Signal processing for interference cancellation
- This talk: Cooperative communication

Cloud Radio Access Network (C-RAN)



C-RAN Architecture

- C-RAN
  - BSs are connected to a centralized, cloud-computing based processor.
  - Backhaul links have high (but not infinite) capacities.
- Motivation
  - Centralized service provisioning, easy BS upgrade, etc.
  - Enable joint multi-cell processing interference management.
- Uplink
  - Joint decoding in the cloud.
  - Virtual multiple-access channel with BSs as relays.
- Downlink
  - Joint encoding in the cloud.
  - Virtual broadcast channel with BSs as relays.

This talk: Downlink transmission strategies in C-RAN with finite backhaul.

Information Theoretic Problem Setup

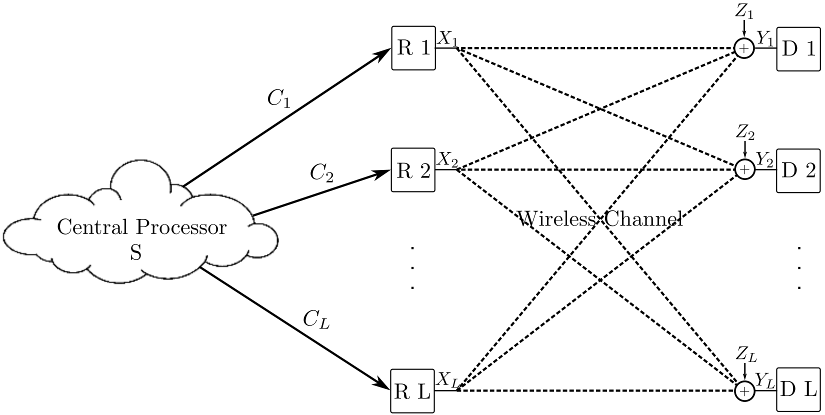


Figure: C-RAN downlink

- Infinite backhaul case: Downlink C-RAN is just a broadcast channel.
- This talk: Practical and more challenging case of finite backhaul.

Existing Transmission Strategies for Downlink C-RAN

BSs need to broadcast: Beamforming + dirty paper coding
BSs also act as relays:

- Decode-and-forward relaying strategy (Data-sharing strategy):
  - User messages are shared with BSs for joint beamforming, e.g., [Marsch and Fettweis, 2009].
  - To limit backhaul, we need to form clusters [Ng et al., 2008], [Zakhour and Gesbert, 2011], [Zhao et al., 2013].
- Compression-and-forward relaying strategy (Compression-based strategy):
  - Precode at the cloud, compress the signals and send compressed versions to BSs. [Simeone et al., 2009], [Marsch and Fettweis, 2008].
  - Benefits of multivariate compression studied in [Park et al., 2013].
- Compute-and-forward relaying strategy [Nazer et al., 2009]:
  - Reverse-CoF and integer-forcing ideas studied [Hong and Caire, 2013].

How to Best Utilize the Limited Backhaul

Which transmission and relaying strategy should the cloud and BSs adopt?

- Data-sharing strategy:
  - To limit backhaul, we need to limit the size of BS clusters.
- Compression-based strategy:
  - To limit the backhaul, we need to compress the beamformed signals.
- System-level comparison is difficult.
  - Data-sharing strategy: BS clusters need to be optimized, along with the beamforming design.
  - Compression-based strategy: Quantization noise levels need to be optimized, along with the beamformers.
  - Network wide optimization in each case needs to take into account user scheduling, power control, etc.
  - Impact due to practical modulation and coding, practical quantization not clear.

Our Contributions

- Optimization framework for data-sharing and compression strategies:
  - Data-sharing: Use of weighted l_1 approximation of l_0 norm to approximate the cluster size, based on [Dai and Yu, 2014].
  - Compression: Joint optimization of quantization noise levels and beamformers using of WSR - WMMSE equivalence.
  - Algorithms account for losses due to practical modulation (SNR gap) and practical quantization (rate-distortion gap).
- System-level performance comparison on a heterogeneous network:
  - Compression outperforms data-sharing for high backhaul capacities.
  - Data-sharing superior to compression strategy for low backhaul.
  - At moderate backhaul capacities, both are comparable.
- New hybrid strategy to balance the trade-off:
  - A unified framework that combines both data-sharing and compression-based strategies.
  - Intuition: Send direct data for strong users without any quantization noises and compress rest of the beamformed signals.
  - Noticeable performance gain at moderate backhaul capacities.

Problem Statement

- CRAN with L single-antenna BSs serving K single-antenna users.
- Received signal at user k is $y_k = \mathbf{h}_k^H \mathbf{x} + z_k$ where
  - $\mathbf{x} = [x_1, \cdots, x_L]^T$ is the aggregate signal from the L BSs.
  - $\mathbf{h}_k = [h_{1,k}, \cdots, h_{L,k}]^T$ is the channel from the L BSs to the user k.
  - z_k is the additive zero-mean Gaussian noise with variance σ^2.
- Network resources:
  - Backhaul capacity between BS l to the central processor: C_l.
  - Power constraint at BS l: P_l.
- All user data available at the central processor. CSI known to the central processor and all the BSs.
- Objective: Maximize the log utility of the system.

Data-sharing Strategy

- Transmitted signal $\mathbf{x}$ from all BSs is $\mathbf{x} = \sum_{k=1}^{K} \mathbf{w}_k s_k$ where
  - s_k: zero-mean unit-variance Gaussian signal for user k.
  - $\mathbf{w}_k = [w_{1,k}, \ldots, w_{L,k}]^T$: beamforming direction for user k from L BSs. If BS l does not participate in transmitting to user k, $w_{l,k} = 0$.
- Signal-to-noise-interference-ratio at user k, $\mathrm{SINR}_k = \frac{|\mathbf{h}_k^H \mathbf{w}_k|^2}{\sum_{j \neq k} |\mathbf{h}_k^H \mathbf{w}_j|^2 + \sigma^2}$.
- Achievable rate for user k is $R_k = \log(1 + \frac{\mathrm{SINR}_k}{\Gamma_m})$. Γ_m is the SNR gap.
- Γ_m captures the extra amount of power needed to achieve a given rate when using practical QAM constellations, instead of Gaussian signaling. Typical values: 9 dB (uncoded), 8.5 dB (moderate coding).
- Deciding which subset of BSs should serve each user is non-trivial. We follow the trick used in [Dai and Yu, 2014] to approximate the cluster size, using weighted l_1 norm approximation to l_0 norm.

Optimization of Data-sharing Strategy

$$
\begin{aligned}
\underset{w_{l,k}}{\text{maximize}} \quad & \sum_{k=1}^{K} \alpha_k R_k && \text{(1a)} \\
\text{subject to} \quad & \sum_{k=1}^{K} |w_{l,k}|^2 \le P_l, \quad \forall l && \text{(1b)} \\
& \sum_{k=1}^{K} \mathbb{1}\left\{|w_{l,k}|^2\right\} R_k \le C_l, \quad \forall l && \text{(1c)}
\end{aligned}
$$

- Trick: $\mathbb{1}\left\{|w_{l,k}|^2\right\} = \left\| |w_{l,k}|^2 \right\|_0 \approx \beta_{l,k}|w_{l,k}|^2$ where $\beta_{l,k}$ is updated iteratively $\beta_{l,k} = \frac{1}{|w_{l,k}|^2+\tau}$ using $|w_{l,k}|^2$ from the previous iteration.
- Extend equivalence between WSR-WMMSE with the SNR gap.
  - Closed form expressions for receive beamformers and MSE weights.
  - Transmit beamforming optimization becomes a QCQP problem.
  - To reduce computations: combine the l_0-l_1 approximation inside the WMMSE updates.

Optimization Algorithm for Data-sharing

Algorithm 1 WSR maximization for data-sharing strategy

Initialization: $\{\beta_{l,k}\}, \{\mathbf{w}_k\}, \{R_k\}$;

Repeat:

1. For fixed $\{\mathbf{w}_k\}$, compute the MMSE receivers and the corresponding MSE;
2. Update the MSE weights;
3. For fixed MMSE receivers, MSE weights, and $\{R_k\}$ in (1c), find the optimal transmit beamformer $\{w_{l,k}\}$ by solving a QCQP program;
4. Update $\{\beta_{l,k}\}$. Compute the achievable rate $\{R_k\}$;

Until convergence

Compression-based Strategy

- Precoded signals intended for BSs formed at central processor, $\hat{\mathbf{x}} = [\hat{x}_1, \cdots, \hat{x}_L]^T = \sum_{k=1}^{K} \mathbf{w}_k s_k$.
- Quantization for $\hat{\mathbf{x}}$ modeled as $\mathbf{x} = \hat{\mathbf{x}} + \mathbf{e}$, where $\mathbf{e}$ is the quantization noise with covariance $\mathbf{Q}$, assumed to be independent of $\hat{\mathbf{x}}$.
- Achievable rate for user k is again $R_k = \log(1 + \frac{\mathrm{SINR}_k}{\Gamma_m})$ where $\mathrm{SINR}_k = \frac{|\mathbf{h}_k^H \mathbf{w}_k|^2}{\sum_{j \neq k} |\mathbf{h}_k^H \mathbf{w}_j|^2 + \sigma^2 + |\mathbf{h}_k^H \mathbf{Q} \mathbf{h}_k|}$.
- Assuming ideal quantizer and independent quantization of BSs signals (diagonal $\mathbf{Q}$ with quantization noise levels $q_1, \ldots, q_L$), the backhaul capacity C_l must satisfy $\log\left(1 + \frac{\sum_{k=1}^{K} |w_{l,k}|^2}{q_l}\right) \leq C_l$.
- Multivariate compression (generic $\mathbf{Q}$) is also possible [Park et al., 2013], but the backhaul capacity region has an exponential number of terms. Computationally difficult.

Gap to rate-distortion

- Recall the SNR gap Γ_m: Extra amount of power when using QAM signaling instead of Gaussian signals. Similar notion for rate-distortion result.
- The backhaul relation $\log\left(1+\frac{\sum_{k=1}^{K}|w_{l,k}|^2}{q_l}\right) \leq C_l$ assumes a vector Gaussian quantization codebook.
- When using practical quantizers, extra amount of induced SNR is necessary to maintain the same quantization rate. This can be captured by rate-distortion gap Γ_q.
- Backhaul relation with the gap: $\log\left(1+\frac{\Gamma_q\sum_{k=1}^{K}|w_{l,k}|^2}{q_l}\right) \leq C_l$.
- Typical values: 2.72 for fixed-rate (uncoded) uniform scalar quantizer, 1.42 with variable-rate entropy coding, 1 for ideal quantizer.

Optimization of Compression-based Strategy

$$\begin{aligned} \underset{w_{l,k}, q_l}{\text{maximize}} \quad & \sum_{k=1}^{K} \alpha_k R_k && \text{(2a)} \\ \text{subject to} \quad & \sum_{k=1}^{K} |w_{l,k}|^2 + q_l \leq P_l, \quad \forall l && \text{(2b)} \\ & \sum_{k=1}^{K} |w_{l,k}|^2 - \frac{2^{C_l} - 1}{\Gamma_q} \, q_l \leq 0, \quad \forall l && \text{(2c)} \end{aligned}$$

- Extend the WSR-WMMSE equivalence with quantization noise levels.
  - Closed form expression for receive beamformers and MSE weights.
  - Transmit beamformers and quantization noise levels are *jointly* optimized by solving a convex program.
  - Convergence to a local optimal solution guaranteed.
- [Park et al., 2013] optimize the WSR directly using a majorization minimization (MM) algorithm, but with a SDP rank relaxation.

Optimization Algorithm for Compression-based Strategy

Algorithm 2 WSR maximization for compression strategy

Initialization: $\{\mathbf{w}_k\}, \{q_l\}$;

Repeat:

1. For fixed $\{\mathbf{w}_k\}, \{q_l\}$, compute the MMSE receivers and the corresponding MSE;
2. Update the MSE weights;
3. For fixed MMSE receivers and MSE weights, find the optimal transmit beamformers $\{\mathbf{w}_k\}$ and quantization noise levels $\{q_l\}$ jointly by solving a QCQP program;

Until convergence

Optimization structure in Step 3 can further be exploited to eliminate the optimization of quantization noise levels $\{q_l\}$. Resulting program is QCQP in transmit beamformers $\{\mathbf{w}_k\}$.

Performance Comparison: Simulation Setup

7-cell wrapped-around heterogeneous network with two tiers

Channel bandwidth	10 MHz
Distance between cells	0.8 km
Number of users/cell	30
Number of macro-BSs/cell	1
Number of pico-BSs/cell	3
Max. Tx power at macro-BS	43 dBm
Max. Tx Power at pico-BS	30 dBm
Antenna gain	15 dBi
Background noise	-169 dBm/Hz
Path loss from macro-BS to user	$128.1 + 37.6 \log_{10}(d)$
Path loss from pico-BS to user	$140.7 + 36.7 \log_{10}(d)$
Log-normal shadowing	8 dB
Rayleigh small scale fading	0 dB
SNR gap (Γ_m)	9 dB
Rate-distortion gap (Γ_q)	4.3 dB

Table: Simulation Parameters

Performance Comparison

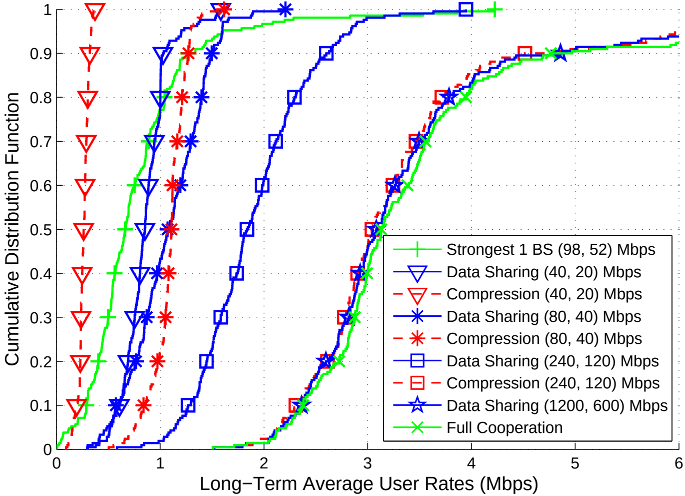


Figure: Comparison of cumulative distribution of user rates for the data-sharing and compression strategies.

New Hybrid Data-sharing and Compression Strategy

Balance the trade-off

- In data-sharing strategy:
  - Backhaul links carry user messages.
- In compression-based strategy:
  - Backhaul links carry compressed signals.
- In the hybrid strategy:
  - Part of backhaul is used to send direct messages for some users and remaining to carry the compressed signal of the rest of the users
- Intuition: Direct data for strong users; compression for rest.

Hybrid Strategy

A unified approach

- Direct data beamforming:
  - Signals computed at the BSs using direct data, $\mathbf{x^d} = \sum_{k=1}^{K} \mathbf{w}_k^d s_k$.
  - $\mathbf{w}_k^d = [w_{1,k}^d, \ldots, w_{L,k}^d]^T$: direct data beamforming direction for user k.
  - If BS l does not participate in transmitting to user k, $w_{l,k}^d = 0$.
  - Backhaul consumed at BS l: $\sum_{k=1}^{K} \mathbb{1}\{|w_{l,k}^d|^2\} R_k$.
- Compressed signal beamforming:
  - Signals to be compressed at central processor, $\hat{\mathbf{x^c}} = \sum_{k=1}^{K} \mathbf{w}_k^c s_k$.
  - $\mathbf{w}_k^c = [w_{1,k}^c, \ldots, w_{L,k}^c]^T$: compressed signal beamformers for user k.
  - Quantization for $\hat{\mathbf{x^c}}$ modeled as $\mathbf{x^c} = \hat{\mathbf{x^c}} + \mathbf{e}$, where $\mathbf{e}$ is the quantization noise with covariance $\mathbf{Q}$, independent of $\hat{\mathbf{x}}$.
  - Backhaul consumed at BS l: $\log\left(1 + \frac{\Gamma_q \sum_{k=1}^{K} |w_{l,k}^c|^2}{q_l}\right)$.
- Achievable rate for user k is again $R_k = \log(1 + \frac{\mathrm{SINR}_k}{\Gamma_m})$ where $\mathrm{SINR}_k = \frac{|\mathbf{h}_k^H \mathbf{w}_k|^2}{\sum_{j \neq k} |\mathbf{h}_k^H \mathbf{w}_j|^2 + \sigma^2 + |\mathbf{h}_k^H \mathbf{Q} \mathbf{h}_k|}$, if we let $\mathbf{w}_k^d + \mathbf{w}_k^c = \mathbf{w}_k$.

Optimization of Hybrid Strategy

$$
\begin{aligned}
\underset{w^d_{l,k}, w^c_{l,k}}{\text{maximize}} \quad & \sum_{k=1}^{K} \alpha_k R_k && \text{(3a)}\\
\text{subject to} \quad & \sum_{k=1}^{K} |w_{l,k}|^2 + q_l \le P_l, \quad \forall l && \text{(3b)}\\
& \sum_{k=1}^{K} \mathbb{1}\left\{|w^d_{l,k}|^2\right\} R_k + \log\left(1 + \frac{\Gamma_q \sum_{k=1}^{K} |w^c_{l,k}|^2}{q_l}\right) \le C_l, \quad \forall l && \text{(3c)}\\
& w^d_{l,k} + w^c_{l,k} = w_{l,k}, \quad \forall l, k. && \text{(3d)}
\end{aligned}
$$

- Data-sharing backhaul term: $\mathbb{1}\{|w^d_{l,k}|^2\} = \||w^d_{l,k}|^2\|_0 \approx \beta^d_{l,k}|w^d_{l,k}|^2$ where $\beta^d_{l,k}$ is updated iteratively $\beta^d_{l,k} = \frac{1}{|w^d_{l,k}|^2+\tau}$.
- Compression backhaul term: successive convex approximation on the first part $\log(q_l + \Gamma_q \sum_{k=1}^{K} |w^c_{l,k}|^2)$
- Beamformers optimized for the equivalent WMMSE optimization problem.

Performance of Hybrid Strategy

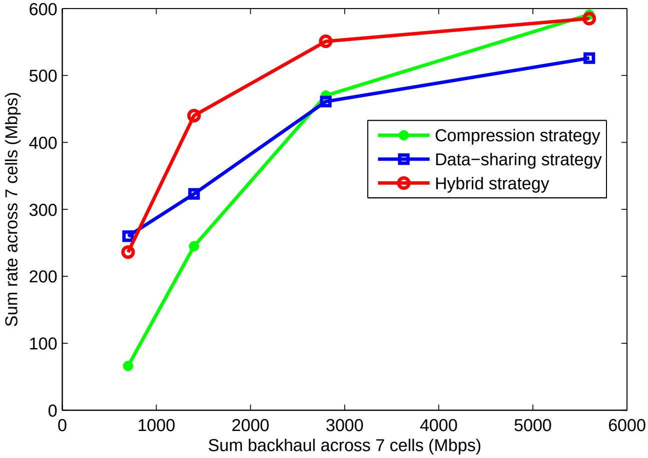


Figure: Comparison of sum rate vs. sum backhaul capacity for the data-sharing, compression, and hybrid strategies.

References I

Dai, B. and Yu, W. (2014).
Sparse beamforming and user-centric clustering for downlink cloud radio access network.
IEEE Access, 2:1326–1339.

Hong, S.-N. and Caire, G. (2013).
Compute-and-forward strategies for cooperative distributed antenna systems.
IEEE Trans. Inf. Theory, 59(9):5227–5243.

Marsch, P. and Fettweis, G. (2008).
On base station cooperation schemes for downlink network MIMO under a constrained backhaul.
In *Proc. IEEE Global Commun. Conf. (Globecom)*.

References II

Marsch, P. and Fettweis, G. (2009).
On downlink network mimo under a constrained backhaul and imperfect channel knowledge.
In *Proc. IEEE Global Commun. Conf. (Globecom)*.

Ng, B. L., Evans, J., Hanly, S., and Aktas, D. (2008).
Distributed downlink beamforming with cooperative base stations.
IEEE Trans. Inf. Theory, 54(12):5491–5499.

Park, S.-H., Simeone, O., Sahin, O., and Shamai, S. (2013).
Joint precoding and multivariate backhaul compression for the downlink of cloud radio access networks.
IEEE Trans. Signal Process., 61(22):5646–5658.

Simeone, O., Somekh, O., Poor, H., and Shamai, S. (2009).
Downlink multicell processing with limited-backhaul capacity.
EURASIP J. Advances Singal Process.

References III

Zakhour, R. and Gesbert, D. (2011).
Optimized data sharing in multicell MIMO with finite backhaul capacity.
IEEE Trans. Signal Process., 59(12):6102–6111.

Zhao, J., Quek, T., and Lei, Z. (2013).
Coordinated multipoint transmission with limited backhaul data transfer.
"IEEE Trans. Wireless Commun.", 12(6):2762–2775.

Thanks for listening!

Any questions/comments/thoughts?