

Cooperative MIMO Precoding with Distributed CSI: A Hierarchical Approach

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SPAWC 2018 - Kalamata, Greece



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Introduction

- **Network MIMO System:** distributed TXs sharing user data symbols and channel state information (CSI) cooperatively serve several RXs → **cooperative precoding design**.
- **Distributed CSI (D-CSI):** CSI is known **imperfectly** and **differently** across the TXs due to limited and uneven feedback.
- **Team decision problem:** multiple decentralized decision makers aim at coordinating their strategies while not being able to accurately predict the actions taken by the others.
- **Hierarchical D-CSI:** enforced by a suitable information exchange mechanism between TXs at a certain signaling/power cost → can be leveraged to yield implementable and efficient distributed precoding solutions.

Downlink Network MIMO System Model

- N TXs, n th TX equipped with M_n antennas ($M \triangleq \sum_{n=1}^N M_n$), K single-antenna RXs.
- **Channels:** $\mathbf{h}_{kn} \in \mathbb{C}^{M_n \times 1}$ between TX n and RX k , $\mathbf{h}_k \triangleq [\mathbf{h}_{k1}^T \dots \mathbf{h}_{kN}^T]^T \in \mathbb{C}^{M \times 1}$ between the N TXs and RX k , and $\mathbf{H} \triangleq [\mathbf{h}_1 \dots \mathbf{h}_K] \in \mathbb{C}^{M \times K}$ between the N TXs and the K RXs, with $\mathbf{h}_k \sim \mathcal{CN}(\mathbf{0}, \Sigma_k)$.

- **Multiuser precoding matrix:**

$$\mathbf{W} \triangleq [\mathbf{w}_1 \dots \mathbf{w}_K] = \begin{bmatrix} \mathbf{W}^{(1)} \\ \vdots \\ \mathbf{W}^{(N)} \end{bmatrix}$$

with $\mathbf{w}_k \in \mathbb{C}^{M \times 1}$ beamforming vector used by the N TXs to serve RX k and $\mathbf{W}^{(n)} \in \mathbb{C}^{M_n \times K}$ precoding submatrix used by TX n to serve the K RXs.

- **Receive signal at RX k :** $y_k \triangleq \mathbf{h}_k^H \mathbf{x} + z_k$, with $\mathbf{x} \triangleq \mathbf{W} \mathbf{s} \in \mathbb{C}^{M \times 1}$ obtained by precoding the user data symbol vector $\mathbf{s} \in \mathbb{C}^{K \times 1}$ and $z_k \sim \mathcal{CN}(0, \sigma^2)$ noise at RX k .

- **Sum rate:**

$$R(\mathbf{H}, \mathbf{W}) \triangleq \sum_{k=1}^K \log_2 \left(1 + \frac{|\mathbf{h}_k^H \mathbf{w}_k|^2}{\sum_{j \neq k} |\mathbf{h}_k^H \mathbf{w}_j|^2 + \sigma^2} \right).$$

Regularized Zero Forcing Precoding

Regularized zero forcing (RZF) precoding is adopted at each TX:

$$\mathbf{W}_{\text{rzf}}^{(n)}(\hat{\mathbf{H}}^{(n)}, \alpha^{(n)}) \triangleq \sqrt{P_n} \frac{\Delta_n^T \hat{\mathbf{H}}^{(n)} ((1 - \alpha^{(n)}) (\hat{\mathbf{H}}^{(n)})^H \hat{\mathbf{H}}^{(n)} + \alpha^{(n)} \mathbf{I}_K)^{-1}}{\|\Delta_n^T \hat{\mathbf{H}}^{(n)} ((1 - \alpha^{(n)}) (\hat{\mathbf{H}}^{(n)})^H \hat{\mathbf{H}}^{(n)} + \alpha^{(n)} \mathbf{I}_K)^{-1}\|_F}$$

with $\alpha^{(n)} \in [0, 1]$ regularization factor and

$$\Delta_n \triangleq [\mathbf{0}_{M_n \times \sum_{\ell=1}^{n-1} M_\ell} \quad \mathbf{I}_{M_n} \quad \mathbf{0}_{M_n \times \sum_{\ell=n+1}^N M_\ell}]^T \in \mathbb{C}^{M \times M_n}$$

block selection matrix.

Team Decision Precoding Problem

D-CSI:

$$\mathbf{W}_{\star}^{(n)} \triangleq \underset{\mathbf{W}^{(n)}}{\operatorname{argmax}} \mathbb{E}_{\{\hat{\mathbf{H}}^{(\ell)}\}_{\ell \neq n} | \hat{\mathbf{H}}^{(n)}} \left[\max_{\{\mathbf{W}^{(\ell)}\}_{\ell \neq n}} \mathbb{E}_{\mathbf{H} | \hat{\mathbf{H}}^{(n)}} \left[R(\mathbf{H}, \mathbf{W}^{(n)}(\hat{\mathbf{H}}^{(n)}), \{\mathbf{W}^{(\ell)}(\hat{\mathbf{H}}^{(\ell)})\}_{\ell \neq n}) \right] \right]$$

$$\text{s.t. } \|\mathbf{W}^{(\ell)}(\hat{\mathbf{H}}^{(\ell)})\|_F^2 \leq P_\ell, \quad \ell = 1, \dots, N$$

Hierarchical D-CSI:

$$\mathbf{W}_{\star, h}^{(n)} \triangleq \underset{\mathbf{W}^{(n)}}{\operatorname{argmax}} \mathbb{E}_{\{\hat{\mathbf{H}}^{(\ell)}\}_{\ell=n+1}^N | \hat{\mathbf{H}}^{(n)}} \left[\max_{\{\mathbf{W}^{(\ell)}\}_{\ell=n+1}^N} \mathbb{E}_{\mathbf{H} | \hat{\mathbf{H}}^{(n)}} \left[R(\mathbf{H}, \{\mathbf{W}_{\star, h}^{(\ell)}\}_{\ell=1}^{n-1}, \mathbf{W}^{(n)}(\hat{\mathbf{H}}^{(n)}), \{\mathbf{W}^{(\ell)}(\hat{\mathbf{H}}^{(\ell)})\}_{\ell=n+1}^N) \right] \right]$$

$$\text{s.t. } \|\mathbf{W}^{(\ell)}(\hat{\mathbf{H}}^{(\ell)})\|_F^2 \leq P_\ell, \quad \ell = n, \dots, N$$

D-CSI Model

Each TX n has a different estimate of \mathbf{H} , denoted by $\hat{\mathbf{H}}^{(n)} \triangleq [\hat{\mathbf{h}}_1^{(n)} \dots \hat{\mathbf{h}}_K^{(n)}] \in \mathbb{C}^{M \times K}$, given by

$$\hat{\mathbf{H}}^{(n)} = \sqrt{1 - \epsilon_n^2} \mathbf{H} + \epsilon_n \mathbf{E}^{(n)}$$

where $\epsilon_n \in [0, 1]$ and $\mathbf{E}^{(n)} \triangleq [\mathbf{e}_1^{(n)} \dots \mathbf{e}_K^{(n)}]$, with $\mathbf{e}_k^{(n)} \sim \mathcal{CN}(0, \Upsilon^{(n)})$, $\forall k = 1, \dots, K$.

Cond. distributions of $\mathbf{H} | \hat{\mathbf{H}}^{(n)}$ and $\{\hat{\mathbf{H}}^{(\ell)}\}_{\ell \neq n} | \hat{\mathbf{H}}^{(n)}$:

- $\mathbf{h}_k | \hat{\mathbf{h}}_k^{(n)} \sim \mathcal{CN}(\boldsymbol{\mu}_k^{(n)}, \Sigma_k^{(n)})$, with $\boldsymbol{\mu}_k^{(n)} \triangleq \sqrt{1 - \epsilon_n^2} \Sigma_k ((1 - \epsilon_n^2) \Sigma_k + \epsilon_n^2 \Upsilon^{(n)})^{-1} \hat{\mathbf{h}}_k^{(n)}$, $\Sigma_k^{(n)} \triangleq \Sigma_k - (1 - \epsilon_n^2) \Sigma_k ((1 - \epsilon_n^2) \Sigma_k + \epsilon_n^2 \Upsilon^{(n)})^{-1} \Sigma_k$.
- $\hat{\mathbf{h}}_k^{(\ell)} | \hat{\mathbf{h}}_k^{(n)} \sim \mathcal{CN}(\boldsymbol{\mu}_k^{(\ell n)}, \Sigma_k^{(\ell n)})$, with $\boldsymbol{\mu}_k^{(\ell n)} \triangleq \sqrt{1 - \epsilon_\ell^2} \boldsymbol{\mu}_k^{(n)}$, $\Sigma_k^{(\ell n)} \triangleq (1 - \epsilon_\ell^2) \Sigma_k^{(n)} + \epsilon_\ell^2 \Upsilon^{(\ell)}$.

Algorithms for the Case of 2 TXs

- **Optimal approach:**

$$\alpha_{\star, h}^{(1)} = \underset{\alpha^{(1)} \in [0, 1]}{\operatorname{argmax}} \mathbb{E}_{\mathbf{H} | \hat{\mathbf{H}}^{(1)}} \left[\max_{\alpha^{(2)} \in [0, 1]} R(\mathbf{H}, \mathbf{W}_{\text{rzf}}^{(1)}(\hat{\mathbf{H}}^{(1)}, \alpha^{(1)}), \mathbf{W}_{\text{rzf}}^{(2)}(\mathbf{H}, \alpha^{(2)})) \right]$$

$$\alpha_{\star, h}^{(2)} = \underset{\alpha^{(2)} \in [0, 1]}{\operatorname{argmax}} R(\mathbf{H}, \mathbf{W}_{\text{rzf}}^{(1)}(\hat{\mathbf{H}}^{(1)}, \alpha_{\star, h}^{(1)}), \mathbf{W}_{\text{rzf}}^{(2)}(\mathbf{H}, \alpha^{(2)})).$$

- **Naive approach:** local CSI is assumed **perfect** and **shared** by more informed TXs

$$\alpha_{\text{NA}, h}^{(1)} = \underset{\alpha^{(1)} \in [0, 1]}{\operatorname{argmax}} R(\hat{\mathbf{H}}^{(1)}, \mathbf{W}_{\text{rzf}}^{(1)}(\hat{\mathbf{H}}^{(1)}, \alpha^{(1)}), \mathbf{W}_{\text{rzf}}^{(2)}(\hat{\mathbf{H}}^{(1)}, \alpha^{(1)})),$$

$$\alpha_{\text{NA}, h}^{(2)} = \underset{\alpha^{(2)} \in [0, 1]}{\operatorname{argmax}} R(\mathbf{H}, \mathbf{W}_{\text{rzf}}^{(1)}(\hat{\mathbf{H}}^{(1)}, \alpha_{\text{NA}, h}^{(1)}), \mathbf{W}_{\text{rzf}}^{(2)}(\mathbf{H}, \alpha^{(2)})).$$

- **Locally robust approach:** local CSI is assumed **imperfect** and **shared** by more informed TXs

$$\alpha_{\text{LR}, h}^{(1)} = \underset{\alpha^{(1)} \in [0, 1]}{\operatorname{argmax}} \mathbb{E}_{\mathbf{H} | \hat{\mathbf{H}}^{(1)}} \left[R(\mathbf{H}, \mathbf{W}_{\text{rzf}}^{(1)}(\hat{\mathbf{H}}^{(1)}, \alpha^{(1)}), \mathbf{W}_{\text{rzf}}^{(2)}(\hat{\mathbf{H}}^{(1)}, \alpha^{(1)})) \right]$$

$$\alpha_{\text{LR}, h}^{(2)} = \underset{\alpha^{(2)} \in [0, 1]}{\operatorname{argmax}} R(\mathbf{H}, \mathbf{W}_{\text{rzf}}^{(1)}(\hat{\mathbf{H}}^{(1)}, \alpha_{\text{LR}, h}^{(1)}), \mathbf{W}_{\text{rzf}}^{(2)}(\mathbf{H}, \alpha^{(2)})).$$

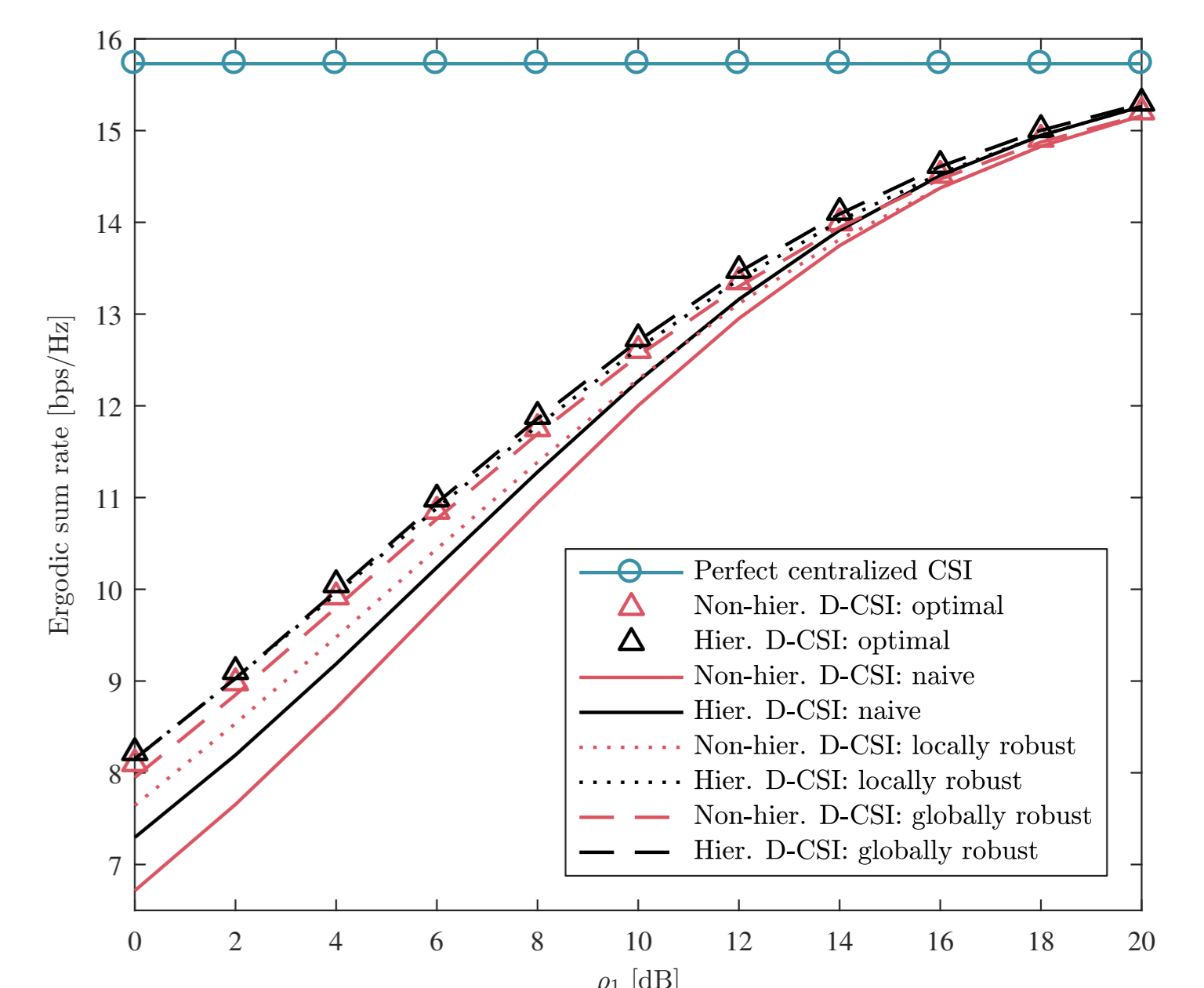
- **Globally robust approach:** local CSI is assumed **imperfect** and **not shared** by more informed TXs (neglecting the possibly different regularization factors adopted by the latter)

$$\alpha_{\text{GR}, h}^{(1)} = \underset{\alpha^{(1)} \in [0, 1]}{\operatorname{argmax}} \mathbb{E}_{\mathbf{H} | \hat{\mathbf{H}}^{(1)}} \left[R(\mathbf{H}, \mathbf{W}_{\text{rzf}}^{(1)}(\hat{\mathbf{H}}^{(1)}, \alpha^{(1)}), \mathbf{W}_{\text{rzf}}^{(2)}(\mathbf{H}, \alpha^{(1)})) \right]$$

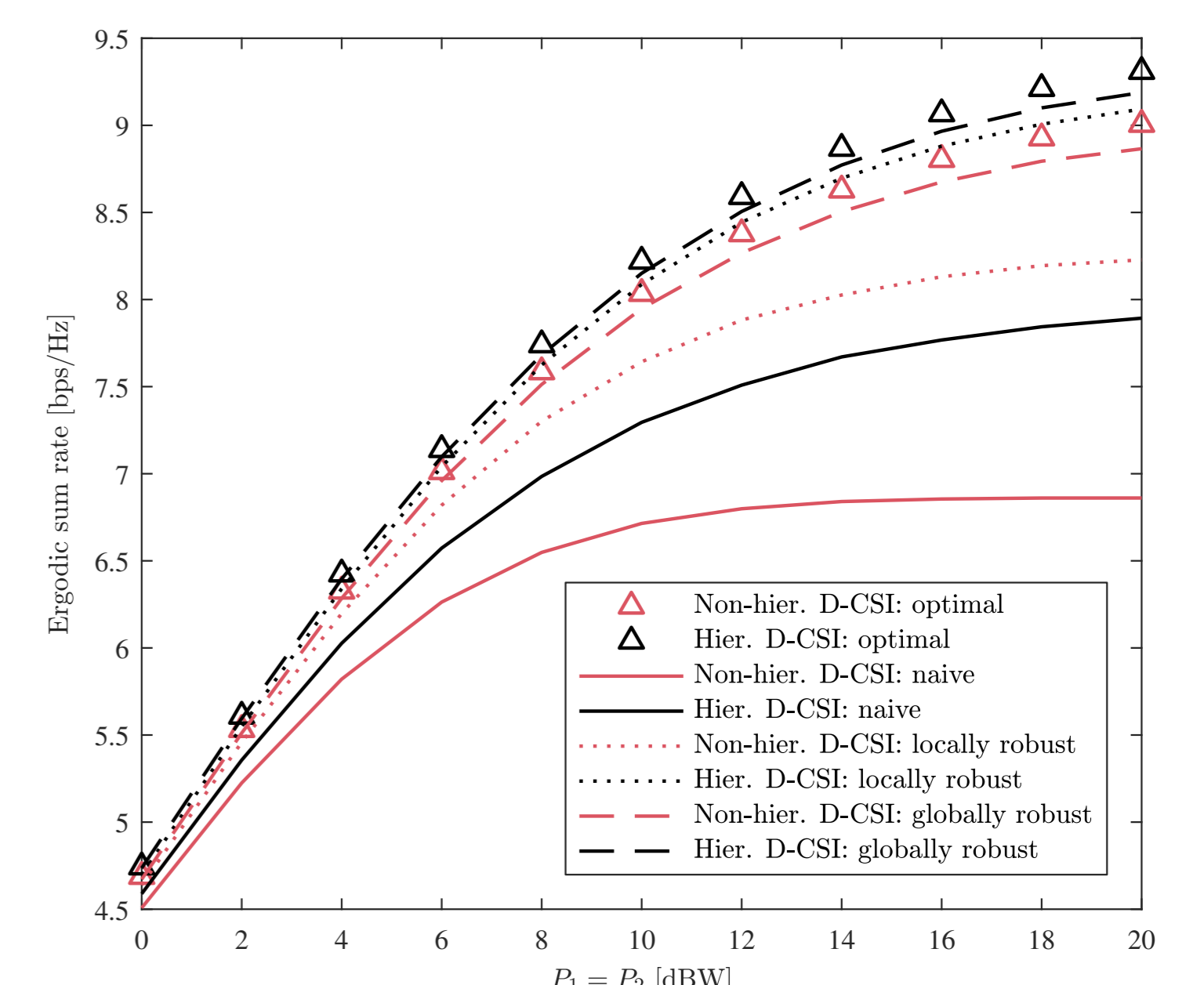
$$\alpha_{\text{GR}, h}^{(2)} = \underset{\alpha^{(2)} \in [0, 1]}{\operatorname{argmax}} R(\mathbf{H}, \mathbf{W}_{\text{rzf}}^{(1)}(\hat{\mathbf{H}}^{(1)}, \alpha_{\text{GR}, h}^{(1)}), \mathbf{W}_{\text{rzf}}^{(2)}(\mathbf{H}, \alpha^{(2)})).$$

Numerical Results

- $N = 2$ TXs (with 4 transmit antennas) facing each other at distance $d = 40$ m, $K = 5$ angularly equispaced RXs in $[\pi/4, 3\pi/4]$ between the TXs; ULAs at the TXs (uniform distribution of the AoDs with angle spread $\Delta\theta = \pi/8$); error covariance matrices $\{\Upsilon^{(n)} = \mathbf{I}\}_{n=1}^N$, pathloss exponent $\eta = 2$, noise power $\sigma^2 = 0$ dBm.



Ergodic sum rate VS feedback SNR of TX 1 $\rho_1 \triangleq (1 - \epsilon_1^2)/\epsilon_1^2$, with $P_1 = P_2 = 10$ dBW.



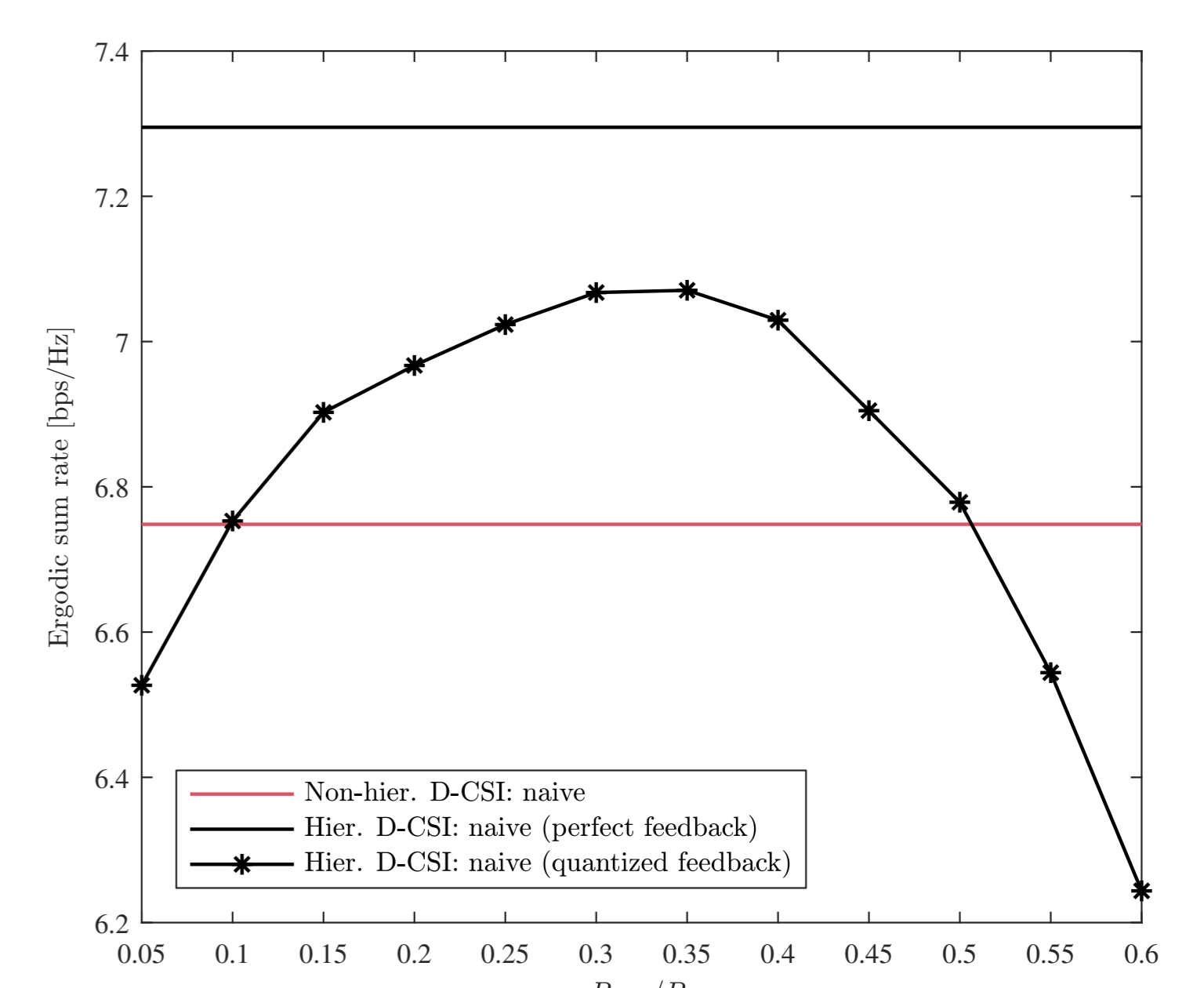
Ergodic sum rate VS per-TX power constraint, with $\rho_1 = 0$ dB.

- **Information exchange VS cooperation gain:** Feedback from TX 1 to TX 2, with $P_1 = P_{1, \text{fb}} + P_{1, \text{tx}}$ and number of feedback bits

$$\xi \triangleq \left\lfloor BT \log_2 \left(1 + d^{-\eta} \frac{P_{1, \text{fb}}}{\sigma^2} \right) \right\rfloor.$$

Given the common codebook $\mathcal{W} \triangleq \{\hat{\mathbf{W}}_q^{(1)}\}_{q=1}^{2^\xi}$, TX 1 computes $\mathbf{W}_{\text{rzf}}^{(1)}(\hat{\mathbf{H}}^{(1)}, \alpha^{(1)})$ and sends the index

$$\hat{q} \triangleq \underset{q \in [1, 2^\xi]}{\operatorname{argmin}} \|\hat{\mathbf{W}}_q^{(1)} - \mathbf{W}_{\text{rzf}}^{(1)}(\hat{\mathbf{H}}^{(1)}, \alpha^{(1)})\|_F.$$



Ergodic sum rate VS feedback power, with $P_1 = P_2 = 10$ dBW, $P_{1, \text{tx}} = 10 \log_{10}(P_1 - P_{1, \text{fb}})$ dBW, $\rho_1 = 0$ dB, $B = 1$ kHz, and $T = 5$ ms.