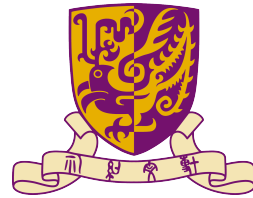


# Robust Symbol-Level Precoding: A Symbol-Perturbed Zero-Forcing Structure

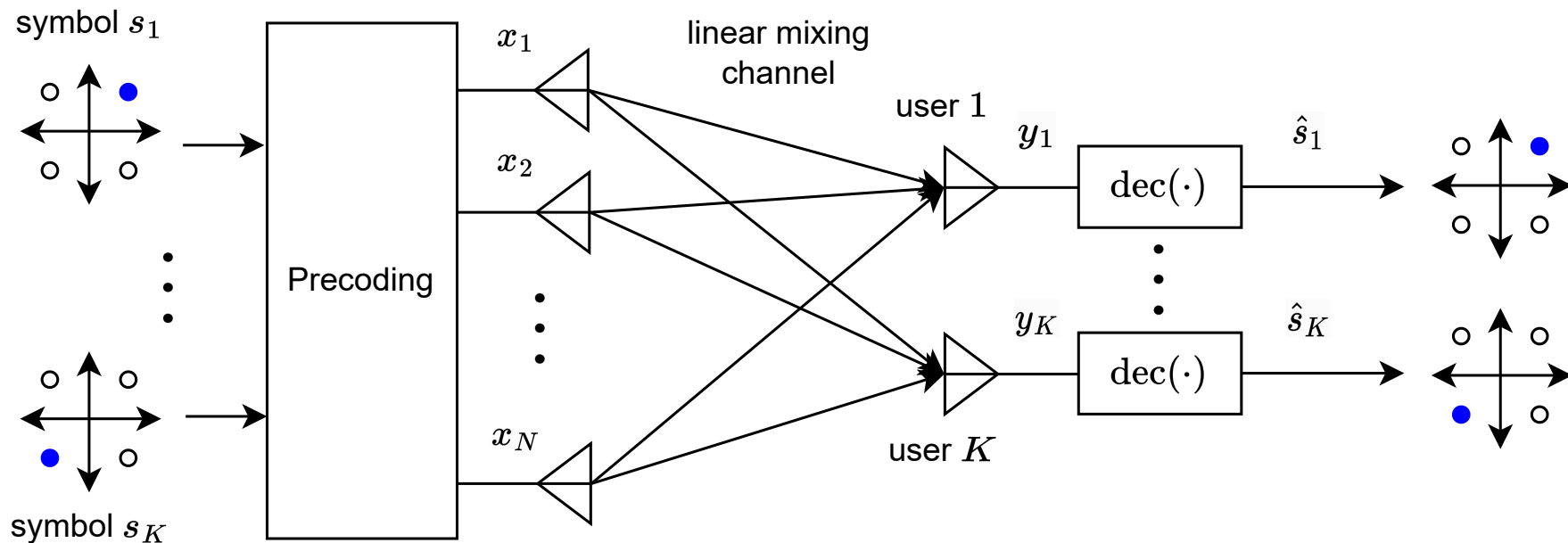
Wai-Yiu Keung, Yatao Liu & Wing-Kin Ma



The Chinese University of Hong Kong

April 17, 2024

# Scenario



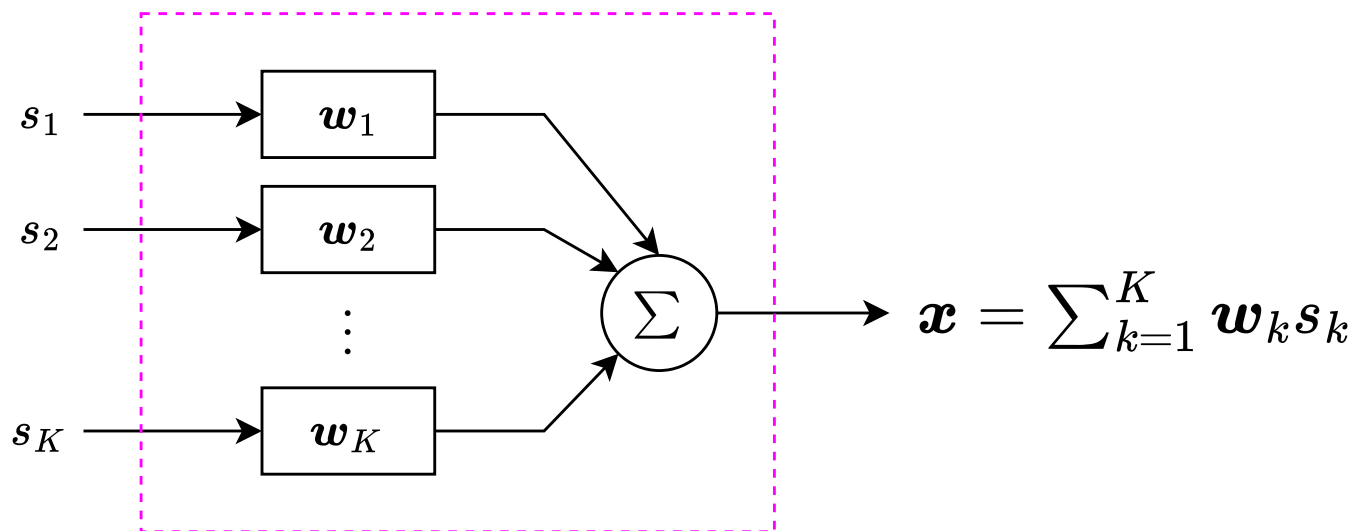
- MU-MISO downlink system:  $y_k = \mathbf{h}_k^H \mathbf{x} + \text{noise}$ ; 4-QAM symbols
- design the tx. signal  $\mathbf{x}$  s.t. the decision

$$\hat{s}_k = \text{dec}(y_k) = \text{sgn}(\Re(y_k)) + j \cdot \text{sgn}(\Im(y_k))$$

has a **high probability** to achieve  $\hat{s}_k = s_k$  for all  $k$

- solution: **linear beamforming** and **symbol-level precoding**

# Linear Beamforming



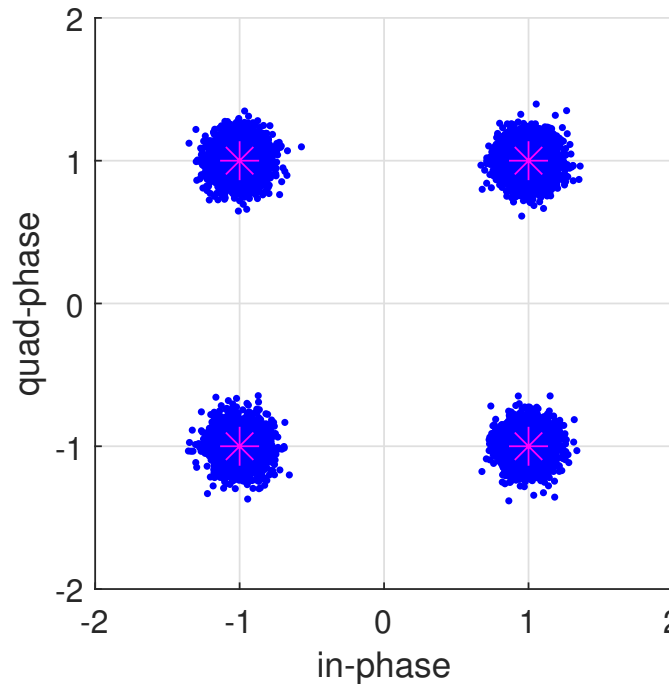
- rx. signal model:  $y_k = \underbrace{\mathbf{h}_k^H \mathbf{w}_k s_k}_{\text{desired signal}} + \underbrace{\sum_{k \neq j} \mathbf{h}_k^H \mathbf{w}_j s_j}_{\text{interference}} + \text{noise}$

- e.g., the zero-forcing (ZF) beamformer  $\mathbf{w}_k = [\mathbf{H}^\dagger]_k \rightarrow \mathbf{x} = \mathbf{H}^\dagger \mathbf{s}$

- treat MUI as enemy, e.g.,

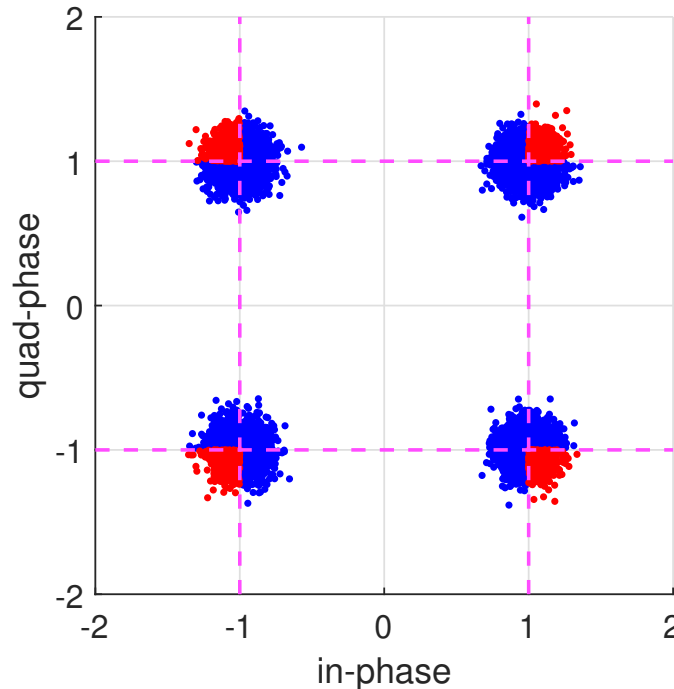
$$\begin{aligned} & \underset{\{\mathbf{w}_k\}_{k=1}^K}{\text{minimize}} && \text{signal power} = \sum_{k=1}^K \|\mathbf{w}_k\|_2^2 \\ & \text{subject to} && \text{SINR}_k = \frac{|\mathbf{h}_k^H \mathbf{w}_k|^2}{\sum_{j=1, j \neq k}^K |\mathbf{h}_k^H \mathbf{w}_j|^2 + \sigma^2} \geq \gamma \end{aligned}$$

# Is Interference Enemy?



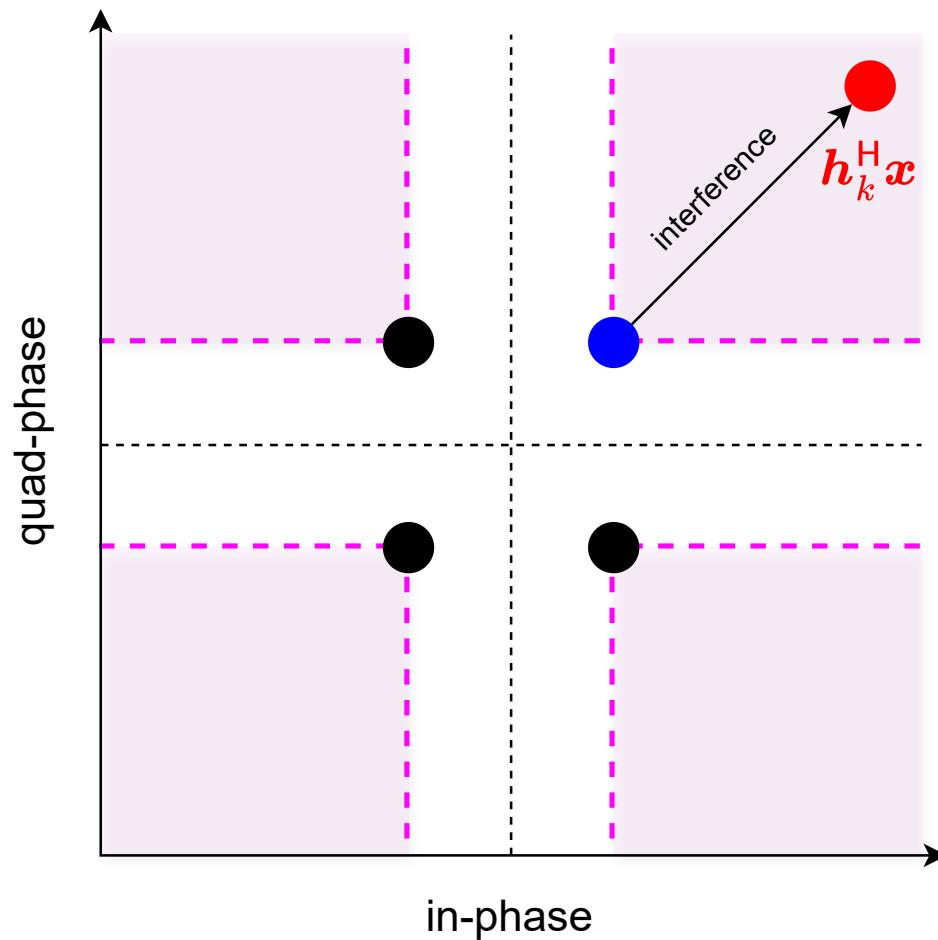
- linear beamforming seeks to minimize MUI s.t. rx signals are close to the target symbols
- or we want to shape  $\mathbf{h}_k^H \mathbf{x}$  to be close to  $s_k$
- but if we look at the symbol constellation structure...

# Interference Is NOT Always Enemy



- constellation has its own structure
- interference is **constructive** for  $\mathbf{h}_k^H \mathbf{x}$  being pushed toward **desired regions**
- **symbol-level precoding**: use interference to **push**  $\mathbf{h}_k^H \mathbf{x}$  deeper

# Symbol-Level Precoding: Intuition



- **goal:** design  $x \in \mathbb{C}^N$  s.t. each  $h_k^H x$  is pushed toward the desired region

# History of SLP Structure

- SLP w/ linear structure:

$$\boldsymbol{x} = \sum_{k=1}^K \boldsymbol{w}_k s_k = \boldsymbol{W} \boldsymbol{s}$$

$\boldsymbol{W}$  is symbol-dependent for constructive interference [MA09, MZ15]

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- **General non-linear structure:** treat SLP as a non-linear function [HKO18, KMCO21]

$$\boldsymbol{x} = \mathcal{P}(\boldsymbol{s}).$$

–  $\boldsymbol{x}$  is found directly by optimization

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- Perturbed-ZF structure: use basic linear algebra [LSML22]

$$\mathbf{x} = \underbrace{\mathbf{H}^\dagger}_{\text{channel inv.}} \left( \underbrace{\mathbf{s}}_{\text{symbol}} + \underbrace{\mathbf{u}}_{\text{perturbation}} \right) + \underbrace{\boldsymbol{\eta}}_{\text{null-space of } \mathbf{H}^\dagger}$$

– **equivalent** to the general non-linear SLP structure

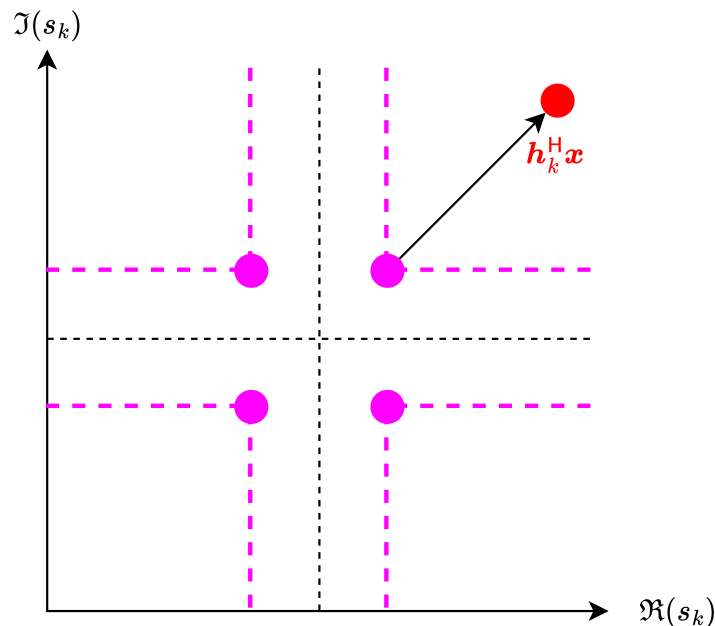
# Symbol Error Probability Type SLP

- consider symbol error probability (SEP) constrained power-min SLP:

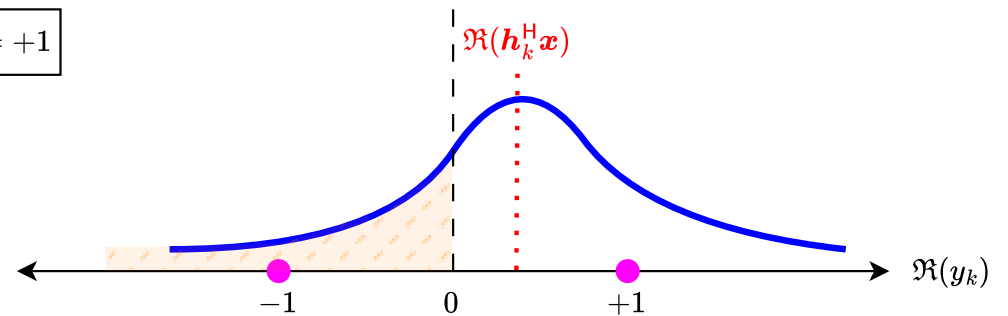
$$\begin{aligned} & \underset{\mathbf{x} \in \mathbb{C}^N}{\text{minimize}} && \|\mathbf{x}\|_2^2 \\ & \text{subject to} && \text{SEP}_k \leq \varepsilon \end{aligned} \quad (1)$$

which optimizes over  $\mathbf{x}$  directly

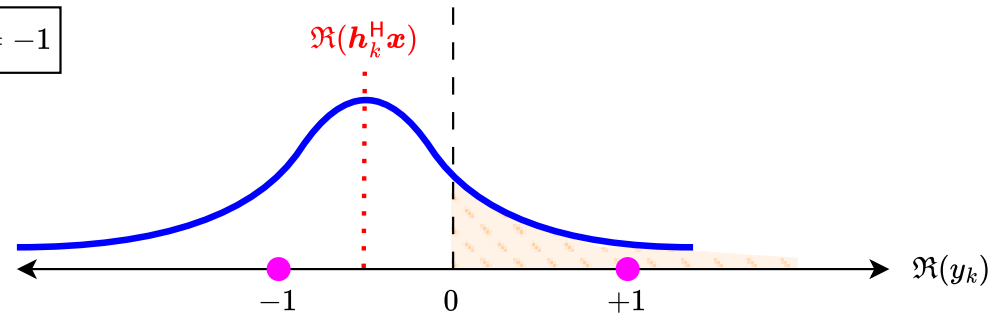
- but what does SEP (shaded area) have to do with SLP?



$$\Re(s_k) = +1$$



$$\Re(s_k) = -1$$



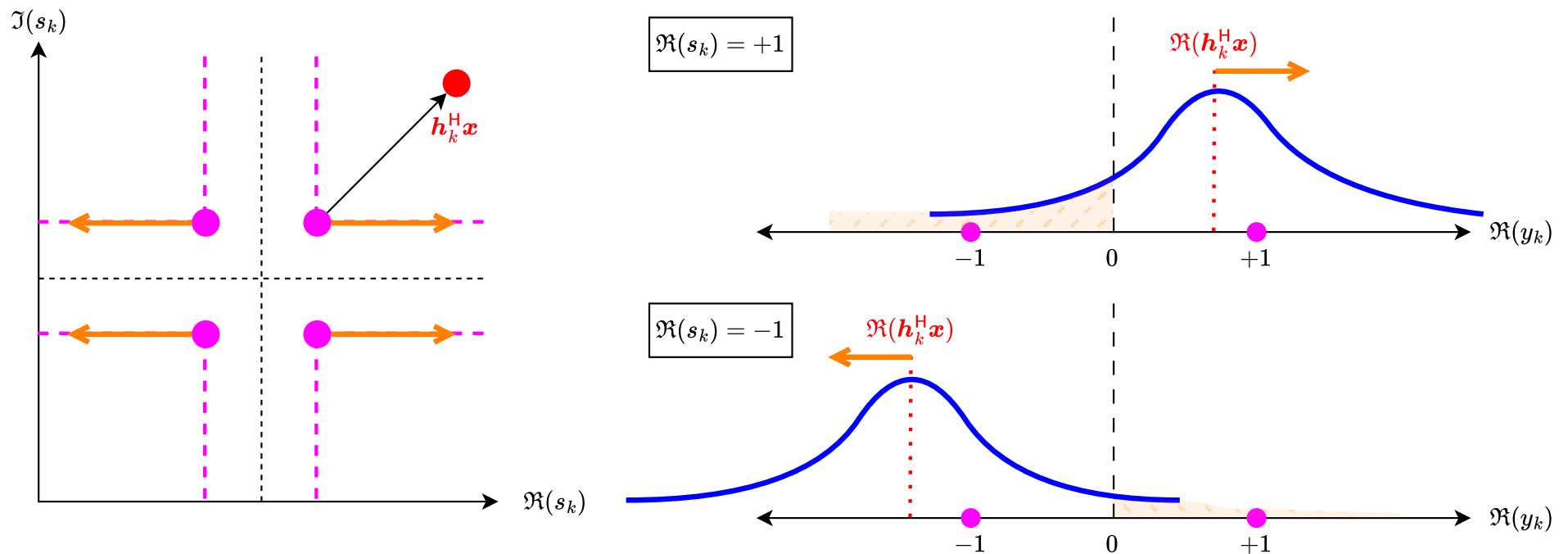
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- insight:** smaller SEP (in real & imag parts)  $\iff$  push  $\mathbf{h}_k^H \mathbf{x}$  deeper



# Zero-Forcing Interpretation of SLP

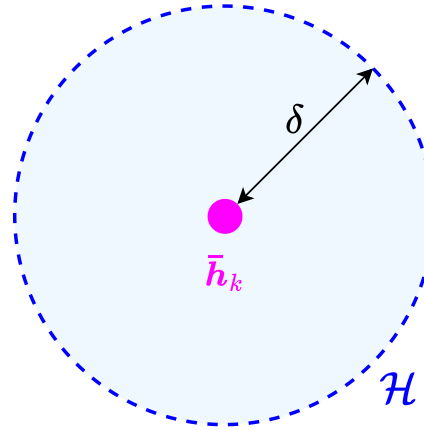
$$\begin{aligned} & \underset{\mathbf{x} \in \mathbb{C}^N}{\text{minimize}} && \|\mathbf{x}\|_2^2 \\ & \text{subject to} && \text{SEP}_k \leq \varepsilon \end{aligned} \tag{1}$$

- our previous work [LSML22] interpreted this SLP by a linear structure

$$\mathbf{x}^* = \underbrace{\mathbf{H}^\dagger}_{\text{channel inv.}} \left( \underbrace{\mathbf{s}}_{\text{symbol vector}} + \underbrace{\mathbf{u}^*}_{\text{perturbation}} \right)$$

- **implication:** SLP is essentially a symbol-perturbed ZF!
- **this work:** extend the work to worst-case robust SLP

# This Work: Imperfect Channel State Information



- [LSML22] assumes perfect CSI; here we consider worst-case robust settings

$$\mathbf{h}_k \in \mathcal{H} = \left\{ \mathbf{h}_k \in \mathbb{C}^N \mid \|\bar{\mathbf{h}}_k - \mathbf{h}_k\|_2 \leq \delta \right\}$$

where  $\bar{\mathbf{h}}_k$  is the presumed channel;  $\delta$  is an error radius

- worst-case robust SLP formulation:

$$\begin{aligned} \min_{\mathbf{x} \in \mathbb{C}^N} \quad & \|\mathbf{x}\|_2^2 \\ \text{s.t.} \quad & \text{SEP}_k \leq \varepsilon, \text{ for all } \mathbf{h}_k \in \mathcal{H}, k = 1, \dots, K \end{aligned}$$

we study whether the SLP-ZF interpretation holds

# Worst-Case Robust Symbol-Level Precoding

$$\begin{aligned} \min_{\mathbf{x} \in \mathbb{C}^N} \quad & \|\mathbf{x}\|_2^2 \\ \text{s.t.} \quad & \text{SEP}_k \leq \varepsilon, \text{ for all } \mathbf{h}_k \in \mathcal{H}, k = 1, \dots, K \end{aligned}$$

- the worst-case SEP constraints are written as:

$$\Re(\mathbf{s}) \circ \Re(\bar{\mathbf{H}}\mathbf{x}) \geq \boldsymbol{\beta} + \boldsymbol{\delta}\|\mathbf{x}\|_2, \quad \Im(\mathbf{s}) \circ \Im(\bar{\mathbf{H}}\mathbf{x}) \geq \boldsymbol{\beta} + \boldsymbol{\delta}\|\mathbf{x}\|_2,$$

where  $\boldsymbol{\beta}$  is element-wise defined by  $\beta_k = \frac{\sigma}{\sqrt{2}} Q^{-1}(1 - \sqrt{1 - \varepsilon_k})$

- resulting SLP problem:

$$\begin{aligned} \min_{\mathbf{x} \in \mathbb{C}^N} \quad & \|\mathbf{x}\|_2^2 \\ \text{s.t.} \quad & \Re(\mathbf{s}) \circ \Re(\bar{\mathbf{H}}\mathbf{x}) \geq \boldsymbol{\beta} + \boldsymbol{\delta}\|\mathbf{x}\|_2, \\ & \Im(\mathbf{s}) \circ \Im(\bar{\mathbf{H}}\mathbf{x}) \geq \boldsymbol{\beta} + \boldsymbol{\delta}\|\mathbf{x}\|_2. \end{aligned} \tag{2}$$

which is a SOCP

# Proof Idea of the worst-case SEP constraints

- assume the real-valued case and  $s_k = 1$  for simplicity
- worst-case SEP:

$$\max_{\mathbf{h}_k \in \mathcal{H}} \text{SEP}_k = \max_{\mathbf{h}_k \in \mathcal{H}} Q \left( \frac{\mathbf{h}_k^\top \mathbf{x}}{\sigma} \right) = Q \left( \frac{\min_{\mathbf{h}_k \in \mathcal{H}} \mathbf{h}_k^\top \mathbf{x}}{\sigma} \right)$$

- by Cauchy-Schwarz inequality

$$\begin{aligned} \min_{\mathbf{h}_k \in \mathcal{H}} \mathbf{h}_k^\top \mathbf{x} &= \min_{\|\mathbf{e}_k\|_2 \leq \delta} (\bar{\mathbf{h}}_k + \mathbf{e}_k)^\top \mathbf{x} \\ &= \bar{\mathbf{h}}_k^\top \mathbf{x} - \delta \|\mathbf{x}\|_2 \end{aligned}$$

$$\text{recall } \mathcal{H} = \{ \mathbf{h}_k \in \mathbb{C}^N \mid \|\bar{\mathbf{h}}_k - \mathbf{h}_k\|_2 \leq \delta \}$$

## ZF Interpretation on Robust SLP?

$$\begin{aligned} \min_{\mathbf{x} \in \mathbb{C}^N} \quad & \|\mathbf{x}\|_2^2 \\ \text{s.t.} \quad & \Re(\mathbf{s}) \circ \Re(\bar{\mathbf{H}}\mathbf{x}) \geq \beta + \delta \|\mathbf{x}\|_2, \\ & \Im(\mathbf{s}) \circ \Im(\bar{\mathbf{H}}\mathbf{x}) \geq \beta + \delta \|\mathbf{x}\|_2. \end{aligned} \tag{2}$$

- we derived that the optimum to (2) is

$$\mathbf{x}^* = \bar{\mathbf{H}}^\dagger(\mathbf{s} + \mathbf{u}^*)$$

i.e., a symbol-perturbed ZF scheme of the presumed channel

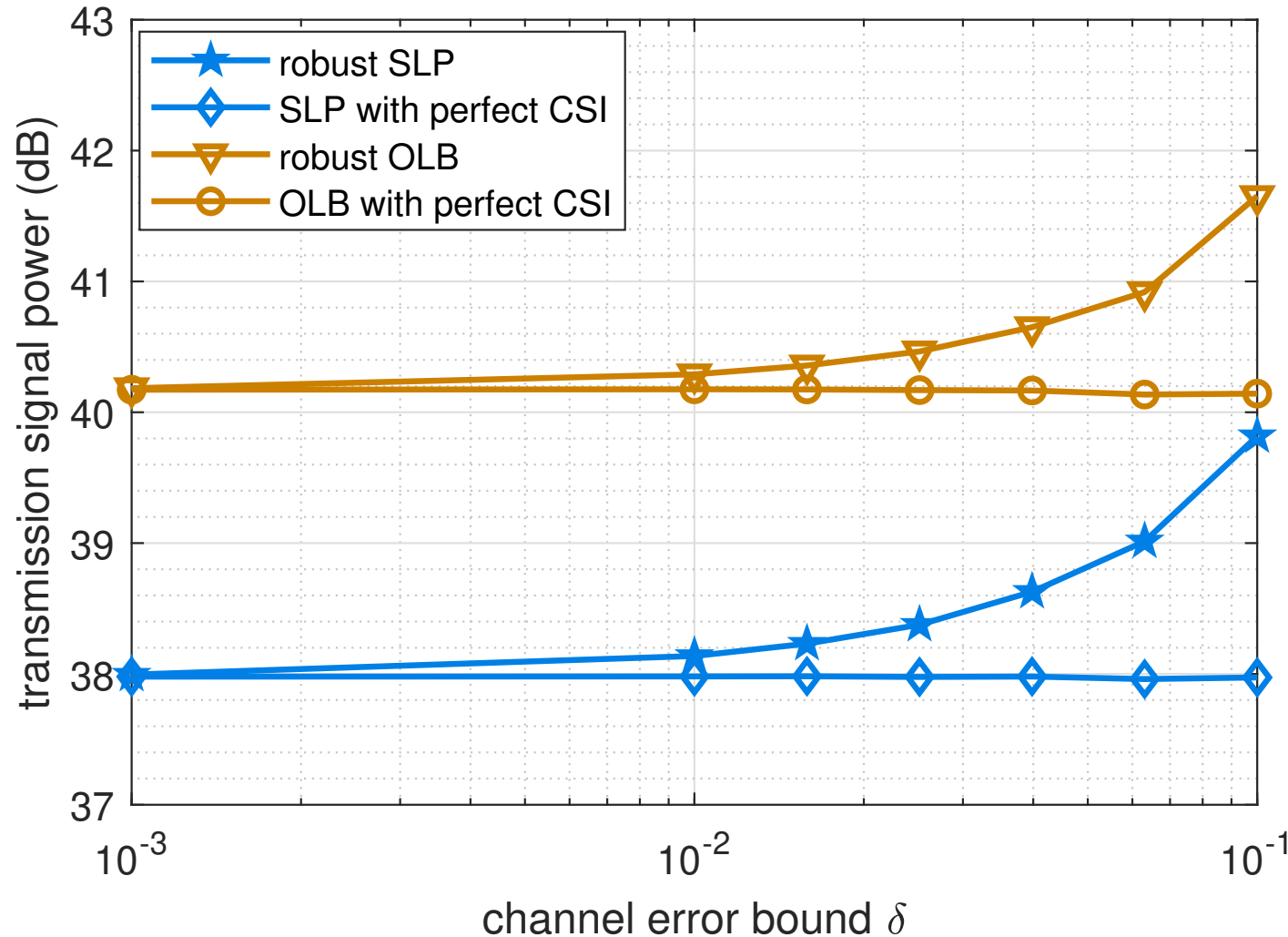
- substitute the above to (2) yields:

$$\begin{aligned} \min_{\mathbf{u}} \quad & (\mathbf{s} + \mathbf{u})^H \mathbf{R}(\mathbf{s} + \mathbf{u}) \\ \text{s.t.} \quad & \Re(\mathbf{s}) \circ \Re(\mathbf{u}) \geq \beta - 1 + \delta \sqrt{(\mathbf{s} + \mathbf{u})^H \mathbf{R}(\mathbf{s} + \mathbf{u})}, \\ & \Im(\mathbf{s}) \circ \Im(\mathbf{u}) \geq \beta - 1 + \delta \sqrt{(\mathbf{s} + \mathbf{u})^H \mathbf{R}(\mathbf{s} + \mathbf{u})} \end{aligned} \tag{3}$$

where  $\mathbf{R} = (\bar{\mathbf{H}}\bar{\mathbf{H}}^H)^{-1}$

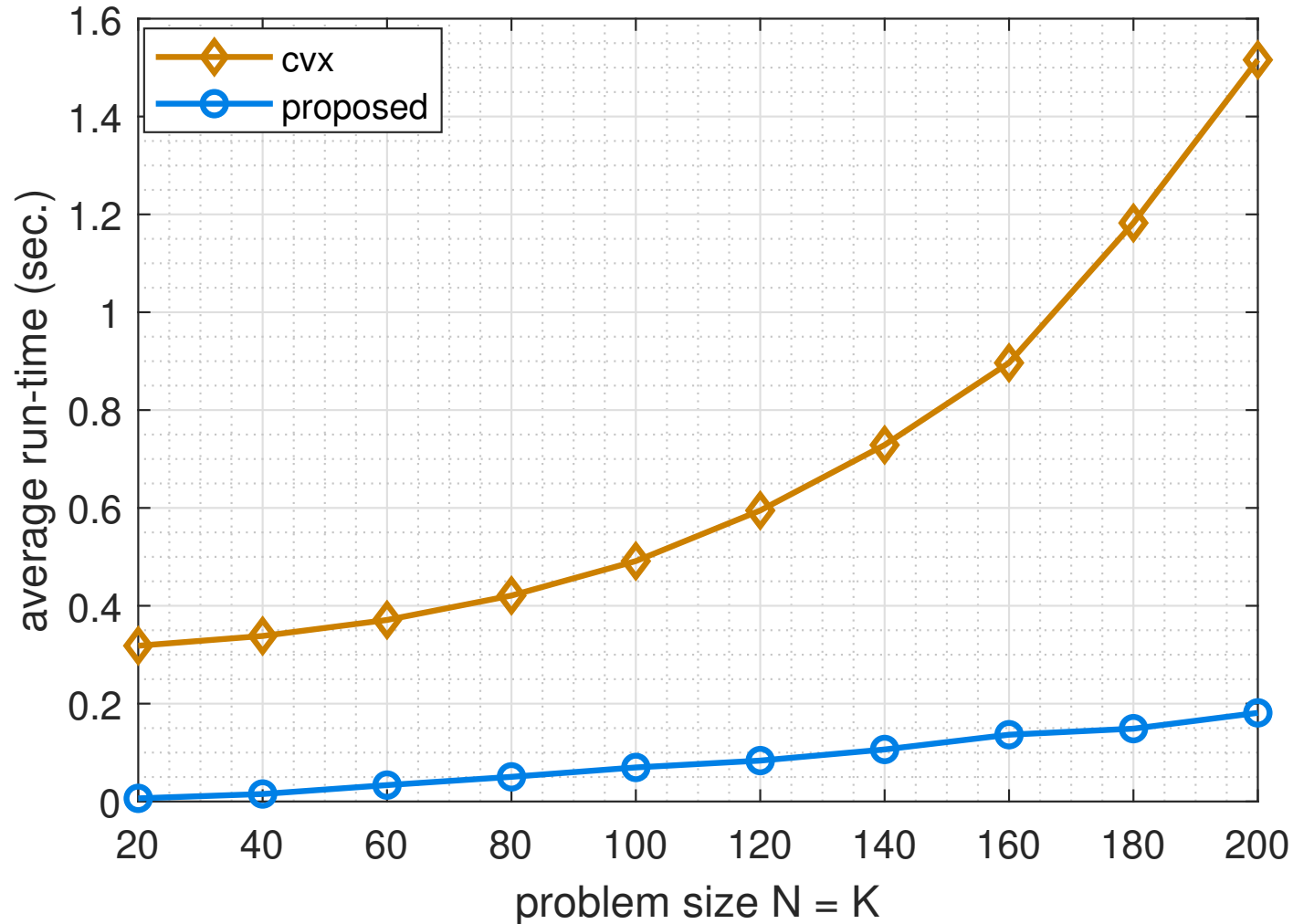
- (3) is SOCP but we don't call CVX; we custom-build an algo. by i) fixed point iterations & ii) QP with bounded constraints

# Experiment: Signal Power Versus Channel Error



- **settings:** problem size  $(N, K) = (8, 6)$ ;  $\text{SEP} \leq 10^{-3}$  for all users; noise  $\sim \mathcal{CN}(0, 1)$
- **benchmark:** robust linear beamforming in [MPSC17]

# Runtime Performance of the Proposed Algorithm



- **settings:** error bound  $\delta = 10^{-2}$ ;  $\text{SEP} \leq 10^{-3}$  for all users; noise  $\sim \mathcal{CN}(0, 1)$
- **benchmark:** use CVX to solve the original SLP problem (2) directly

# Take-home Points

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# Thank you!

**Upcoming in SPCOM-P5.4:** *Transmitting Data Through RIS: A Spatial Sigma-Delta Modulation Approach*, by W.-Y. Keung, H.-V. Cheng & W.-K. Ma

## Key References

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