



# Channel Estimation and Spectral Efficiency of Reflecting Intelligent Surface Aided Communications

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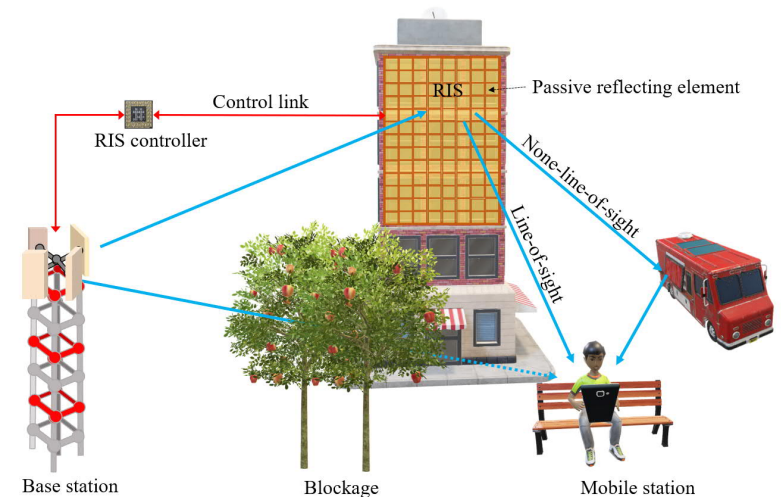
# Introduction

## – Reconfigurable intelligent surfaces (RISs)

- Low-cost and low-energy consumption passive reflecting elements
- Customize physical propagation environment
- Cost-efficient and energy-efficient

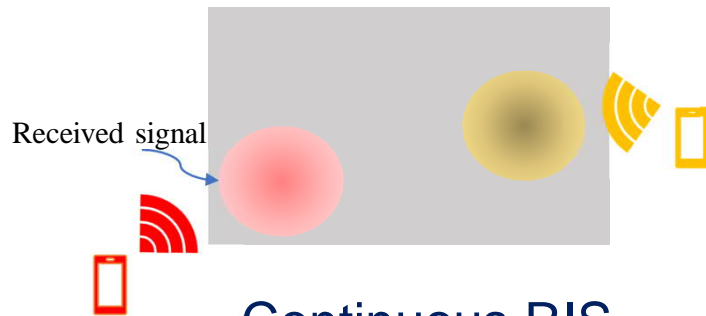
## – Challenges:

- Passive reflection in RISs limits the beamforming gains.
- Performance loss due to limited phase shift resolution.
- Channel estimation



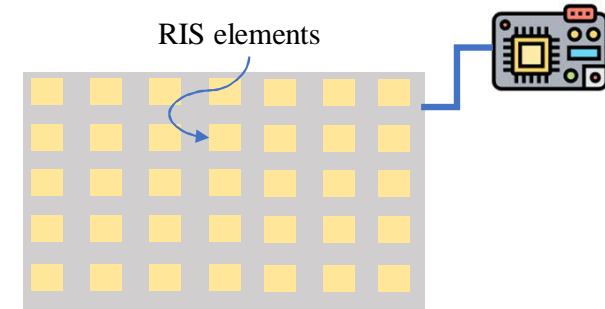


# What is a RIS? Continuous vs. Discrete



Continuous RIS

Mainly used as active transceivers



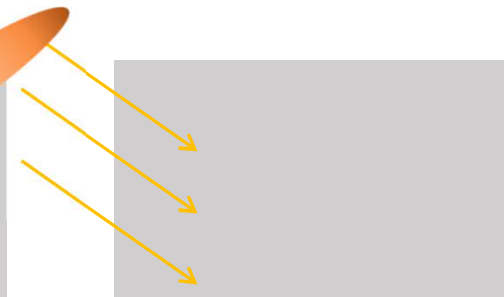
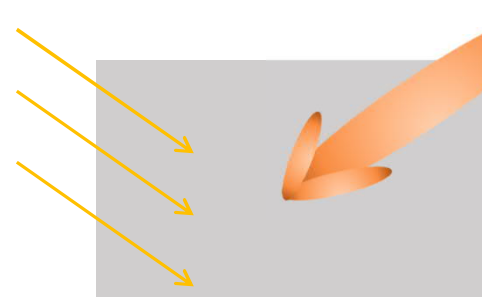
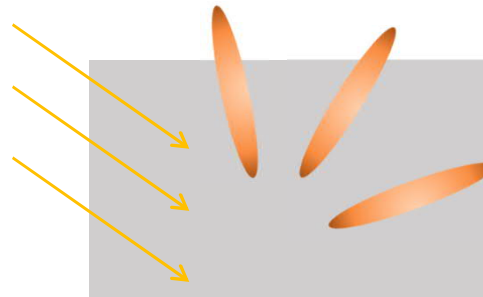
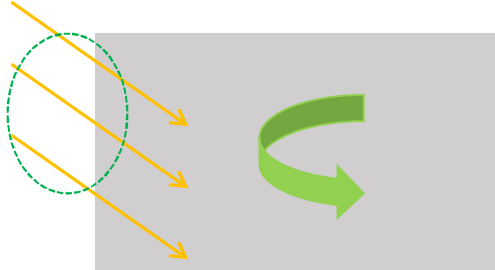
Discrete RIS

Mainly used as passive reflectors

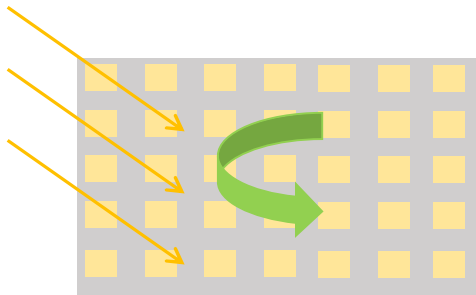


# RIS Operation Modes

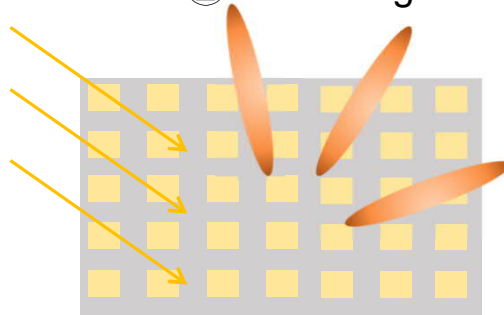
Incident signal



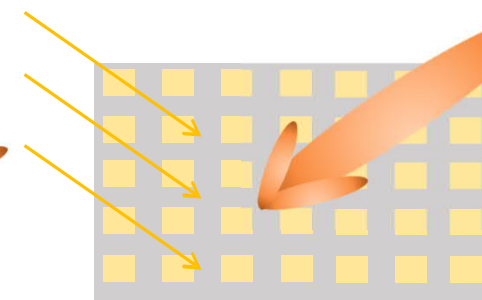
① Polarization



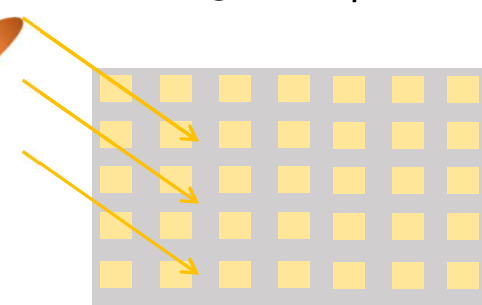
② Scattering



③ Beamforming



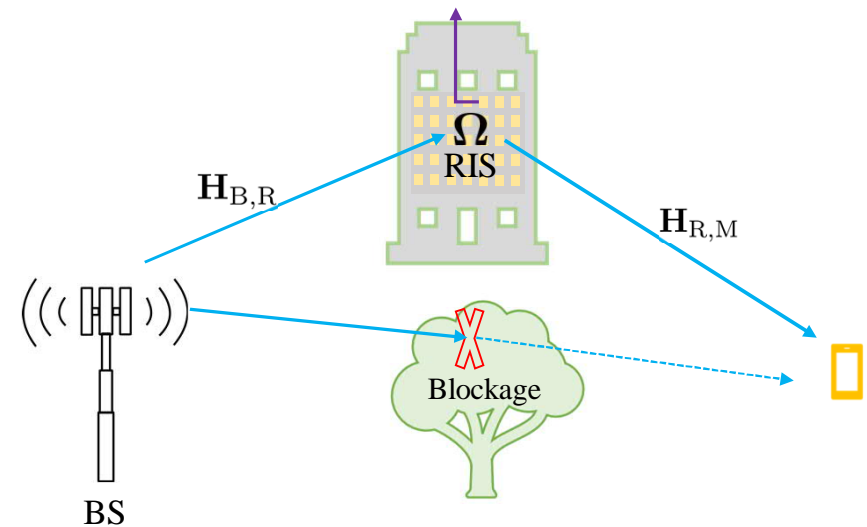
④ Absorption





# Channel Estimation with RIS

- RIS is a passive element.
- Channel observed in the final receiver only.
- Product channel observed
- Estimation of the component channels is difficult.



An example system application for downlink transmission.



# Channel Estimation Approaches

- Purely passive RIS based CE
- Two-stage approach with matrix factorization and completion [1]
- Matrix-calibration-based cascaded CE [2]
- Active sensors-based CE
- Deep learning [3]
- Compressive sensing [4]

[1] Z.-Q. He and X. Yuan, "Cascaded channel estimation for large intelligent metasurface assisted massive MIMO," IEEE Wireless Commun. Lett., vol. 9, no. 2, pp. 210–214, Feb. 2019.

[2] H. Liu, X. Yuan, and Y.-J. A. Zhang, "Matrix-calibration-based cascaded channel estimation for reconfigurable intelligent surface assisted multiuser MIMO," IEEE JSAC, 2020

[3] A. Taha, M. Alrabeiah, and A. Alkhateeb, "Enabling large intelligent surfaces with compressive sensing and deep learning," Apr. 2019.[Online]. Available: <https://arxiv.org/abs/1904.10136>

[4] R. Schroeder, J. He, and M. Juntti, "Passive RIS vs. Hybrid RIS: A Comparative Study on Channel Estimation", arXiv, 2020.



# Parametric Channel Model

- Direct channel between BS and RIS

$$\mathbf{H}_{B,R} = \sum_{l=0}^{L_{B,R}} \rho_{B,R,l} \boldsymbol{\alpha}(\phi_{B,R,l}) \boldsymbol{\alpha}^H(\theta_{B,R,l})$$

$\rho_{B,R,l}$ : Propagation path gains      $\phi_{B,R,l}$ : Angle of arrival      $\theta_{B,R,l}$ : Angle of departure      $\boldsymbol{\alpha}(\cdot)$ : Array response vector

$$= \mathbf{A}(\phi_{B,R}) \text{diag}(\rho_{B,R}) \mathbf{A}^H(\theta_{B,R})$$

$l = 0$  : LoS path  
 $l \geq 1$  : NLoS paths

- Composite channel

$$\Omega = \text{diag}(\exp\{j\omega_1\}, \dots, \exp\{j\omega_{N_R}\}) \in \mathbb{C}^{N_R \times N_R}$$

RIS phase control matrix ⇒ Diagonal, unit-modulus

$$\mathbf{H} = \mathbf{H}_{R,M} \Omega \mathbf{H}_{B,R}$$

Tandem channels via RIS



# Proposed Channel Sounding [He-21]

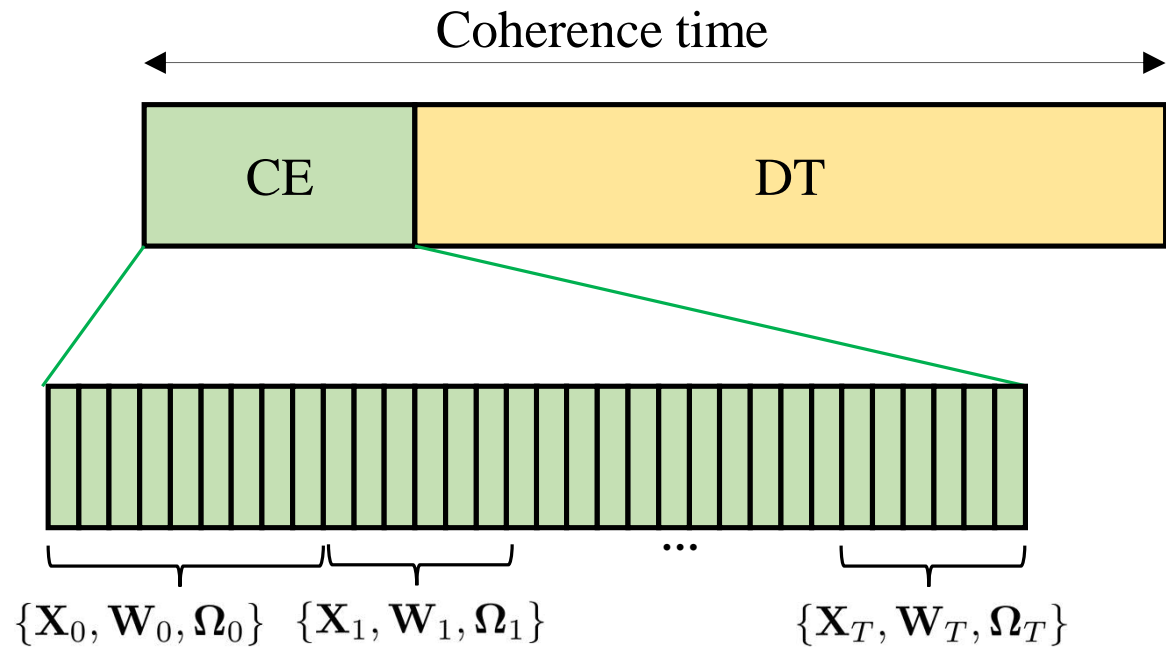
- CE and DT
- CE divided multi-sub-blocks

Stage 1 sounding

$$\mathbf{Y}_0 = \mathbf{W}_t^H \mathbf{H}(\Omega_0) \mathbf{X}_t + \mathbf{W}_t^H \mathbf{Z}_0, \quad t = 0$$

Stage 2 sounding

$$\mathbf{Y}_t = \mathbf{W}_t^H \mathbf{H}(\Omega_t) \mathbf{X}_t + \mathbf{W}_t^H \mathbf{Z}_t, \quad t = 1, \dots, T$$



Note that we try different phase control matrices





# Two-Stage Channel Estimation

## - Stage 1 CE

To be estimated

$$\mathbf{H} = \mathbf{A}(\phi_{R,M}) \mathbf{G}_0 \mathbf{A}^H(\theta_{B,R})$$

$$\mathbf{G}_0 = \text{diag}(\rho_{R,M}) \mathbf{A}^H(\theta_{R,M}) \mathbf{\Omega}_0 \mathbf{A}(\phi_{B,R}) \text{diag}(\rho_{B,R}),$$

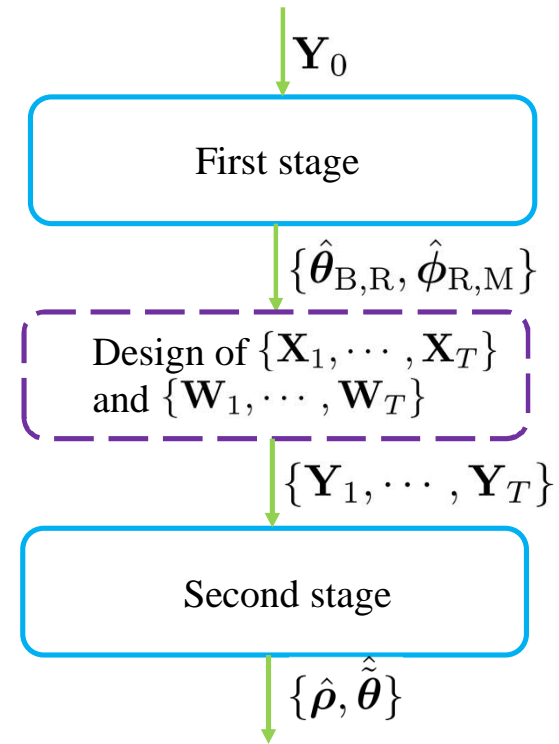
## - Stage 2 CE

$$\mathbf{X}_t = \frac{1}{\sqrt{N_B}} \mathbf{A}(\hat{\theta}_{B,R}), \quad \Rightarrow \quad \mathbf{A}^H(\theta_{B,R}) \mathbf{X}_t \approx \sqrt{N_B} \mathbf{I},$$

$$\mathbf{W}_t = \frac{1}{\sqrt{N_M}} \mathbf{A}(\hat{\phi}_{R,M}) \quad \Rightarrow \quad \mathbf{W}_t^H \mathbf{A}(\phi_{R,M}) \approx \sqrt{N_M} \mathbf{I}.$$

For  $t = 1, \dots, T$

Usually  $L_{B,R}$  and  $L_{R,M}$  are quite small!





# Atomic Norm Minimization (AMN)

– Stage 1:  $\phi_{R,M} \min \frac{\mu}{2} \|\bar{\mathbf{U}}\|_{\mathcal{A}_M} + \frac{1}{2} \|\mathbf{Y}_0 - \mathbf{W}_0^H \bar{\mathbf{U}}\|_F^2, \quad \theta_{B,R} \min \frac{\eta}{2} \|\tilde{\mathbf{U}}\|_{\mathcal{A}_M} + \frac{1}{2} \|\mathbf{Y}_0^H - \mathbf{X}_0^H \tilde{\mathbf{U}}\|_F^2,$

$$\bar{\mathbf{U}} = \mathbf{A}(\phi_{R,M}) \mathbf{G}_0 \mathbf{A}^H(\theta_{B,R}) \mathbf{X}_0 = \mathbf{A}(\phi_{R,M}) \bar{\mathbf{C}} \quad \tilde{\mathbf{U}} = \mathbf{A}(\theta_{B,R}) \mathbf{G}_0^H \mathbf{A}^H(\phi_{R,M}) \mathbf{W}_0 = \mathbf{A}(\theta_{B,R}) \tilde{\mathbf{C}}$$

$$\bar{\mathbf{C}} = \mathbf{G}_0 \mathbf{A}_t^H(\theta_{B,R}) \mathbf{X}_0$$

$$\tilde{\mathbf{C}} = \mathbf{G}_0^H \mathbf{A}^H(\phi_{R,M}) \mathbf{W}_0$$

– Stage 2:

$$\{\hat{\mathbf{v}}, \hat{\mathbf{h}}_i, \hat{z}\} = \arg \min_{\mathbf{v}, \mathbf{h}_i, z} 0.5 \nu_i z + \frac{\nu_i}{2N_R} \text{Tr}(\text{Toep}(\mathbf{v}))$$

$$+ \frac{1}{2} \|\mathbf{[Y]}_{i,:}^T - \sqrt{N_B N_M} \bar{\mathbf{\Omega}} \mathbf{h}_i\|_2^2$$

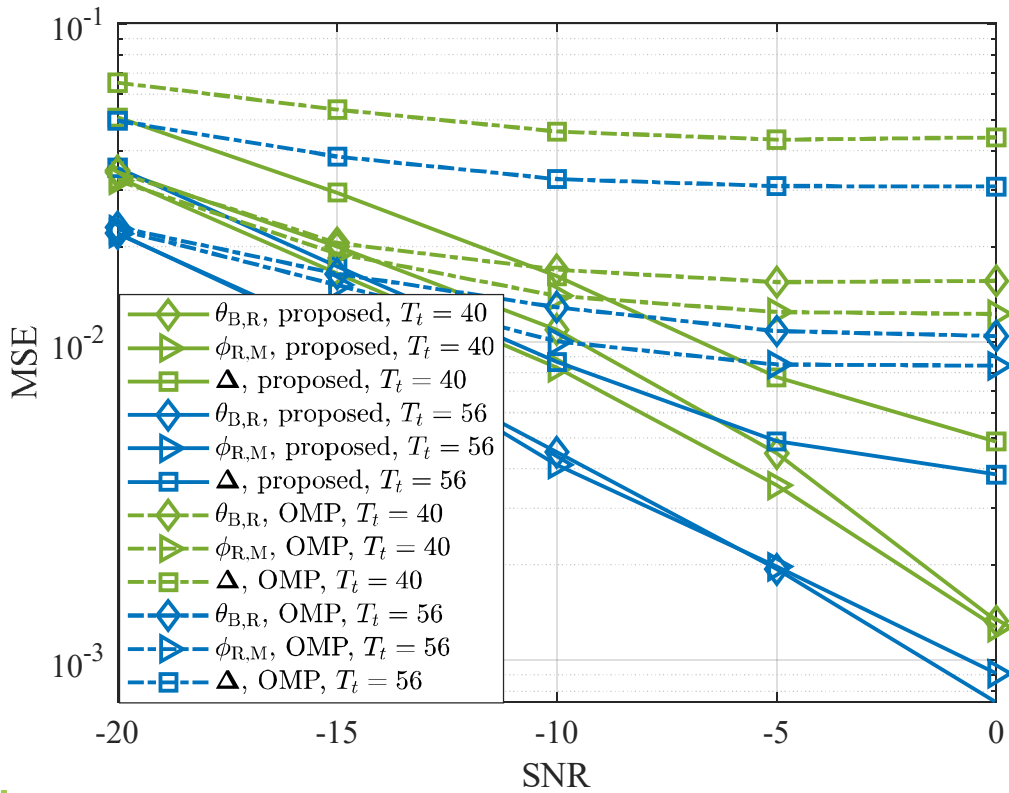
$$\text{s.t.} \begin{bmatrix} \text{Toep}(\mathbf{v}) & \mathbf{h}_i \\ \mathbf{h}_i^H & z \end{bmatrix} \succeq \mathbf{0}, \text{ for } i = 1, \dots, L_{B,R} L_{R,M},$$

$$\hat{\rho}_i = (\boldsymbol{\alpha}(\hat{\theta}_i))^\dagger \hat{\mathbf{h}}_i,$$

$$\mathbf{h}_i = \rho_i \boldsymbol{\alpha}(\tilde{\theta}_i)$$



# Estimation Performance



$$\text{MSE}(\sin(\theta_{B,R})) = \mathbb{E} \left[ \frac{\|\sin(\theta_{B,R}) - \sin(\hat{\theta}_{B,R})\|_2^2}{L_{B,R}} \right],$$

$$\text{MSE}(\sin(\phi_{R,M})) = \mathbb{E} \left[ \frac{\|\sin(\phi_{R,M}) - \sin(\hat{\phi}_{R,M})\|_2^2}{L_{R,M}} \right],$$

$$\text{MSE}(\sin(\Delta)) = \mathbb{E} \left[ \frac{\|\sin(\Delta) - \sin(\hat{\Delta})\|_F^2}{L_{B,R} L_{R,M}} \right],$$

$$[\Delta]_{mn} = \text{asin}(\sin([\phi_{B,R}]_n) - \sin([\theta_{R,M}]_m))$$

$$N_B = N_M = 16, N_R = 32$$

$$L_{B,R} = L_{R,M} = 2$$

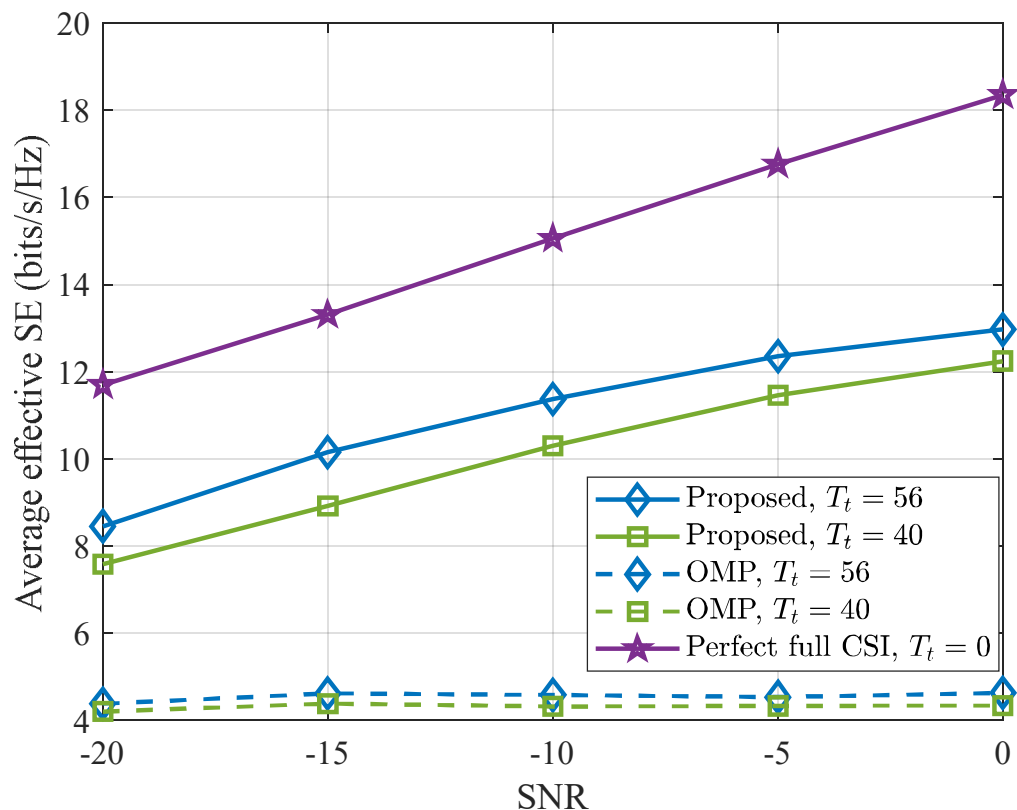
Training overhead 1

$$N_0 = M_0 = T = 10 \text{ with } T_t = 40$$

Training overhead 2

$$N_0 = M_0 = T = 14 \text{ with } T_t = 56$$

# Spectral Efficiency Performance



$$R = \mathbb{E} \left[ \frac{T_c - T_t}{T_c} \log_2 \left( 1 + \frac{|\mathbf{w}^H \hat{\mathbf{H}} \mathbf{f}|^2}{\sigma^2 + \text{var}(\mathbf{w}^H \mathbf{H}_e(\boldsymbol{\Omega}^*) \mathbf{f})} \right) \right]$$

$$N_B = N_M = 16, N_R = 32$$

$$L_{B,R} = L_{R,M} = 2$$

Training overhead 1

$$N_0 = M_0 = T = 10 \text{ with } T_t = 40$$

Training overhead 2

$$N_0 = M_0 = T = 14 \text{ with } T_t = 56$$



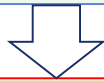
# Summary and Conclusions

- RIS channel estimation is challenging and not always feasible
- We assumed *known sparse channel structure* to derive a superresolution algorithm based on ANM.
- Two-stage optimization problems.
- RIS phase control matrix designed to maximize the power of effective channel based on the estimates in the second stage.
- Joint beamforming at BS and MS
- Active receiver at RIS could enhance and simplify CE.

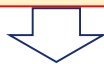


# Hybrid Relay – RIS [Nguyen-21]

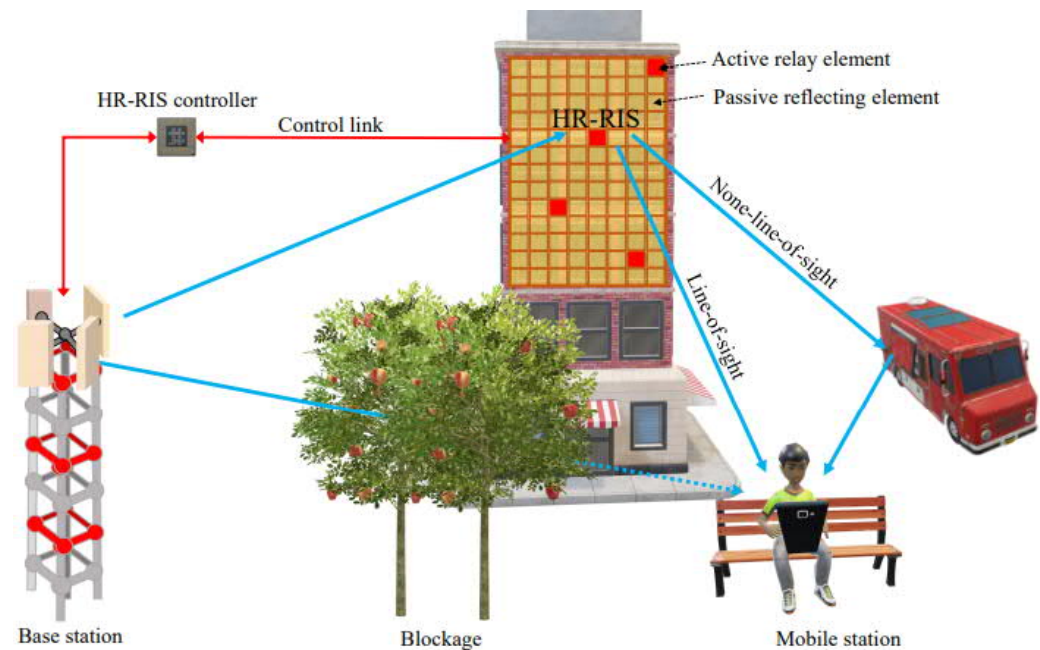
- Very large RISs are required [1], [2].
- A few more elements only provide small gain.



*Replacing a few passive elements by relays:*  
⇒ *Small loss in passive BF gains*  
⇒ *Significant active relaying gains*



**Hybrid relay-reflecting intelligent surface (HR-RIS)**



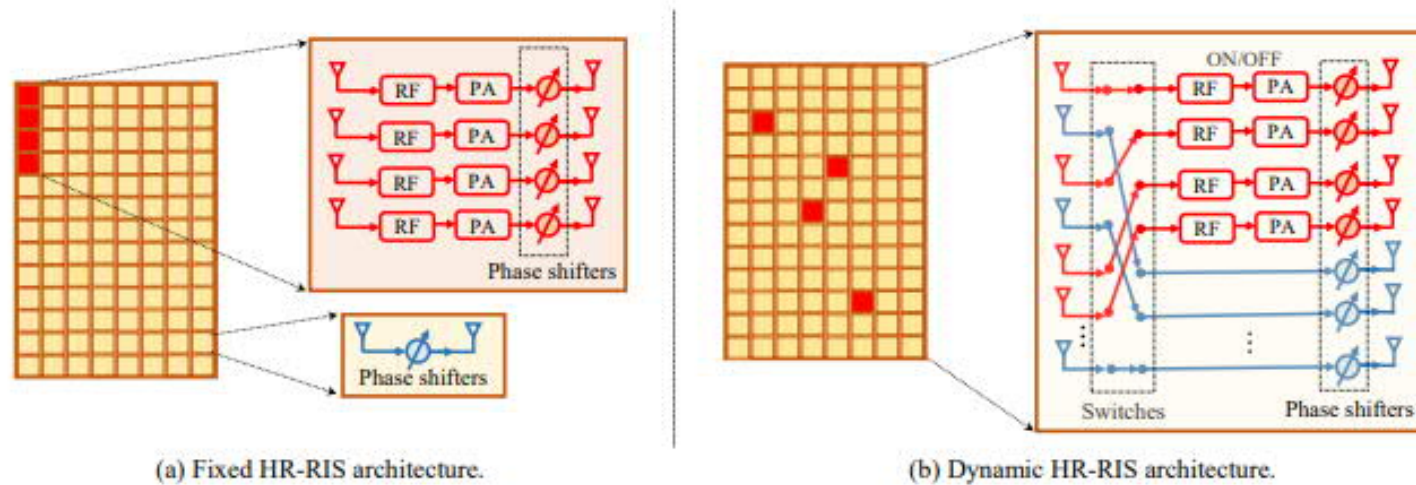
[1] Q. Wu and R. Zhang, "Intelligent reflecting surface enhanced wireless network via joint active and passive beamforming," *IEEE Trans. Wireless Commun.*, vol. 18, no. 11, pp. 5394–5409, Aug. 2019.

[2] E. Bjornson, O. Ozdogan, and E. G. Larsson, "Intelligent reflecting " surface versus decode-and-forward: How large surfaces are needed to beat relaying?" *IEEE Wireless Commun. Lett.*, vol. 9, no. 2, pp. 244–248, Oct. 2020.

T. N. Nguyen, Q.-D. Vu, K. C. Lee & M. Juntti, "Hybrid relay-reflecting intelligent surface-assisted wireless communication". *IEEE Transactions on Signal Processing*, submitted February 2021. <https://arxiv.org/abs/2103.03900>



# HR-RIS Architectures



- Configure and fix in advance during manufacturing  $\Rightarrow$  **fixed** HR-RIS architecture [3]
- Dynamically optimize based on CSI  $\Rightarrow$  **dynamic** HR-RIS architecture [3]
- Active element: RF, power amp., phase shifter
- Passive element: only phase shifter



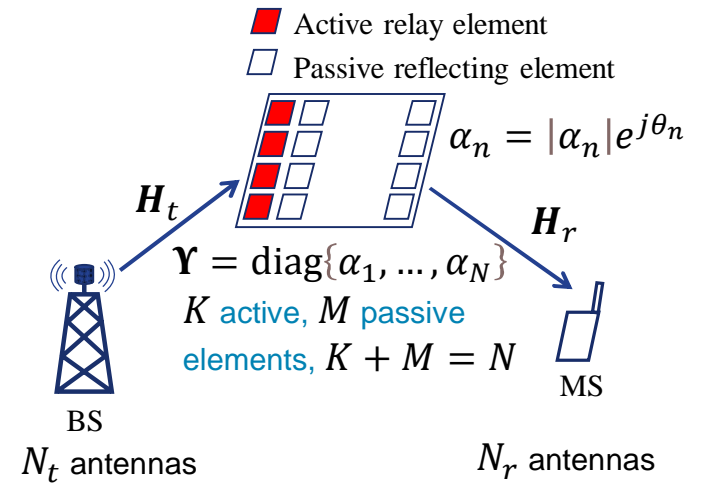
# System Model

– The received signal at the MS:

$$y = \underbrace{H_r \Phi H_t x}_{\text{reflected signal}} + \underbrace{H_r \Psi H_t x}_{\text{relayed signal}} + \underbrace{H_r \Psi n_H}_{\text{amplified noise}} + \underbrace{n_{MS}}_{\text{noise at MS}} \quad (1)$$

- $H_r \Psi n_H \sim CN(\mathbf{0}, \sigma^2 H_r \Psi \Psi^H H_r^H)$
- $n_{MS} \sim CN(\mathbf{0}, \sigma^2 I_{N_r})$
- $n \triangleq H_r \Psi n_H + n_{MS} \sim CN(\mathbf{0}, \sigma^2 (I_{N_r} + H_r \Psi \Psi^H H_r^H))$

$$\Rightarrow y = H_r \Upsilon H_t x + n \quad (2)$$



$\mathbb{A}$ : positions of  $K$  active elements

$$\Upsilon = \Phi + \Psi$$

$\Psi$  contains only active coefficients

$\Phi$  contains only passive coefficients





# SE Maximization

- Spectral efficiency (SE)

$$f_0(\{\alpha_n\}) = \log_2 |\mathbf{I}_{N_r} + \rho \mathbf{H}_r \mathbf{\Upsilon} \mathbf{H}_t \mathbf{H}_t^H \mathbf{\Upsilon}^H \mathbf{H}_r^H \mathbf{R}^{-1}| \quad (3)$$

$$\leq \log_2 |\mathbf{R} + \rho \mathbf{H}_r \mathbf{\Upsilon} \mathbf{H}_t \mathbf{H}_t^H \mathbf{\Upsilon}^H \mathbf{H}_r^H| \triangleq f(\{\alpha_n\}) \quad (4)$$

$$\mathbf{R} = \mathbf{I}_{N_r} + \mathbf{H}_r \mathbf{\Psi} \mathbf{\Psi}^H \mathbf{H}_r^H, \rho = P_{BS}/\sigma^2$$

- Transmit power of active elements:  $P_a = \text{trace}(\mathbf{\Psi}(P_{BS} \mathbf{H}_t \mathbf{H}_t^H + \sigma^2 \mathbf{I}_{N_r}) \mathbf{\Psi}^H)$  (5)
- HR-RIS is designed to maximize the SE

$$(P0) \left\{ \begin{array}{ll} \text{maximize} & f(\{\alpha_n\}) \\ & \{\alpha_n\} \\ \text{subject to} & |\alpha_n| = 1, \forall n \in \mathbb{A} \\ & P_a \leq P_a^{max} \end{array} \right.$$



# Alternating Optimization Approach

- Let  $\mathbf{r}_n$  be the  $n$ th column of  $\mathbf{H}_r$ ,  $\mathbf{t}_n^H$  be the  $n$ th row of  $\mathbf{H}_t$ .
- $\mathbf{Y}$  and  $\mathbf{\Psi}$  are diagonal  $\Rightarrow \mathbf{H}_r \mathbf{Y} \mathbf{H}_t = \sum_{n=1}^N \alpha_n \mathbf{r}_n \mathbf{t}_n^H$ ,  $\mathbf{H}_r \mathbf{\Psi} = \sum_{n=1}^N \alpha_n \mathbf{r}_n$ . (6)

$$\Rightarrow f(\alpha_n) = \log_2 |\mathbf{A}_n + |\alpha_n|^2 \mathbf{B}_n + \alpha_n \mathbf{C}_n + \alpha_n^* \mathbf{C}_n^H| \quad (7)$$

$$P_a = \sum_{n \in \mathbb{A}} |\alpha_n|^2 \xi_n, \text{ where } \xi_n = \sigma^2 + P_{BS} \|\mathbf{t}_n\|^2$$

( $\mathbf{A}_n$ ,  $\mathbf{B}_n$ , and  $\mathbf{C}_n$  are all independent of  $\alpha_n$ .)

$$(P) \begin{cases} \text{maximize} & f(\alpha_n) \\ & \alpha_n \\ \text{subject to} & |\alpha_n| = 1, n \notin \mathbb{A} \\ & |\alpha_n|^2 \leq \frac{P_a^{max} - \sum_{i \in \mathbb{A}, i \neq n} |\alpha_i|^2 \xi_i}{\xi_n}, n \in \mathbb{A} \end{cases}$$

NN1    **Optimization -> Optimization**  
Nhan Nguyen, 20/04/2021



# Alternating Optimization (2)

$$\begin{aligned} f(\alpha_n) &= \log_2 |\mathbf{A}_n + |\alpha_n|^2 \mathbf{B}_n + \alpha_n \mathbf{C}_n + \alpha_n^* \mathbf{C}_n^H| \\ &= \log_2 |\mathbf{A}_n| + \log_2 \underbrace{|\mathbf{I}_{N_r} + |\alpha_n|^2 \mathbf{A}_n^{-1} \mathbf{B}_n + \alpha_n \mathbf{A}_n^{-1} \mathbf{C}_n + \alpha_n^* \mathbf{A}_n^{-1} \mathbf{C}_n^H|}_{\triangleq \mathbf{D}_n} \\ &= \log_2 |\mathbf{A}_n| + \log_2 |\mathbf{D}_n| + \log_2 |\mathbf{I}_{N_r} + \alpha_n \mathbf{E}_n^{-1} \mathbf{C}_n + \alpha_n^* \mathbf{E}_n^{-1} \mathbf{C}_n^H| \quad (\mathbf{E}_n \triangleq \mathbf{A}_n \mathbf{D}_n) \\ &= \log_2 |\mathbf{A}_n| + \log_2 (1 + |\alpha_n|^2 \underbrace{\gamma_n}_{\text{sole non-zero eigenvalue of } \mathbf{A}_n^{-1} \mathbf{B}_n}) + \log_2 (1 + |\alpha_n|^2 \underbrace{|\lambda_n|^2}_{\text{sole non-zero eigenvalue of } \mathbf{E}_n^{-1} \mathbf{C}_n} + 2\Re(\alpha_n \lambda_n) + c_n) \quad [4] \end{aligned} \quad (8)$$

- Phase of  $\alpha_n^*$  is  $-\arg\{\lambda_n\}$
- $f(\alpha_n^*)$  monotonically increases with  $|\alpha_n^*|$

$$\alpha_n^* = \begin{cases} \sqrt{\frac{P_a^{\max} - \bar{P}_a}{\xi_n}} e^{-j \arg\{\lambda_n\}}, n \in \mathbb{A} \\ e^{-j \arg\{\lambda_n\}}, \text{ otherwise} \end{cases} \quad (9)$$



# Alternating Optimization Algorithm

$$|\alpha_n^*|^2 = \frac{P_a^{max} - \sum_{i \in \mathbb{A}, i \neq n} |\alpha_i|^2 \xi_i}{\sigma^2 + P_{BS} \|\mathbf{t}_n\|^2}, n \in \mathbb{A} \quad (10)$$

→ With a limited power budget  $P_a^{max}$ , the HR-RIS with a small number of active elements is easier to attain SE gains.

→ With a fixed  $P_a^{max}$ , a lower  $P_{BS}$  and/or smaller  $\|\mathbf{t}_n\|^2$  (caused by severe path loss) can result in a higher  $|\alpha_n^*|^2$ , and thus, provide a higher SE gains.

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**Algorithm 1** Find  $\Upsilon^*$  for HR-RIS

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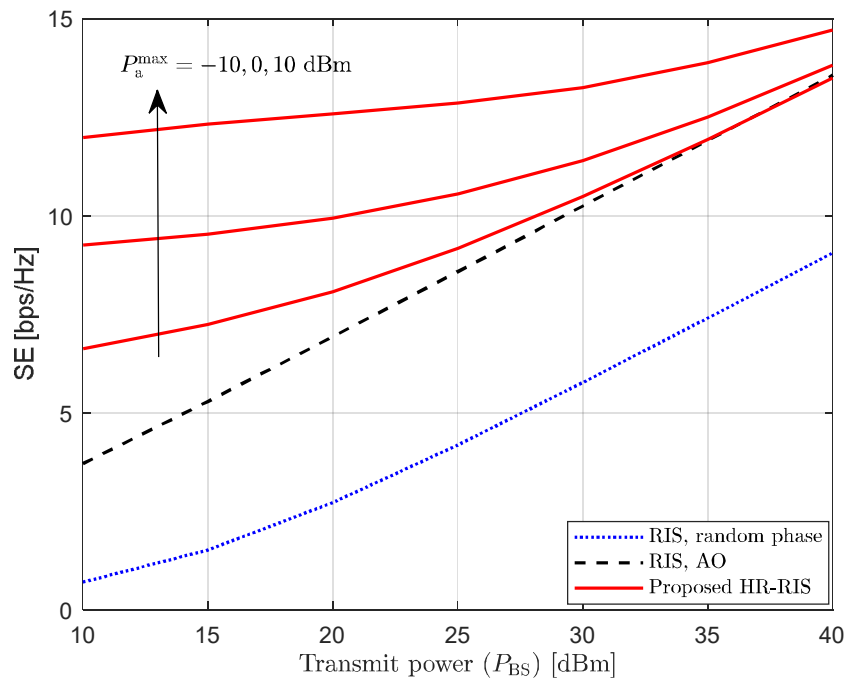
**Input:**  $H_t, H_r, \mathbb{A}$ .

**Output:**  $\Upsilon^*$ .

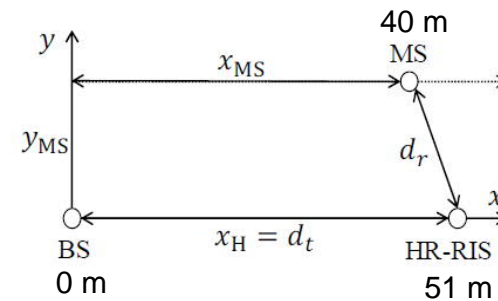
- 1: Randomly generate  $\{\alpha_n\}$  with  $|\alpha_n| = 1$  for  $n \notin \mathbb{A}$  and  $\sum_{n \in \mathbb{A}} |\alpha_n|^2 \xi_n = P_a^{max}$  for  $n \in \mathbb{A}$ .
  - 2: **while** not converge **do**
  - 3:   **for**  $n = 1 \rightarrow N$  **do**
  - 4:     Compute  $A_n, B_n$ , and  $C_n$  based on (9)-(14).
  - 5:      $D_n = I_{N_r} + |\alpha_n|^2 A_n^{-1} B_n$ ,  $E_n = A_n D_n$ .
  - 6:     Find  $\lambda_n$  as the sole non-zero eigenvalue of  $E_n^{-1} C_n$ .
  - 7:     Compute  $\alpha_n^*$  based on (23).
  - 8:   **end for**
  - 9:   Check convergence.
  - 10: **end while**
  - 11:  $\Upsilon^* = \text{diag} \{\alpha_1^*, \dots, \alpha_N^*\}$ .
-



# Example: SE vs. TX Power



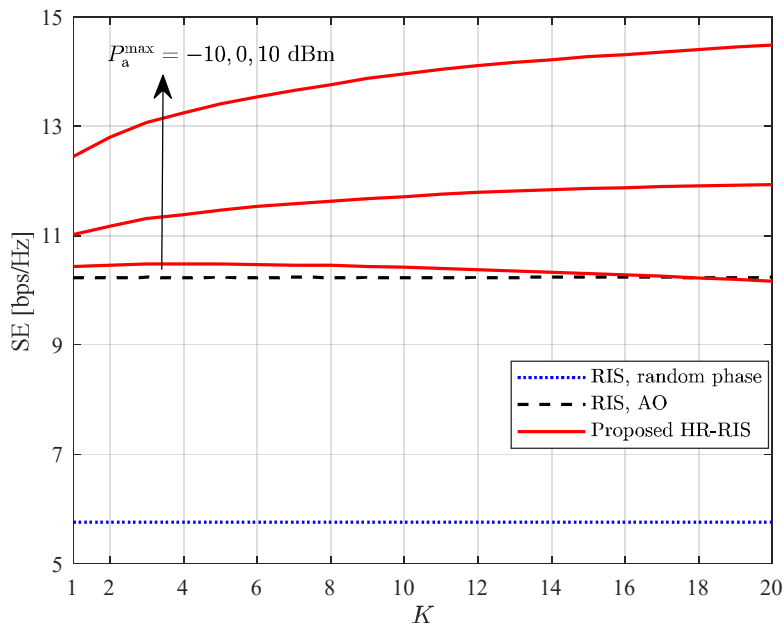
$$N_t = 32, N_r = 2, N = 50, K = 4$$



- The proposed HR-RIS scheme can provide significant improvement in SE compared with the conventional RIS.
- The SE improvement is more significant at low  $P_{BS}$ .



# Example: SE vs. No. Active Elements

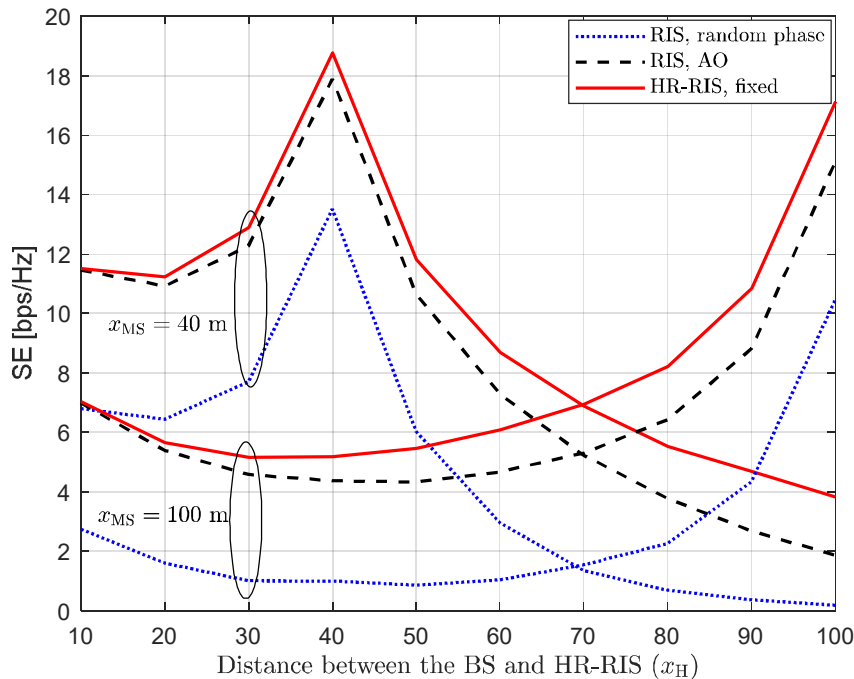


$$N_t = 32, N_r = 2, N = 50, P_{BS} = 30 \text{ dBm}$$

- Deploying more active elements at the HR-RIS does not always provide a higher SE.
- For low  $P_a^{max}$ , HR-RIS with a large number of active elements can have performance loss.



# Example: SE vs. Distance



- Both RIS and HR-RIS performs the best when they are close to the MS.
- When the RIS/HR-RIS moves far away from the BS, HR-RIS attains more significant active beamforming gains (due to more severe path loss).

$$N_t = 32, N_r = 2, N = 50, P_{BS} = 30 \text{ dBm}, \text{ and } P_a^{max} = 0 \text{ dBm}$$





# Summary and Conclusions

- HR-RIS can provide semi-passive beamforming gains to achieve higher SE compared to the conventional RIS.
- Only a few elements are connected to PA to serve as active relays, while the other serve as passive reflection elements.
- HR-RIS can be designed and optimized by alternating optimization:
  - A small number of active elements is sufficient for a satisfying SE gain. Deploying many active elements does not always provide higher SE.
  - HR-RIS can attain a more significant SE gain when the transmit power at the BS is small and/or when the BS-HR-RIS distance is large.



# Future Research

- Hybrid receive architectures can enhance the CE and positioning
- Position aware beamforming can enhance CE and communications
- SE and energy efficiency optimization of HR-RIS
- Implementation aspects