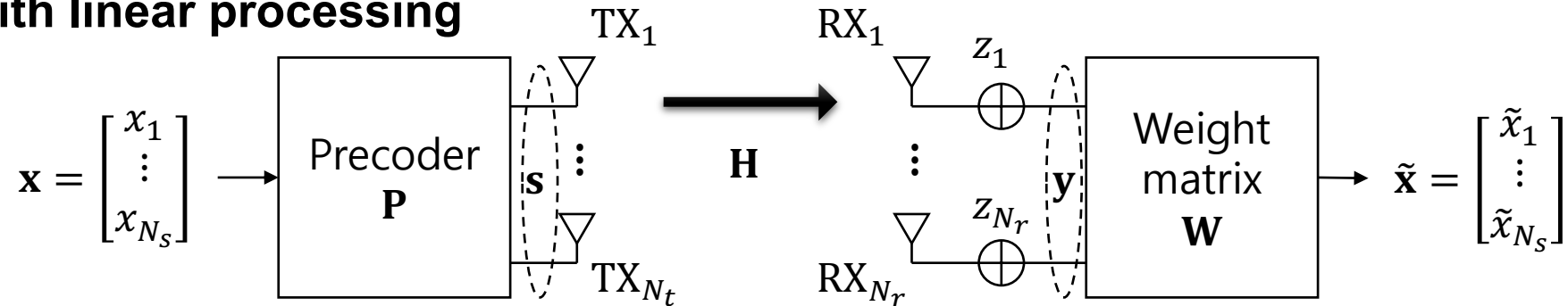


# Assignment 07

- **MIMO with linear processing**



- ① MIMO with linear processing

- MIMO without CSIT

- ② RxMF
- ③ RxZF
- ④ RxMMSE

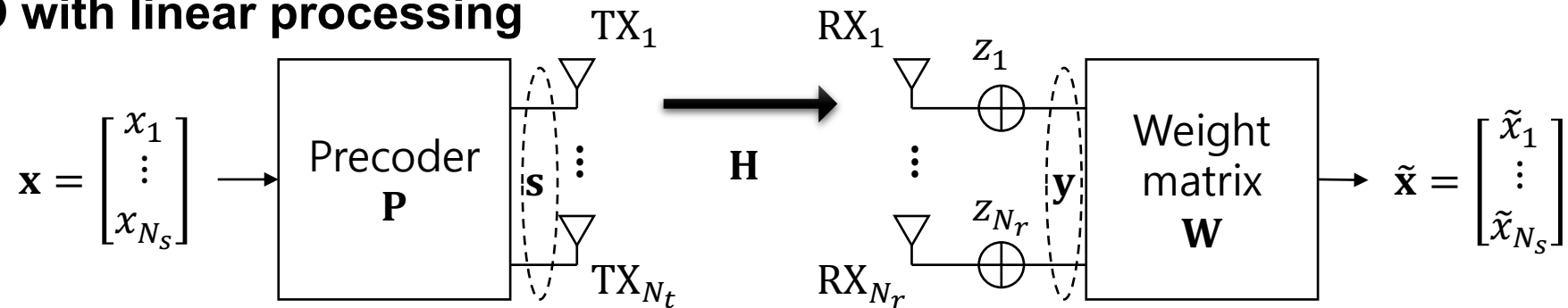
- MIMO with CSIT

- ⑤ Joint SVD

- ⑥ Numerical results

# Assignment 07

## • ① MIMO with linear processing



- Let  $x_i, \forall i = 1, \dots, N_s$  and  $z_i, \forall i = 1, \dots, N_r$  follow zero-mean complex Gaussian distributions.
- Define  $\mathbf{R}_x \triangleq E[\mathbf{x}\mathbf{x}^H] = \mathbf{I}_{N_s}$ ,  $\mathbf{R}_z \triangleq E[\mathbf{z}\mathbf{z}^H]$ ,  $E_s \triangleq E[|\mathbf{s}|^2]$ ,  $N_s \triangleq r = \text{rank}(\mathbf{H}) = \min(N_t, N_r)$ .
- (1) Specify the dimensions of  $\mathbf{P}, \mathbf{H}, \mathbf{W}$ .

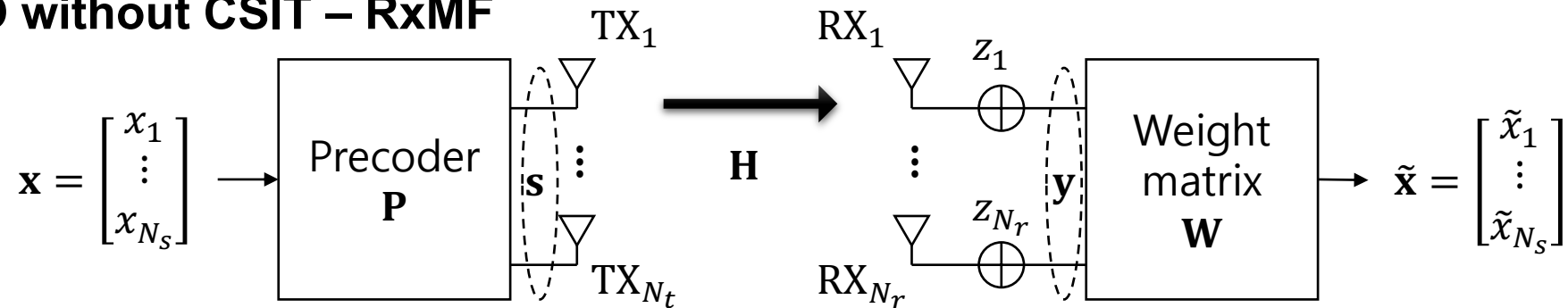
- (2) Write an expression of the post-processed signal  $\tilde{\mathbf{x}}$  in terms of  $\mathbf{W}, \mathbf{H}, \mathbf{P}, \mathbf{x}, \mathbf{z}$ .

- (3) Show that  $E[|\mathbf{s}|^2] = \|\mathbf{P}\|_F^2 = E_s$ .

- 2 • (4) Show that the capacity is expressed by  $C = \log_2 |\mathbf{I}_{N_s} + (\mathbf{W}\mathbf{R}_z\mathbf{W}^H)^{-1}\mathbf{W}\mathbf{H}\mathbf{P}\mathbf{P}^H\mathbf{H}^H\mathbf{W}^H|$ .

# Assignment 07

## • ② MIMO without CSIT – RxMF



- We maximize the correlation between  $\mathbf{x}$  and  $\tilde{\mathbf{x}}$ .
  - Correlation = Cosine  $\propto$  Inner product
  - “Matched” = “Parallel”
- At the same time, we want to minimize the noise portion of  $\tilde{\mathbf{x}}$ .
- Thus, we solve the following problem:

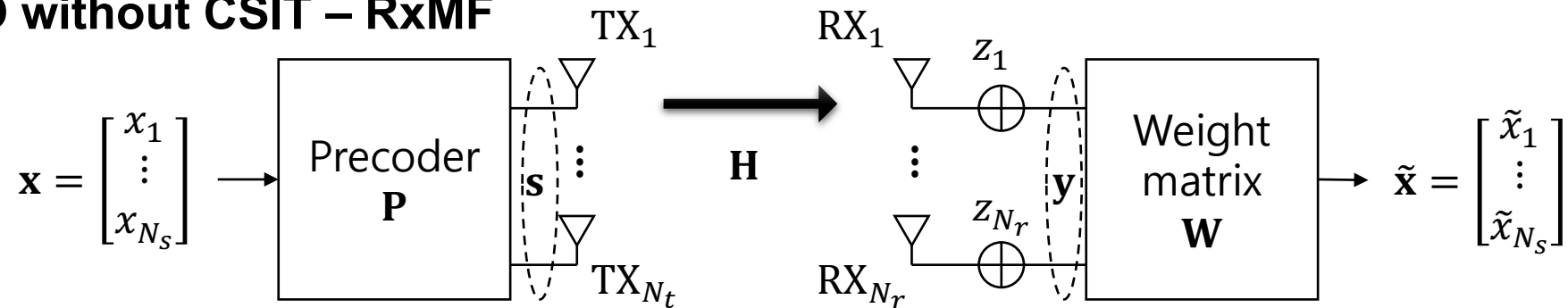
$$\max_{\mathbf{W}} \frac{E[\mathbf{x}^H \tilde{\mathbf{x}}]}{E[|\mathbf{W}\mathbf{z}|^2]}$$

- Since the objective function is a ratio, we may fix the denominator to some  $\delta > 0$  without altering the optimal value.

$$\begin{aligned} &\max_{\mathbf{W}} E[\mathbf{x}^H \tilde{\mathbf{x}}] \\ &\text{s.t. } E[|\mathbf{W}\mathbf{z}|^2] = \delta \end{aligned}$$

# Assignment 07

- ② MIMO without CSIT – RxMF



- (1) Show that  $E[\mathbf{x}^H \tilde{\mathbf{x}}] = \text{tr}(\mathbf{WHP})$  and  $E[|\mathbf{Wz}|^2] = \text{tr}(\mathbf{WR}_z \mathbf{W}^H)$ .

- Using the method of Lagrangian multipliers,

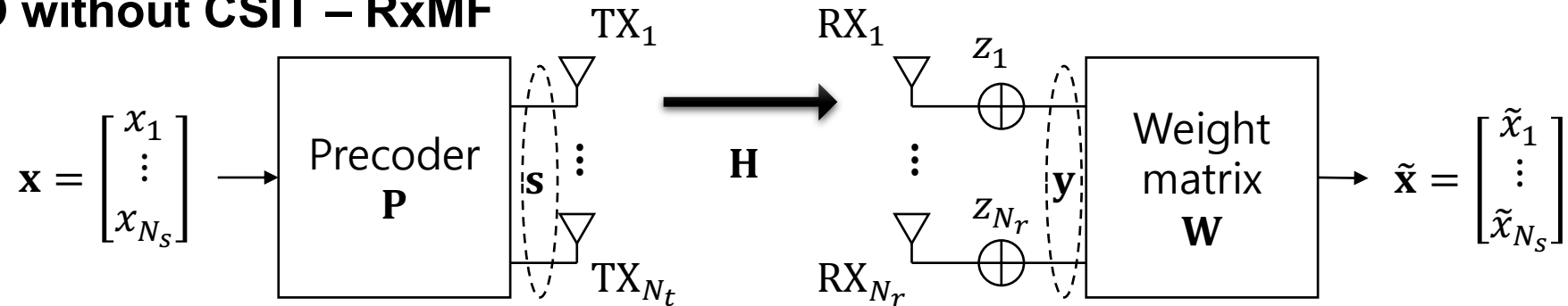
$$\begin{aligned} & \max_{\mathbf{W}} \text{tr}(\mathbf{WHP}) \\ & \text{s.t. } \text{tr}(\mathbf{WR}_z \mathbf{W}^H) = \delta \end{aligned}$$

- The optimal solution is one of the stationary points with  $\frac{\partial g(\mathbf{W}, \lambda)}{\partial \mathbf{W}} = 0, \frac{\partial g(\mathbf{W}, \lambda)}{\partial \lambda} = 0$ .

$$\max_{\mathbf{W}} g(\mathbf{W}, \lambda) \triangleq \text{tr}(\mathbf{WHP}) + \lambda(\text{tr}(\mathbf{WR}_z \mathbf{W}^H) - \delta)$$

# Assignment 07

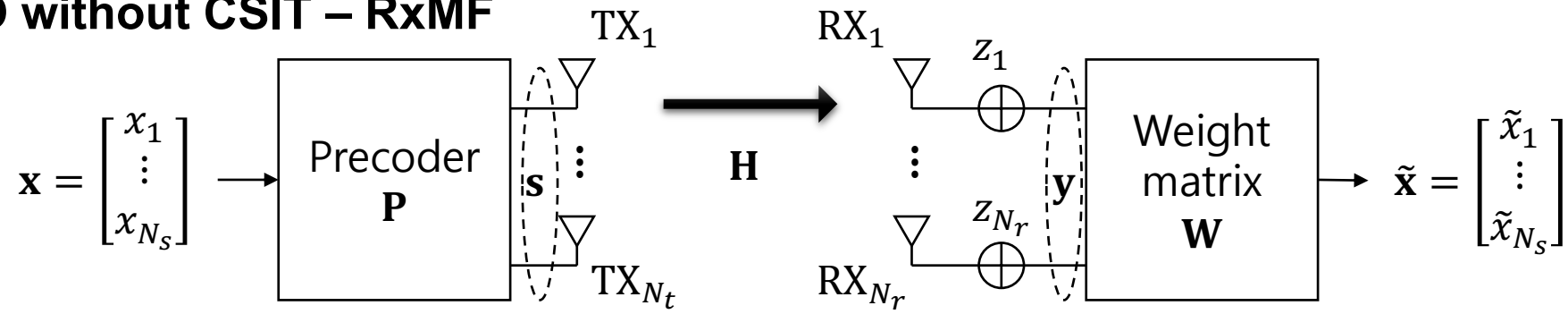
## • ② MIMO without CSIT – RxMF



- (2) Show that  $\frac{\partial g(\mathbf{W}, \lambda)}{\partial \mathbf{W}} = (\mathbf{H}\mathbf{P})^T + \lambda \mathbf{W}^* \mathbf{R}_z^T$  and  $\frac{\partial g(\mathbf{W}, \lambda)}{\partial \lambda} = \text{tr}(\mathbf{W} \mathbf{R}_z \mathbf{W}^H) - \delta$ .
- (3) Letting  $\frac{\partial g(\mathbf{W}, \lambda)}{\partial \mathbf{W}} = \mathbf{0}$ , show that  $\mathbf{W}_{\text{opt}} = -\frac{1}{\lambda} \mathbf{P}^H \mathbf{H}^H \mathbf{R}_z^{-1}$ .
- (4) Letting  $\frac{\partial g(\mathbf{W}, \lambda)}{\partial \lambda} = 0$ , show that  $\lambda_{\text{opt}} = \pm \sqrt{\frac{1}{\delta} \text{tr}(\mathbf{P}^H \mathbf{H}^H \mathbf{R}_z^{-1} \mathbf{H} \mathbf{P})}$ .
- Since  $\delta > 0$  can be freely chosen,  $\lambda_{\text{opt}}$  can also be freely chosen.
- For simplicity, we let  $\delta = \text{tr}(\mathbf{P}^H \mathbf{H}^H \mathbf{R}_z^{-1} \mathbf{H} \mathbf{P})$  and  $\lambda_{\text{opt}} = -1$  such that  $\mathbf{W}_{\text{opt}} = \mathbf{P}^H \mathbf{H}^H \mathbf{R}_z^{-1}$ .
- (5) Show that  $C = \log_2 |\mathbf{I}_{N_s} + \mathbf{P}^H \mathbf{H}^H \mathbf{R}_z^{-H} \mathbf{H} \mathbf{P}|$ .

# Assignment 07

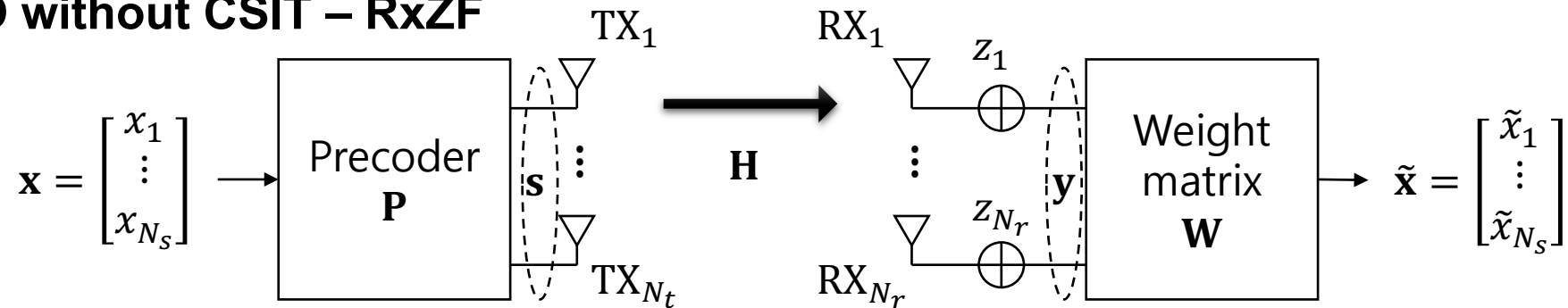
- ② MIMO without CSIT – RxMF



- (6) For AWGN, i.e.,  $\mathbf{R}_z = \sigma_z^2 \mathbf{I}_{N_r}$ , show that  $C = \log_2 \left| \mathbf{I}_{N_s} + \frac{1}{\sigma_z^2} \mathbf{P}^H \mathbf{H}^H \mathbf{H} \mathbf{P} \right|$ .

# Assignment 07

## • ③ MIMO without CSIT – RxZF



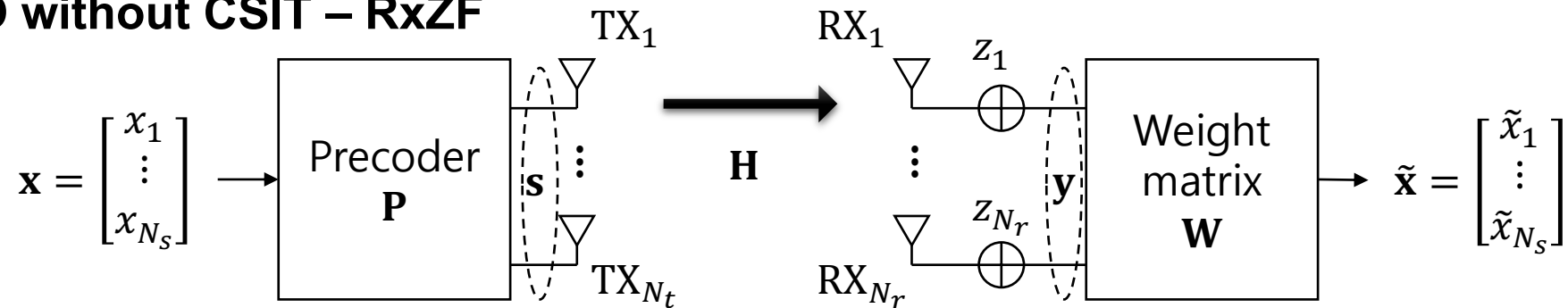
- We suppress the inter-symbol interference in  $\tilde{\mathbf{x}}$  by diagonalizing the symbol portion such that  $\mathbf{WHP}\mathbf{x} = \mathbf{x}$ . (“Zero-forcing” the interference)
  - That is,  $\mathbf{WHP} = \mathbf{I}_{N_s}$
- At the same time, we want to minimize the noise portion of  $\tilde{\mathbf{x}}$ .
- Thus, we solve the following problem:

$$\begin{array}{ll} \min_{\mathbf{W}} & E[|\mathbf{W}\mathbf{z}|^2] \\ \text{s.t.} & \mathbf{WHP} = \mathbf{I}_{N_s} \end{array}$$

- We assume  $\text{rank}(\mathbf{P}) = N_s$ .

# Assignment 07

## ③ MIMO without CSIT – RxZF



- From  $E[|\mathbf{W}\mathbf{z}|^2] = \text{tr}(\mathbf{W}\mathbf{R}_z\mathbf{W}^H)$  and using standard basis vectors  $\mathbf{e}_i$ 's in which the  $i$ -th element is 1 and the other elements are 0,

$$\begin{aligned} \min_{\mathbf{W}} & \text{tr}(\mathbf{W}\mathbf{R}_z\mathbf{W}^H) \\ \text{s.t. } & \mathbf{e}_i^H \mathbf{W}\mathbf{H}\mathbf{P}\mathbf{e}_i = 1, \forall i = 1, \dots, N_s \\ & \mathbf{e}_i^H \mathbf{W}\mathbf{H}\mathbf{P}\mathbf{e}_j = 0, \forall i \neq j \end{aligned}$$

- Using the method of Lagrangian multipliers,

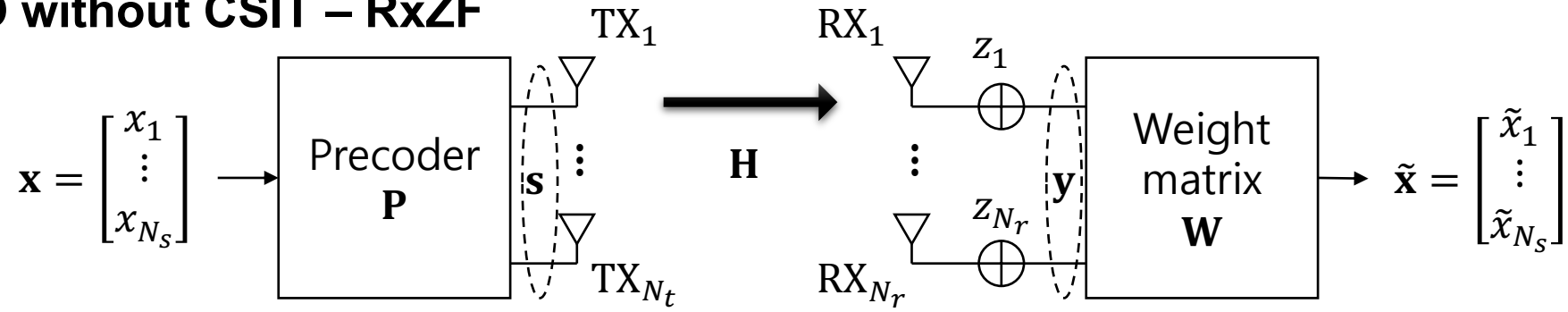
$$\max_{\mathbf{W}} g(\mathbf{W}, \{\lambda_i\}, \{\rho_{ij}\}) \triangleq \text{tr}(\mathbf{W}\mathbf{H}\mathbf{P}) + \sum_{i=1}^{N_s} \lambda_i (\mathbf{e}_i^H \mathbf{W}\mathbf{H}\mathbf{P}\mathbf{e}_i - 1) + \sum_{i \neq j} \rho_{ij} \mathbf{e}_i^H \mathbf{W}\mathbf{H}\mathbf{P}\mathbf{e}_j$$

- The optimal solution is one of the stationary points with  $\frac{\partial g(\mathbf{W}, \{\lambda_i\}, \{\rho_{ij}\})}{\partial \mathbf{W}} = \mathbf{0}$ ,  $\frac{\partial g(\mathbf{W}, \{\lambda_i\}, \{\rho_{ij}\})}{\partial \lambda_i} = 0, \forall i = 1, \dots, N_s$ ,  $\frac{\partial g(\mathbf{W}, \{\lambda_i\}, \{\rho_{ij}\})}{\partial \rho_{ij}} = 0, \forall i \neq j$ .



# Assignment 07

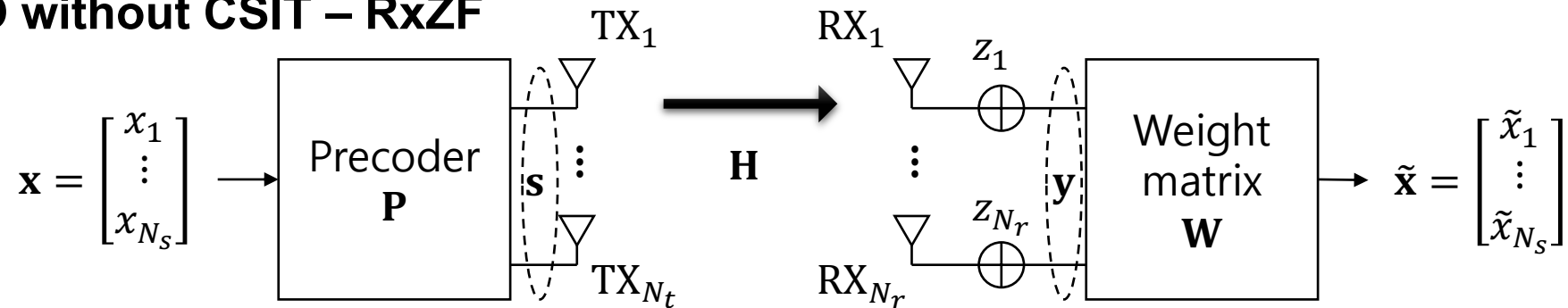
## • ③ MIMO without CSIT – RxZF



- (1) Show that  $\frac{\partial g(\mathbf{W}, \{\lambda_i\}, \{\rho_{ij}\})}{\partial \mathbf{W}} = \mathbf{W}^* \mathbf{R}_z^T + (\mathbf{H} \mathbf{P} \sum_{i=1}^{N_s} \lambda_i \mathbf{e}_i \mathbf{e}_i^H)^T + (\mathbf{H} \mathbf{P} \sum_{i \neq j} \rho_{ij} \mathbf{e}_j \mathbf{e}_i^H)^T$ ,
- (2) Show that  $\frac{\partial g(\mathbf{W}, \{\lambda_i\}, \{\rho_{ij}\})}{\partial \lambda_i} = \mathbf{e}_i^H \mathbf{W} \mathbf{H} \mathbf{P} \mathbf{e}_i - 1, \forall i = 1, \dots, N_s$  and  $\frac{\partial g(\mathbf{W}, \{\lambda_i\}, \{\rho_{ij}\})}{\partial \rho_{ij}} = \mathbf{e}_i^H \mathbf{W} \mathbf{H} \mathbf{P} \mathbf{e}_j, \forall i \neq j$
- (3) Letting  $\frac{\partial g(\mathbf{W}, \{\lambda_i\}, \{\rho_{ij}\})}{\partial \mathbf{W}} = \mathbf{0}$ , show that  $\mathbf{W}_{\text{opt}} = -(\sum_{i=1}^{N_s} \lambda_i \mathbf{e}_i \mathbf{e}_i^H + \sum_{i \neq j} \rho_{ij} \mathbf{e}_j \mathbf{e}_i^H)^H \mathbf{P}^H \mathbf{H}^H \mathbf{R}_z^{-1}$ .
- (4) Letting  $\frac{\partial g(\mathbf{W}, \{\lambda_i\}, \{\rho_{ij}\})}{\partial \lambda_i} = 0, \forall i = 1, \dots, N_s$  and  $\frac{\partial g(\mathbf{W}, \{\lambda_i\}, \{\rho_{ij}\})}{\partial \rho_{ij}} = 0, \forall i \neq j$ , show that  $\mathbf{W}_{\text{opt}} \mathbf{H} \mathbf{P} = \mathbf{I}_{N_s}$ .
- (5) Show that  $\mathbf{W}_{\text{opt}} = (\mathbf{P}^H \mathbf{H}^H \mathbf{R}_z^{-1} \mathbf{H} \mathbf{P})^{-1} \mathbf{P}^H \mathbf{H}^H \mathbf{R}_z^{-1}$ .

# Assignment 07

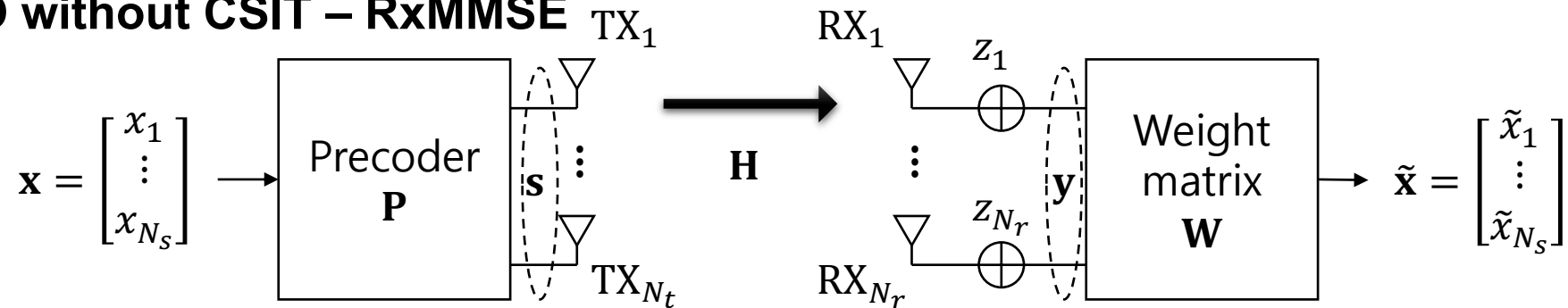
- ③ MIMO without CSIT – RxZF



- (6) Show that  $C = \log_2 |\mathbf{I}_{N_s} + \mathbf{P}^H \mathbf{H}^H \mathbf{R}_z^{-H} \mathbf{H} \mathbf{P}|$ .
- (7) For AWGN, i.e.,  $\mathbf{R}_z = \sigma_z^2 \mathbf{I}_{N_r}$ , show that  $C = \log_2 \left| \mathbf{I}_{N_s} + \frac{1}{\sigma_z^2} \mathbf{P}^H \mathbf{H}^H \mathbf{H} \mathbf{P} \right|$ .

# Assignment 07

## • ④ MIMO without CSIT – RxMMSE



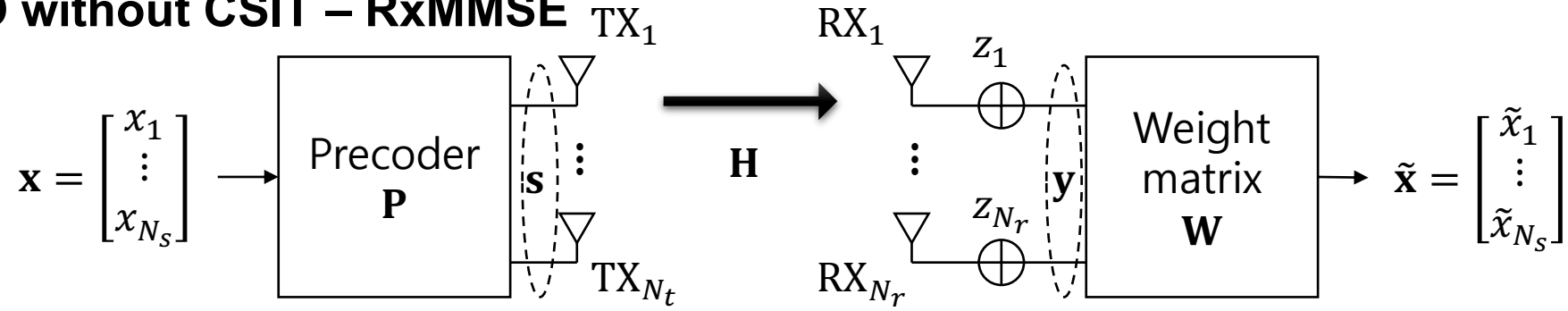
- We minimize the mean square error (MSE) between  $\mathbf{x}$  and  $\tilde{\mathbf{x}}$
- Thus, we solve the following problem:

$$\min_{\mathbf{W}} E[|\mathbf{x} - \tilde{\mathbf{x}}|^2]$$

- (1) Show that  $E[|\mathbf{x} - \tilde{\mathbf{x}}|^2] = \text{tr}(\mathbf{I}_{N_s} - \mathbf{P}^H \mathbf{H}^H \mathbf{W}^H - \mathbf{W} \mathbf{H} \mathbf{P} + \mathbf{W} (\mathbf{H} \mathbf{P} \mathbf{P}^H \mathbf{H}^H + \mathbf{R}_z) \mathbf{W}^H)$ .

# Assignment 07

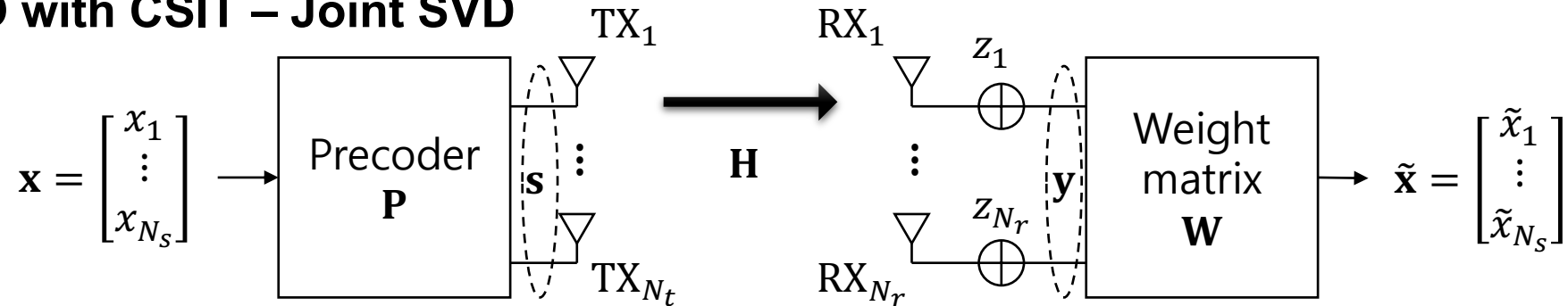
## • ④ MIMO without CSIT – RxMMSE



- Since this is an unconstrained convex problem, the optimal solution is a stationary point with  $\frac{\partial E[|\mathbf{x} - \tilde{\mathbf{x}}|^2]}{\partial \mathbf{W}} = \mathbf{0}$ .
- (2) Show that  $\frac{\partial E[|\mathbf{x} - \tilde{\mathbf{x}}|^2]}{\partial \mathbf{W}} = -(\mathbf{H}\mathbf{P})^T + \mathbf{W}^*(\mathbf{H}\mathbf{P}\mathbf{P}^H\mathbf{H}^H + \mathbf{R}_z)^T$ .
- (3) Letting  $\frac{\partial E[|\mathbf{x} - \tilde{\mathbf{x}}|^2]}{\partial \mathbf{W}} = \mathbf{0}$ , show that  $\mathbf{W}_{\text{opt}} = \mathbf{P}^H\mathbf{H}^H(\mathbf{H}\mathbf{P}\mathbf{P}^H\mathbf{H}^H + \mathbf{R}_z)^{-1}$ .
- (4) Using the Woodbury matrix identity, also show that  $\mathbf{W}_{\text{opt}} = (\mathbf{I}_{N_s} + \mathbf{P}^H\mathbf{H}^H\mathbf{R}_z^{-1}\mathbf{H}\mathbf{P})^{-1}\mathbf{P}^H\mathbf{H}^H\mathbf{R}_z^{-1}$ .
- (5) If  $\text{rank}(\mathbf{P}) = N_s$ , using  $|\mathbf{I} + \mathbf{AB}| = |\mathbf{I} + \mathbf{BA}|$ , show that  $C = \log_2 |\mathbf{I}_{N_s} + \mathbf{P}^H\mathbf{H}^H\mathbf{R}_z^{-1}\mathbf{H}\mathbf{P}|$ .
- (6) If  $\text{rank}(\mathbf{P}) = N_s$ , for AWGN, i.e.,  $\mathbf{R}_z = \sigma_z^2\mathbf{I}_{N_r}$ , show that  $C = \log_2 \left| \mathbf{I}_{N_s} + \frac{1}{\sigma_z^2} \mathbf{P}^H\mathbf{H}^H\mathbf{H}\mathbf{P} \right|$ .

# Assignment 07

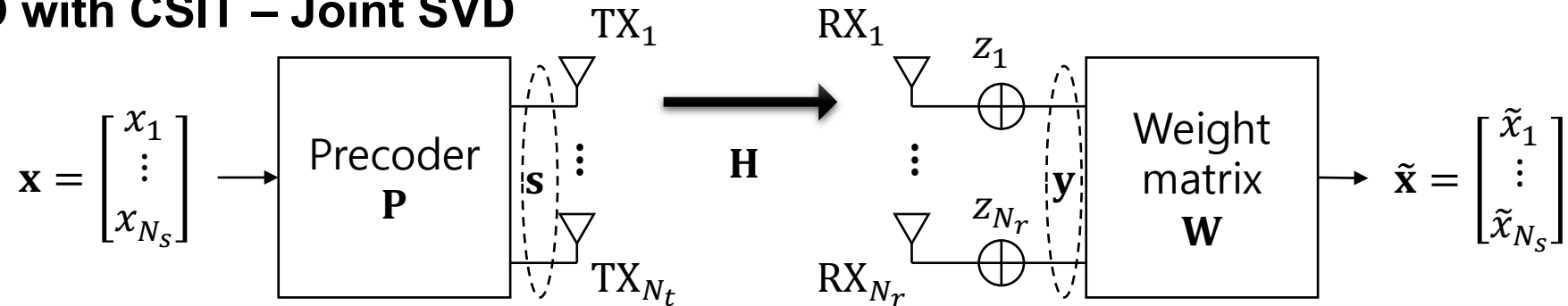
## • ⑤ MIMO with CSIT – Joint SVD



- By SVD,  $\mathbf{H} = \mathbf{U}\mathbf{\Sigma}\mathbf{V}^H = [\mathbf{U}_1 \quad \mathbf{U}_0] \begin{bmatrix} \mathbf{\Sigma}_1 & \mathbf{0} \\ \mathbf{0} & \mathbf{0} \end{bmatrix} \begin{bmatrix} \mathbf{V}_1^H \\ \mathbf{V}_0^H \end{bmatrix} = \mathbf{U}_1 \mathbf{\Sigma}_1 \mathbf{V}_1^H$ , where  $\mathbf{U}_1$  and  $\mathbf{V}_1$  are singular vector matrices corresponding to non-zero singular values in  $\mathbf{\Sigma}_1$ .
- For joint SVD, we set  $\mathbf{P} = \mathbf{V}_1 \mathbf{Q}_1^{1/2}$  for positive diagonal matrix  $\mathbf{Q}_1 \in M_{N_s \times N_s}(\mathbb{R})$  and  $\mathbf{W} = \mathbf{U}_1^H$ .
- (1) Specify the dimensions of  $\mathbf{U}_1, \mathbf{U}_0, \mathbf{\Sigma}_1, \mathbf{V}_1, \mathbf{V}_0$ .
- (2) Show that  $\tilde{\mathbf{x}} = \mathbf{\Sigma}_1 \mathbf{x} + \mathbf{U}_1^H \mathbf{z}$ .
- (3) Show that  $E[|\mathbf{s}|^2] = \text{tr}(\mathbf{Q}_1) = E_s$ .

# Assignment 07

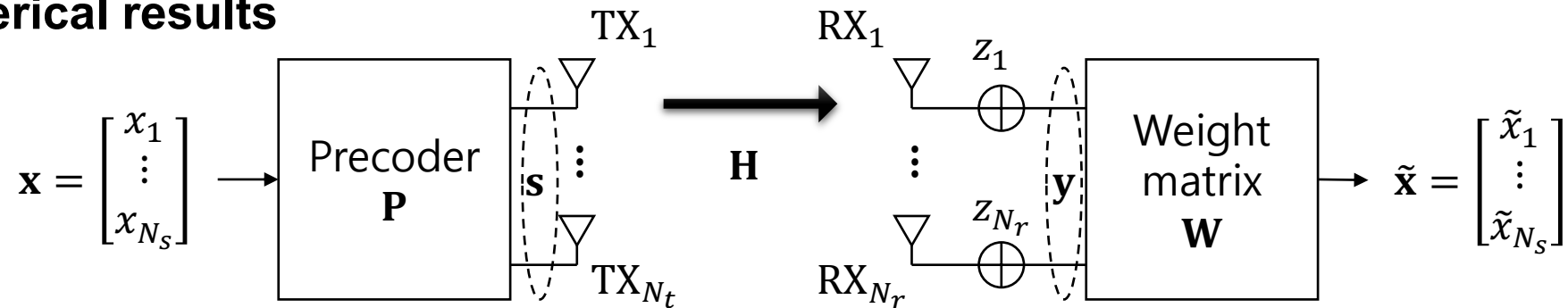
- ⑤ MIMO with CSIT – Joint SVD



- (4) For AWGN, i.e.,  $\mathbf{R}_z = \sigma_z^2 \mathbf{I}_{N_r}$ , show that  $C = \sum_{i=1}^{N_s} \log_2 \left( 1 + \frac{1}{\sigma_z^2} \sigma_{\mathbf{H},i}^2 q_i \right)$ , i.e., achieving the MIMO capacity when  $q_i$ 's are optimized.
- (5) Letting  $\mathbf{P} = \mathbf{V}_1 \mathbf{Q}_1^{1/2}$  for RxMF, RxZF, RxMMSE, show that  $C$  becomes equivalent to the case with CSIT, i.e., achieving the MIMO capacity when  $q_i$ 's are optimized.

# Assignment 07

## • ⑥ Numerical results



- In the absence of the CSIT, one possible design for the precoder is  $\mathbf{P} = \sqrt{\frac{E_s}{N_s}} \begin{bmatrix} \mathbf{I}_{N_s} \\ \mathbf{0}_{(N_t - N_s) \times N_s} \end{bmatrix}$  such that the average transmit energy  $E_s$  is equally distributed to the symbols and by assigning  $x_i$ 's to  $\text{TX}_i$ 's in order. ( $N_t - N_s$  antennas are unused.)
- (1) Show that  $E[|\mathbf{s}|^2] = E_s$ .

# Assignment 07

## • ⑥ Numerical results

### • Setups

- Unit average transmit energy, i.e.,  $E_s = 1$
- AWGN, i.e.,  $\mathbf{R}_z = \sigma_z^2 \mathbf{I}_{N_r}$
- Rayleigh fading channel matrix, i.e.,  $h_{ij} \sim CN(0,1)$

### • Curve 1: MIMO without CSIT

- For  $\mathbf{P} = \sqrt{\frac{E_s}{N_s}} \begin{bmatrix} \mathbf{I}_{N_s} \\ \mathbf{0}_{(N_t-N_s) \times N_s} \end{bmatrix}$ ,
- Curve 1-1: MIMO without CSIT – RxMF
  - $C = \log_2 |\mathbf{I}_{N_s} + (\mathbf{W} \mathbf{R}_z \mathbf{W}^H)^{-1} \mathbf{W} \mathbf{H} \mathbf{P} \mathbf{P}^H \mathbf{H}^H \mathbf{W}^H|$  with  $\mathbf{W} = \mathbf{P}^H \mathbf{H}^H \mathbf{R}_z^{-1}$
- Curve 1-2: MIMO without CSIT – RxZF
  - $C = \log_2 |\mathbf{I}_{N_s} + (\mathbf{W} \mathbf{R}_z \mathbf{W}^H)^{-1} \mathbf{W} \mathbf{H} \mathbf{P} \mathbf{P}^H \mathbf{H}^H \mathbf{W}^H|$  with  $\mathbf{W} = (\mathbf{P}^H \mathbf{H}^H \mathbf{R}_z^{-1} \mathbf{H} \mathbf{P})^{-1} \mathbf{P}^H \mathbf{H}^H \mathbf{R}_z^{-1}$
- Curve 1-3: MIMO without CSIT – RxMMSE
  - $C = \log_2 |\mathbf{I}_{N_s} + (\mathbf{W} \mathbf{R}_z \mathbf{W}^H)^{-1} \mathbf{W} \mathbf{H} \mathbf{P} \mathbf{P}^H \mathbf{H}^H \mathbf{W}^H|$  with  $\mathbf{W} = (\mathbf{I}_{N_s} + \mathbf{P}^H \mathbf{H}^H \mathbf{R}_z^{-1} \mathbf{H} \mathbf{P})^{-1} \mathbf{P}^H \mathbf{H}^H \mathbf{R}_z^{-1}$

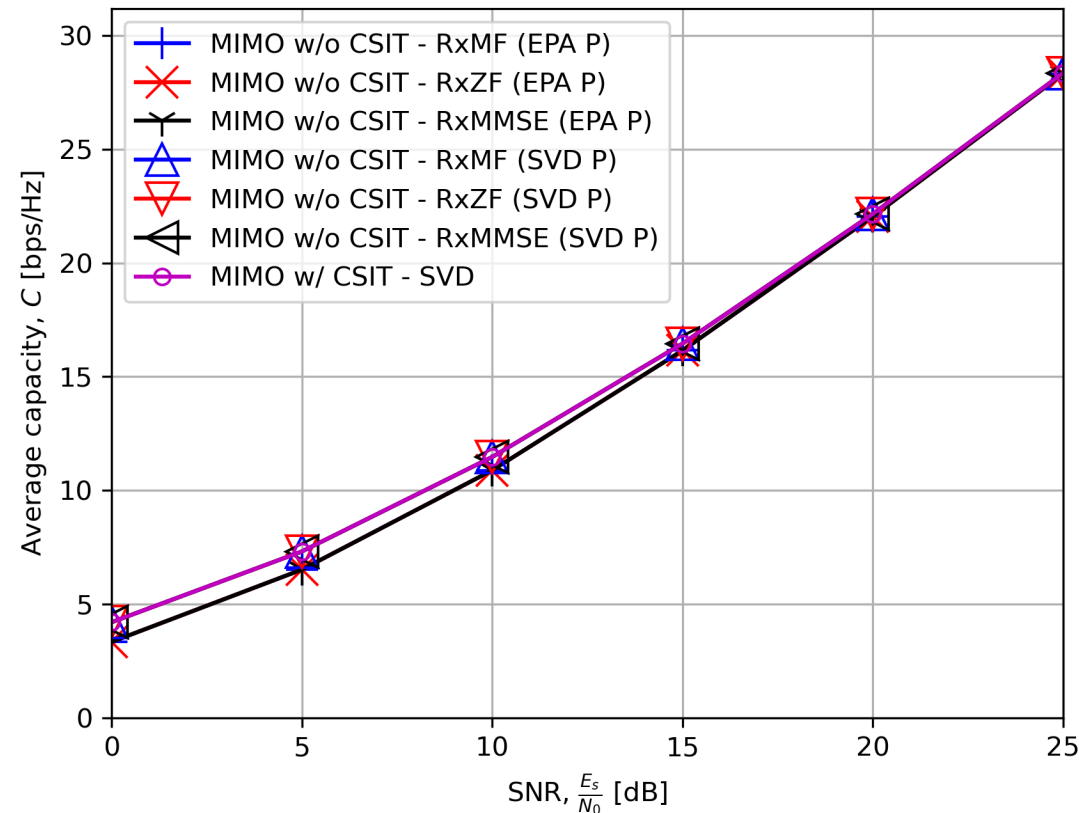


# Assignment 07

- ⑥ Numerical results
  - Setups
    - Unit average transmit energy, i.e.,  $E_s = 1$
    - AWGN, i.e.,  $\mathbf{R}_z = \sigma_z^2 \mathbf{I}_{N_r}$
    - Rayleigh fading channel matrix, i.e.,  $h_{ij} \sim CN(0,1)$
  - Curve 1: MIMO without CSIT
    - For  $\mathbf{P} = \mathbf{V}_1[:, 0:N_{s,\text{opt}}] \mathbf{Q}_{1,\text{opt}}^{1/2} [0:N_{s,\text{opt}}, 0:N_{s,\text{opt}}]$ , where  $N_{s,\text{opt}}$  is the number of non-zero  $q_{i,\text{opt}}$ 's in  $\mathbf{Q}_{\text{opt}}$
    - Curve 1-4: MIMO without CSIT – RxMF
      - $C = \log_2 \left| \mathbf{I}_{N_{s,\text{opt}}} + (\mathbf{W} \mathbf{R}_z \mathbf{W}^H)^{-1} \mathbf{W} \mathbf{H} \mathbf{P} \mathbf{P}^H \mathbf{H}^H \mathbf{W}^H \right|$  with  $\mathbf{W} = \mathbf{P}^H \mathbf{H}^H \mathbf{R}_z^{-1}$
    - Curve 1-5: MIMO without CSIT – RxZF
      - $C = \log_2 \left| \mathbf{I}_{N_{s,\text{opt}}} + (\mathbf{W} \mathbf{R}_z \mathbf{W}^H)^{-1} \mathbf{W} \mathbf{H} \mathbf{P} \mathbf{P}^H \mathbf{H}^H \mathbf{W}^H \right|$  with  $\mathbf{W} = (\mathbf{P}^H \mathbf{H}^H \mathbf{R}_z^{-1} \mathbf{H} \mathbf{P})^{-1} \mathbf{P}^H \mathbf{H}^H \mathbf{R}_z^{-1}$
    - Curve 1-6: MIMO without CSIT – RxMMSE
      - $C = \log_2 \left| \mathbf{I}_{N_{s,\text{opt}}} + (\mathbf{W} \mathbf{R}_z \mathbf{W}^H)^{-1} \mathbf{W} \mathbf{H} \mathbf{P} \mathbf{P}^H \mathbf{H}^H \mathbf{W}^H \right|$  with  $\mathbf{W} = \left( \mathbf{I}_{N_{s,\text{opt}}} + \mathbf{P}^H \mathbf{H}^H \mathbf{R}_z^{-1} \mathbf{H} \mathbf{P} \right)^{-1} \mathbf{P}^H \mathbf{H}^H \mathbf{R}_z^{-1}$
  - Curve 3: MIMO with CSIT – Joint SVD
    - $C = \log_2 \left| \mathbf{I}_{N_s} + (\mathbf{W} \mathbf{R}_z \mathbf{W}^H)^{-1} \mathbf{W} \mathbf{H} \mathbf{P} \mathbf{P}^H \mathbf{H}^H \mathbf{W}^H \right|$  with  $\mathbf{P} = \mathbf{V}_1 \mathbf{Q}_{1,\text{opt}}^{1/2}$  and  $\mathbf{W} = \mathbf{U}_1^H$

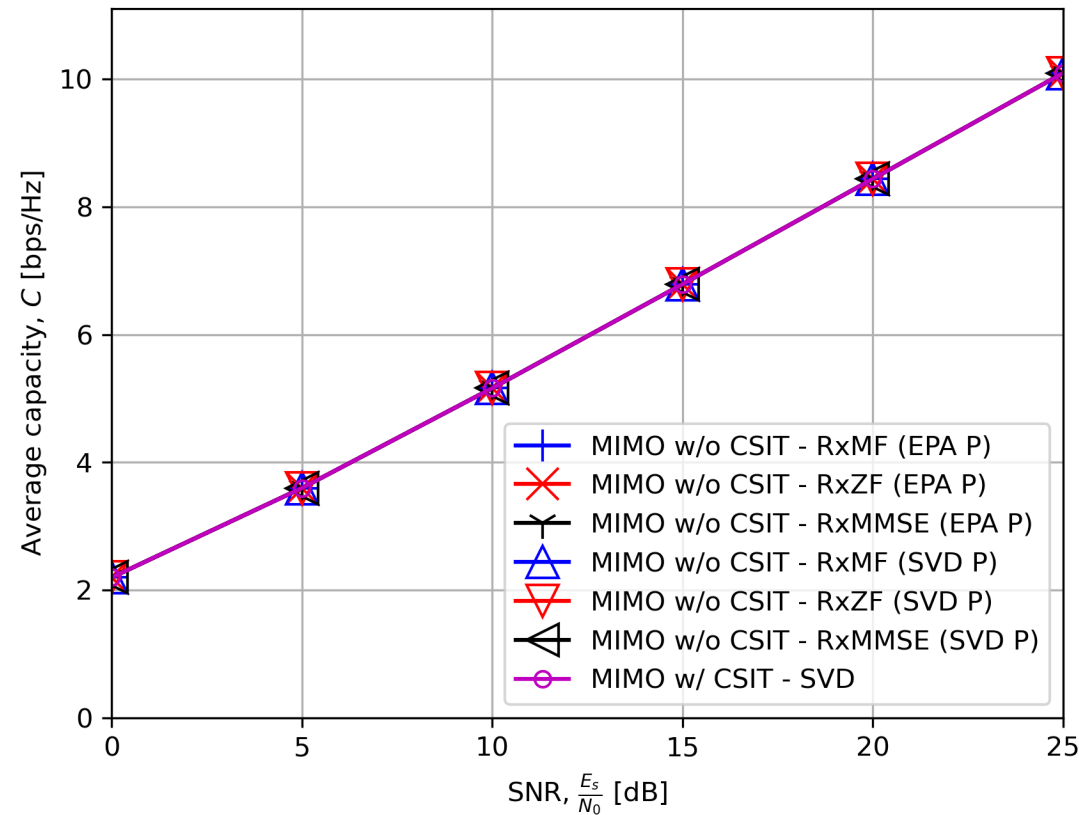
# Assignment 07

- ⑥ Numerical results
  - For  $(N_t, N_r) = (4, 4)$  (Fig. 4.6 of “Introduction to Space-Time Wireless Communications”)
  - 1000 samples



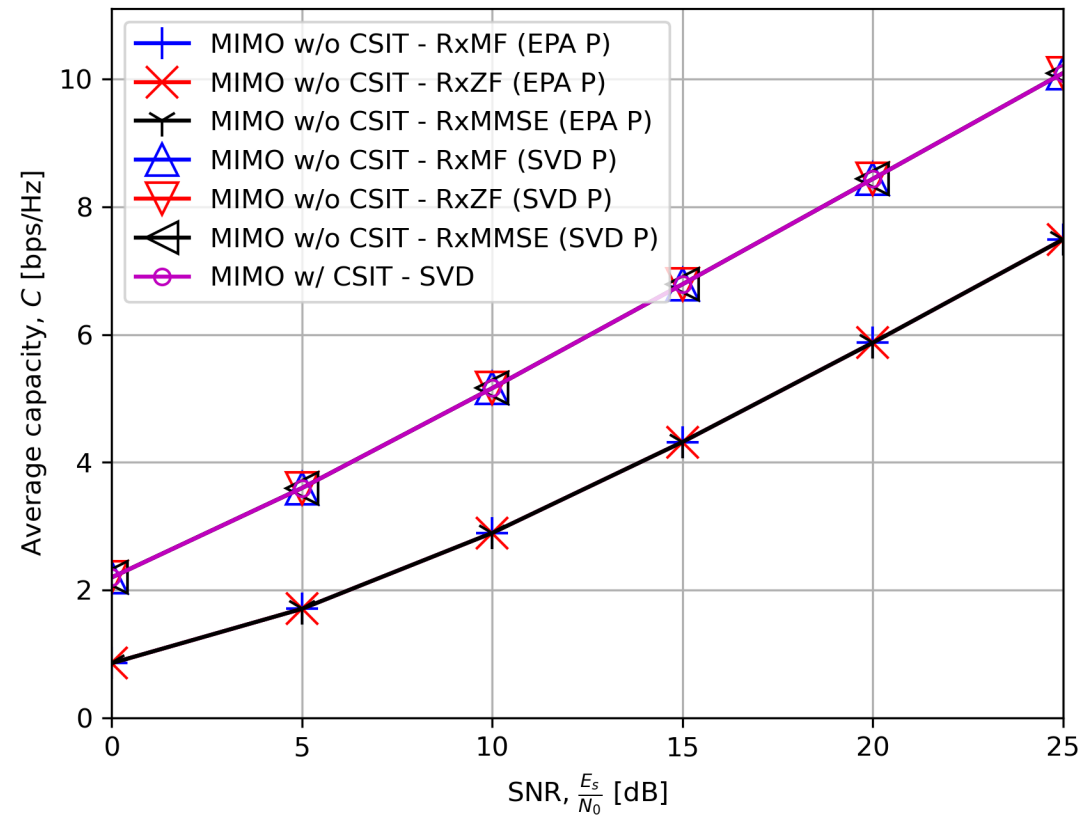
# Assignment 07

- ⑥ Numerical results
  - SIMO with  $(N_t, N_r) = (1, 4)$
  - 1000 samples



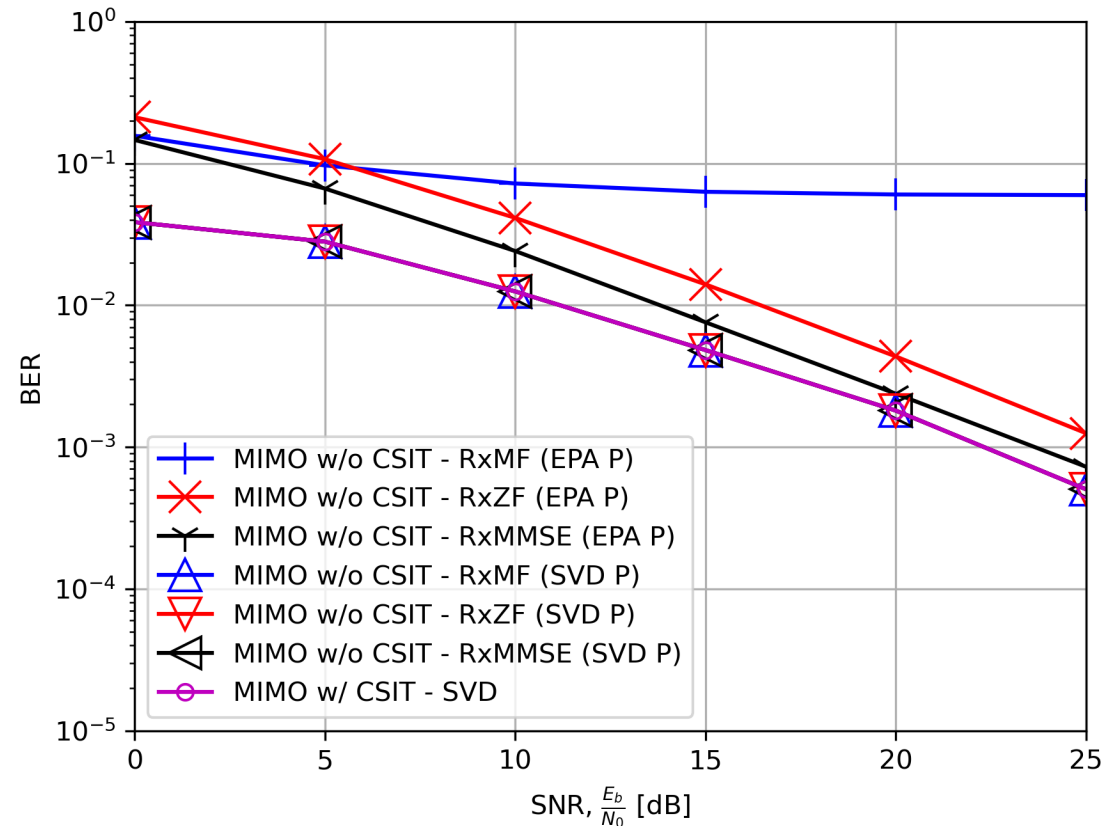
# Assignment 07

- ⑥ Numerical results
  - MISO with  $(N_t, N_r) = (4, 1)$
  - 1000 samples



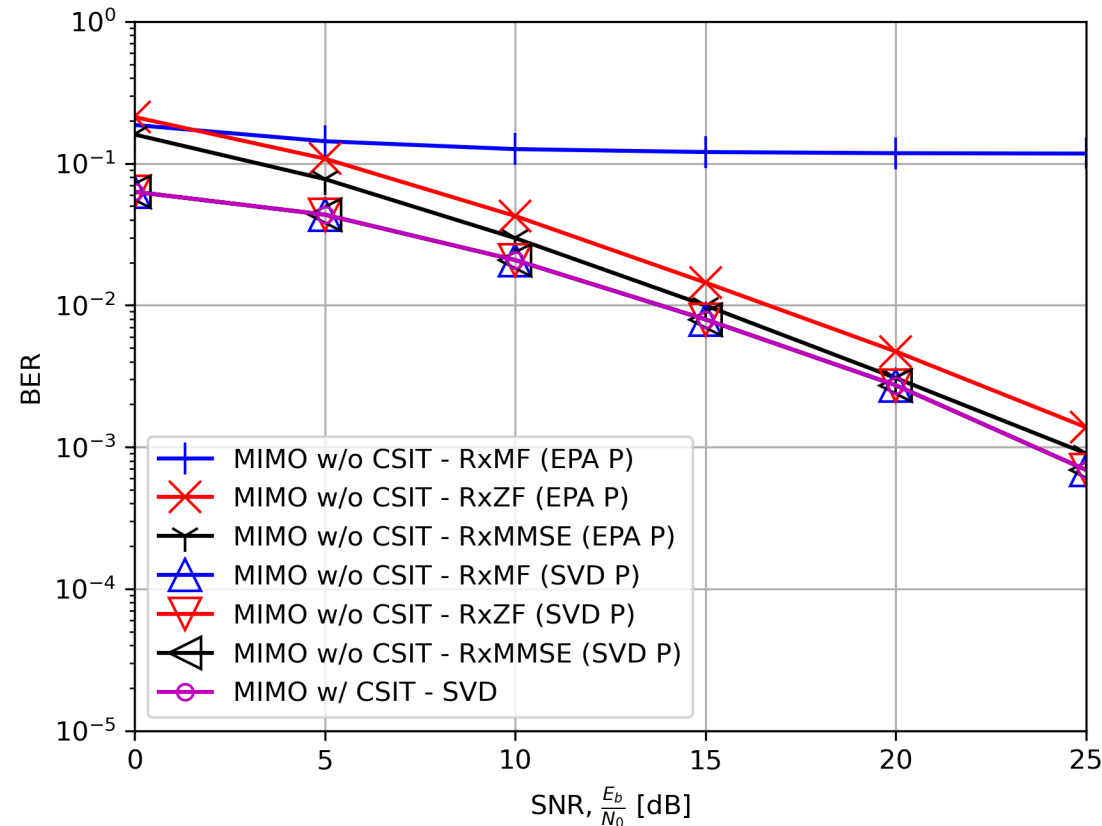
# Assignment 07

- ⑥ Numerical results
  - BPSK for  $(N_t, N_r) = (2, 2)$  (Fig. 2-3 of “Extending the capacity of next generation ... OFDM”)
  - 20000 samples



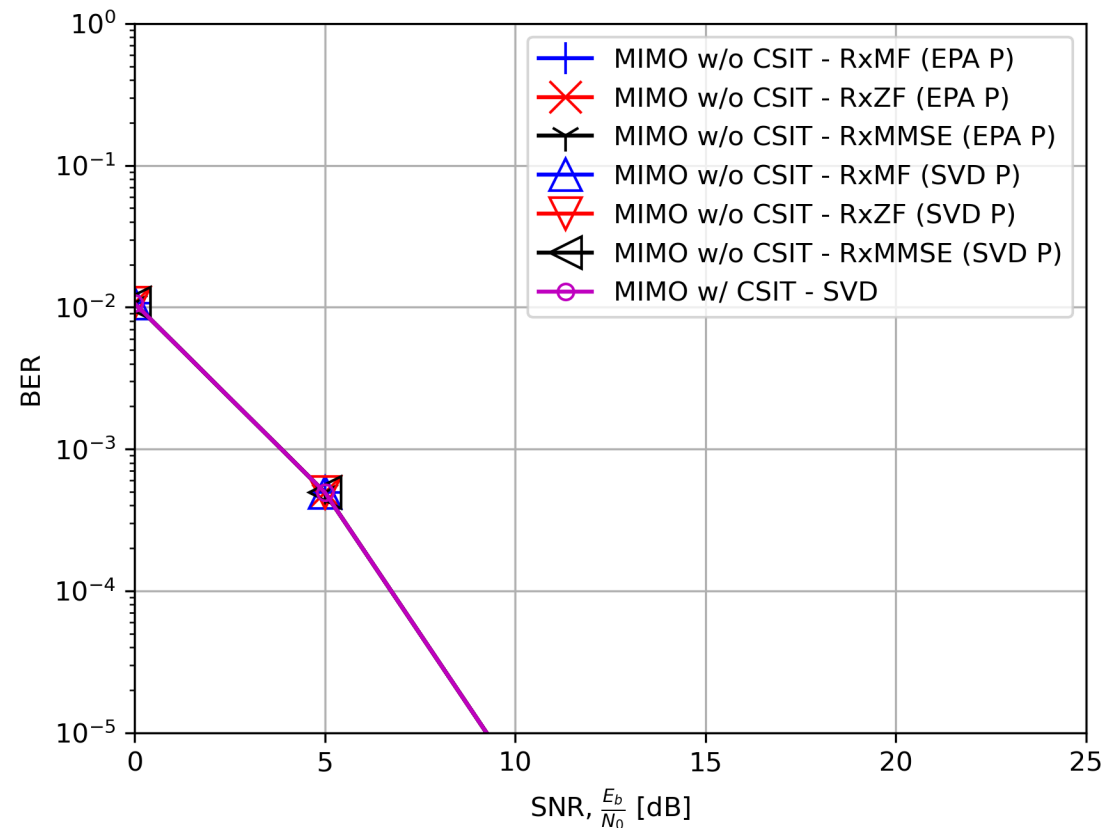
# Assignment 07

- ⑥ Numerical results
  - QPSK for  $(N_t, N_r) = (2, 2)$  (Fig. 2-4 of “Extending the capacity of next generation ... OFDM”)
  - 20000 samples



# Assignment 07

- ⑥ Numerical results
  - SIMO QPSK for  $(N_t, N_r) = (1, 4)$
  - 100000 sample



# Assignment 07

- ⑥ Numerical results
  - MISO QPSK for  $(N_t, N_r) = (4, 1)$
  - 100000 sample

