

## AO-MM:

The objective function of OP4 is given as

$$\frac{\varphi}{\beta_e^2 + \rho_e^2 \|\Theta \mathbf{H} \mathbf{f}\|^2} = R \left[ \frac{\|(\rho_b \hat{\mathbf{g}}_b \Theta \mathbf{H} + \beta_b \mathbf{h}_b) \mathbf{f}\|^2}{\|\sqrt{1 - \rho_b^2 \tilde{\mathbf{g}}_b \Theta \mathbf{H} \mathbf{f}}\|^2 + \frac{\sigma_b^2}{P_A}} + \mathcal{B}_1 \right]. \quad (1)$$

where,  $R = \frac{\alpha}{\beta_e^2 + \rho_e^2 \|\Theta \mathbf{H} \mathbf{f}\|^2}$ . Now, let us perform optimization over  $\Theta$  by fixing  $\mathbf{f}$ . With (1), OP4 can be transformed as

$$\begin{aligned} \text{P1: } \max_{\Theta} & \frac{\|(\rho_b \hat{\mathbf{g}}_b \Theta \mathbf{H} + \beta_b \mathbf{h}_b) \mathbf{f}\|^2}{\|\sqrt{1 - \rho_b^2 \tilde{\mathbf{g}}_b \Theta \mathbf{H} \mathbf{f}}\|^2 + \frac{\sigma_b^2}{P_A}}, \\ \text{s.t. } & 12. \end{aligned} \quad (2)$$

Using (37) and (38), we have

$$\text{P2: } \max_{\mathbf{v}, |v_m|=1} \frac{\mathbf{v}^H \mathbf{y}_1 \mathbf{v} + |\alpha_A|^2 + 2\rho_b \Re\{\mathbf{e}_1^H \mathbf{v}^H \alpha_A^*\}}{\mathbf{v}^H \mathbf{y}_2 \mathbf{v} + \frac{\sigma_b^2}{P_A}}, \quad (3)$$

where  $\mathbf{y}_1 = \rho_b^2 \mathbf{e}_1^H \mathbf{e}_1$ ,  $\mathbf{y}_2 = (1 - \rho_b^2) \mathbf{e}_2^H \mathbf{e}_2$ , and  $\alpha_A = \beta_b \mathbf{h}_b \mathbf{f}$ . Rewrite (3), we have

$$\text{P3: } \min_{\mathbf{v}, |v_m|=1} \frac{\mathbf{v}^H \mathbf{y}_2 \mathbf{v} + \frac{\sigma_b^2}{P_A}}{\mathbf{v}^H \mathbf{y}_1 \mathbf{v} + |\alpha_A|^2 + 2\rho_b \Re\{\mathbf{e}_1^H \mathbf{v}^H \alpha_A^*\}}. \quad (4)$$

This problem belongs to fractional programming. Following [33], we consider the corresponding parametric program:

$$\text{P4: } \min_{\mathbf{v}, |v_m|=1} \mathbf{v}^H \boldsymbol{\theta} \mathbf{v} + \frac{\sigma_b^2}{P_A} - \mu |\alpha_A|^2 - 2\mu \rho_b \Re\{\mathbf{e}_1^H \mathbf{v}^H \alpha_A^*\}, \quad (5)$$

where  $\mu > 0$  is an introduced parameter and  $\boldsymbol{\theta} = \mathbf{y}_2 - \mu \rho_b^2 \mathbf{y}_1$ . Here, we adopt MM algorithm to solve P4 due to its closed-form solution at each iteration [9],[11],[18].[30]. At iteration  $t$ , for any feasible point  $\mathbf{v}(t)$ ,

$$\begin{aligned} & \mathbf{v}^H \boldsymbol{\theta} \mathbf{v} + \frac{\sigma_b^2}{P_A} - \mu |\alpha_A|^2 - 2\Re\{\mu \rho_b \mathbf{e}_1 \mathbf{v}^H \alpha_A^*\} \\ & \leq \lambda_{\max}(\boldsymbol{\theta}) \|\mathbf{v}\|^2 - \Re\{\mathbf{v}^H \boldsymbol{\varphi}\} + q_1, \end{aligned} \quad (6)$$

where  $\boldsymbol{\varphi} = (\lambda_{\max}(\boldsymbol{\theta}) \mathbf{I} - \boldsymbol{\theta}) \mathbf{v}(t) + \mu \rho_b \mathbf{e}_1 \alpha_A^*$ ,  $q_1 = (\lambda_{\max}(\boldsymbol{\theta}) \mathbf{I} - \boldsymbol{\theta}) \mathbf{v} + \frac{\sigma_b^2}{P_A} - \mu |\alpha_A|^2$ . The simplified optimization problem becomes

$$\begin{aligned} \text{P5: } \max_{\mathbf{v}} & \Re\{\mathbf{v}^H \boldsymbol{\varphi}\}, \\ \text{s.t. } & |v_m| = 1, \forall \quad m = 1, \dots, M. \end{aligned} \quad (7)$$

The optimal solution of P5 at iteration  $t$  is

$$\mathbf{v}(t+1) = \left[ e^{j \arg(\varphi_1)}, \dots, e^{j \arg(\varphi_M)} \right]. \quad (8)$$

---

**Algorithm A** MM-Based Algorithm for Phase-shift Matrix

According to [10], the optimal solution  $\mathbf{v}$  can be obtained via an Algorithm A with a computational complexity of  $\mathcal{O}(M^3 + T_{\max}M^2)$ , where  $T_{\max}$  denotes the number of iterations required for convergence [10, D1].

**Require:**  $P_A, \rho_b, \rho_e, R_s, \sigma_b^2, \sigma_e^2, \mathbf{H}, \mathbf{h}_b, \mathbf{h}_e, N_A, M, \delta$

- 1: Initialize  $\mathbf{f}_o$  as a random unitary vector of size  $N_A \times 1$ .
- 2: Set iteration counter  $i = 1$  and maximum iteration limit  $i_{\max}$ .
- 3: **repeat**
- 4:     Obtain  $\mathbf{f}_i^*$  via generalized Rayleigh quotient.
- 5:     Obtain  $\mathbf{v}^*$  using MM algorithm
- 6:     Compute  $P_{\text{out}}(i)$ .
- 7:     Update iteration counter:  $i \leftarrow i + 1$ .
- 8: **until** ( $i < i_{\max}$ ) and  $|P_{\text{out}}(i) - P_{\text{out}}(i - 1)| \leq \delta$
- 9: Set  $\mathbf{v}^* \leftarrow \mathbf{v}_i^*$ ,  $\mathbf{w}^* \leftarrow \mathbf{w}_i^*$ .
- 10: Compute  $\Theta^* \leftarrow \text{diag}(\mathbf{v}^*)$ .
- 11: **return**  $\Theta^*, \mathbf{w}^*$ .

D1: S. Hong, C. Pan, H. Ren, K. Wang and A. Nallanathan, "Artificial-Noise-Aided Secure MIMO Wireless Communications via Intelligent Reflecting Surface," in *IEEE Transactions on Communications*, vol. 68, no. 12, pp. 7851-7866, Dec. 2020.