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Robust Designs of Beamforming and Power Splitting for Distributed Antenna Systems With Wireless Energy Harvesting

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***Abstract*—In this paper, we investigate a multiuser distributed antenna system with simultaneous wireless information and power transmission under the assumption of imperfect channel state information (CSI). In this system, a distributed antenna port with multiple antennas supports a set of mobile stations that can decode information and harvest energy simultaneously via a power splitter. To design robust transmit beamforming vectors and the power splitting factors in the presence of CSI errors, we maximize the average worst-case signal-to-interference-plus-noise ratio (SINR) while achieving an individual energy harvesting constraint for each mobile station. First, we develop an efficient algorithm to convert the max–min SINR problem to a set of "dual" min–max power balancing problems. Then, motivated by the penalty function method, an iterative algorithm based on semidefinite programming is proposed to achieve a local optimal rank-one solution. Also, to reduce the computational complexity, we present another iterative scheme based on the Lagrangian method and the successive convex approximation technique to yield a suboptimal solution. Simulation results are shown to validate the robustness and effectiveness of the proposed algorithms.**

***Index Terms*—Distributed antenna systems, energy harvesting, simultaneous wireless information and power transmission.**

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I. Introduction

For the past decade, there has been a considerable evolution of wireless networks to satisfy demands on high-speed data. Since resources shared among users are limited, a capacity increase is technically challenging in the wireless networks. Recently, a distributed antenna system (DAS) has received a lot of attentions as a new cellular communication structure to expand coverage and increase sum rates [1]–[3].

Unlike conventional cellular systems where all antennas are colocated at the cell center, distributed antenna (DA) ports of the DAS are separated geographically in a cell and are connected with each other by backhaul links [4]. Each DA port in the DAS is usually equipped with its own power amplifier at the analog front-end [4], [5]. Thus, individual power constraint at each antenna should be considered for the DAS unlike the conventional systems that normally impose sum power constraint [5].

In the meantime, one of the limits in current cellular communication systems is the short lifetime of batteries. To combat the battery problem of mobile users, simultaneous wireless information and power transmission (SWIPT) has been studied in [6]–[13]. With the aid of the SWIPT, users can charge their devices based on the received signal [8], [9]. To realize the SWIPT, a colocated receiver has been proposed [10], which employs a power splitter to perform energy harvesting (EH) and information decoding (ID) at the same time [11]. By adopting the power splitting (PS) receiver, the SWIPT scheme for multiple-input single-output downlink systems has been examined in [8] and [11], where perfect channel state information at the transmitter (CSIT) was assumed. In practice, however, due to channel estimation errors and feedback delays, it is not possible to obtain perfect CSIT [14]–[17].

On the other hand, some recent works have investigated SWIPT in the DAS [18]–[25]. Yuan *et al.* [18] have provided several intuitions and revealed the challenges and opportunities in DAS SWIPT systems. In order to improve the energy efficiency of SWIPT, the application of advanced smart antenna technologies has been focused in [19]. In [20], a power management strategy has been studied to supply maximum wireless information transfer with the minimum wireless energy transfer constraint for adopting PS. Moreover, a tradeoff between the power transfer efficiency and the information transfer capacity has been introduced in [21]. The work in [22] examined a design of robust beamforming and PS for multiuser downlink DAS SWIPT. However, only one antenna was considered in each DA

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port. The authors in [23] investigated resource allocation for DAS SWIPT systems based on the worst-case model, where per-DA port power constraint was adopted. In [24], a few open issues and promising research trends in the wireless powered communications area with DAS were introduced. In addition, to achieve a balance between transmission power and circuit power, Dong *et al.* [25] study a system utility minimization problem in a DAS SWIPT system via joint design of remote radio head selection and beamforming. However, the joint optimal design of transmit beamforming and the receive PS factor for SWIPT in DAS PS-based systems with multiple transmit antennas of each DA port has not been considered in the literature yet.

Motivated by the existing literature [18]–[25], in this paper, we study a joint design of robust transmit beamforming at the DA port and the receive PS factors at mobile stations (MSs) in multiuser DAS SWIPT systems with imperfect channel state information (CSI). Channel uncertainties are modeled by the worst-case model as in [22]. Our aim is to maximize the worst-case signal-to-interference-and-noise ratio (SINR) subject to EH constraint and the per-DA port power constraint. The contributions of this work are summarized as follows.

1) For a given SINR target, the original problem is decomposed into a sequence of min–max per-DA port power balancing problems. In order to convert the nonconvex constraint into a linear matrix inequality (LMI), the Schur complement is used to derive the equivalent forms of the SINR constraint and the EH constraint. Furthermore, we prove that a solution of the relaxed semidefinite program (SDP) is always rank-two. Also, to recover a near-optimal rank-one solution, we employ a penalty function method instead of the conventional Gaussian randomization (GR) technique.
2) To reduce the computational complexity, another formulation is expressed for the minimum SINR maximization problem. By employing the Lagrangian multiplier method and the first-order Taylor expansion, the SINR constraint can be approximately reformulated into two convex forms with linear constraints. Then, we propose an iterative algorithm based on the successive convex approximation (SCA) to find a suboptimal solution.

Simulations evaluation have been conducted to provide the robustness and effectiveness of the proposed algorithms. The performance is also compared with other recent conventional schemes in this area. We show that the proposed algorithms have the superior performances in terms of average worst-case rate by extensive simulation results.

The remainder of this paper is organized as follows. In Section II, we describe a system model for the multiuser DAS SWIPT and formulate the worst-case SINR maximization problem subject to per-DA port power and EH constraints. Section III derives the proposed robust joint designs. In Section IV, we present the computational complexity of the proposed algorithms. Simulation results are presented in Section V. Finally, Section VI concludes this paper.

Notation: Lowercase letters are denoted by scalars, boldface lowercase letters are used for vectors, and boldface uppercase letters means matrices. $\|\mathbf{x}\|$ represents the Euclidean norm of a complex vector $\mathbf{x}$ and $\mathrm{diag}(\boldsymbol{x})$ denotes the diagonal matrix whose diagonal element vector is $\boldsymbol{x}$. $|z|$ stands for the norm of a complex number z. For a matrix $\mathbf{M}$, $\mathbf{M}^T$, $\mathbf{M}^H$, $\mathrm{rank}(\mathbf{M})$, and $[\mathbf{M}]_{i,j}$ are defined as trace, transpose, conjugate transpose, rank, and the (i,j)th element, respectively. $\lambda_{\max}(\mathbf{M})$ denotes the maximum eigenvalue of $\mathbf{M}$, and $\mathrm{vec}(\mathbf{M})$ stacks the elements of $\mathbf{M}$ in a column vector. $\mathbf{I}$ defines an identity matrix. $\mathbb{C}^{M\times N}$, $\mathbb{H}^{M\times N}$, and $\mathbb{R}^{M\times N}$ are the set of complex matrices, Hermitian matrices, and real matrices of size $M\times N$, respectively. $\mathbb{H}_+$ equals the set of positive semidefinite (PSD) Hermitian matrices. $\mathbf{0}_{M\times L}$ is a null matrix with size $M\times L$.

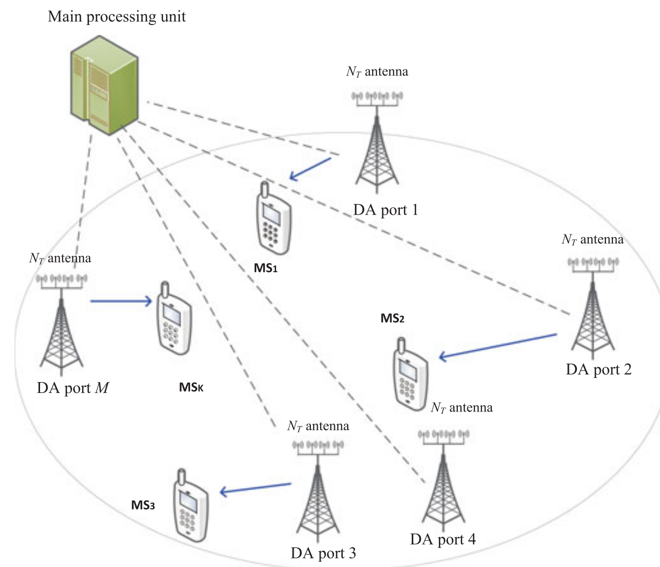

Fig. 1. Structure of a multiuser DAS downlink system.

II. System Model and Problem Formulation

In Fig. 1, we describe a single-cell system model for the multiuser downlink DAS scenario with SWIPT. The DAS consists of M DA ports and K single-antenna MSs. It is assumed that each DA port is equipped with N_T antennas, which have an individual power constraint. All DA ports are physically connected to the main processing unit (MPU) through fiber optics or an exclusive radio frequency (RF) link. Furthermore, all DA ports share the information of user distance and user data, but do not require CSI of all MSs as in [4]. The MS distance information can be simply obtained by measuring the received signal strength indicator [5]. Note that one MS can be supported by several DA ports.

We consider the channel model for DAS, which contains both small-scale and large-scale fading [5]. We denote the channel between the mth DA port $(m = 1,\ldots,M)$ and the kth MS $(k = 1,\ldots,K)$ as $\mathbf{h}_{m,k} = d_{m,k}^{-\gamma/2}\bar{\mathbf{h}}_{m,k}$, where $d_{m,k}$ stands for the distance between the mth DA port and the kth MS, γ indicates the path loss exponent, and $\bar{\mathbf{h}}_{m,k}\in\mathbb{C}^{N_T\times 1}$ equals the channel vector for small-scale fading. For the kth MS, the channel vector is given as $\mathbf{h}_k = [\mathbf{h}_{1,k}^T,\ldots,\mathbf{h}_{M,k}^T]^T$.

Due to channel estimation and quantization errors, CSI is imperfect at each DA port, and we assume that the uncertainty of the channel vectors is determined by $\mathcal{H}_k$ as an Euclidean ball

[10], [14] as

$$\mathcal{H}_k = \left\{ \hat{\mathbf{h}}_k + \Delta\mathbf{h}_k \left| \Delta\mathbf{h}_k^H \mathbf{\Phi}_k \Delta\mathbf{h}_k \leq \varepsilon_k^2 \right. \right\}, \quad k = 1, 2, ..., K \tag{1}$$

where the ball is centered around the actual value of the estimated CSI vector $\hat{\mathbf{h}}_k$ from M DA ports to the kth MS, $\Delta\mathbf{h}_k \in \mathbb{C}^{MN_T\times 1}$ is the norm-bounded uncertainty vector, $\mathbf{\Phi}_k \in \mathbb{C}^{MN_T\times MN_T}$ defines the orientation of the region, and ε_k represents the radius of the ball.

During one time slot, K independent signal streams are conveyed simultaneously to K MSs. Specifically, the transmit beamforming vector $\mathbf{v}_k^m \in \mathbb{C}^{N_T\times 1}$ is allocated for the kth MS at the mth DA port. Thus, we denote the joint transmit beamformer vector $\mathbf{v}_k \in \mathbb{C}^{MN_T\times 1}$ used by M DS ports for the kth MS as $\mathbf{v}_k = \mathrm{vec}([\,\mathbf{v}_{1,k}\ \mathbf{v}_{2,k}\ \ldots\ \mathbf{v}_{M,k}\,])$. Then, the transmitted signal to the kth MS is obtained by

$$\mathbf{x}_k = \mathbf{v}_k s_k \quad \forall k$$

where $s_k \sim \mathcal{CN}(0,1)$ indicates the corresponding transmitted data symbol for the kth MS, which is independent and identically distributed circularly symmetric complex Gaussian random variable with zero mean and unit variance. We assume that each DA port has its own power constraint $P_m (m = 1, ..., M)$. Let us define an $MN_T \times MN_T$ square matrix $\mathbf{D}_m \triangleq \mathrm{diag}(\underbrace{0, ..., 0}_{(m-1)N_T}, \underbrace{1, ..., 1}_{N_T}, \underbrace{0, ..., 0}_{(M-m)N_T})$. Then, the per-DA per power constraint is given as $\sum_{k=1}^K \mathrm{tr}(\mathbf{D}_m \mathbf{v}_k \mathbf{v}_k^H) \leq \alpha P_m, \forall m$.

The received signal at the kth MS is expressed as

$$y_k = \mathbf{h}_k^H \sum_{j=1}^K \mathbf{v}_j s_j + n_k$$

where n_k represents the additive white Gaussian noise (AWGN) with variance σ_k^2 at the kth MS. It is also assumed that each MS splits the received signal power into two parts using a power splitter: one for the EH and the other for the ID [8], [11]. The PS divides the $\rho_k \in (0,1]$ portion and the $1-\rho_k$ portion of the received signal power to the ID and the EH, respectively.

Therefore, the split signal for the ID of the kth MS is written as

$$y_k^{ID} = \sqrt{\rho_k}\left(\mathbf{h}_k^H \sum_{j=1}^K \mathbf{v}_j s_j + n_k\right) + z_k$$

where z_k stands for the AWGN with variance δ_k^2 during the ID process at the kth MS. Then, the received SINR for the kth MS is defined as

$$\mathrm{SINR}_k(\{\mathbf{v}_k\}, \rho_k) = \frac{\rho_k |\mathbf{h}_k^H \mathbf{v}_k|^2}{\rho_k \sum_{j\neq k} |\mathbf{h}_k^H \mathbf{v}_j|^2 + \rho_k \sigma_k^2 + \delta_k^2}. \tag{2}$$

Also, due to the broadcast nature of wireless channels, the energy carried by all signals, i.e., the $1-\rho_k$ portion of $\mathbf{v}_k$, can be harvested at the kth MS, and the split signal for the EH of the kth MS is thus given as

$$y_k^{EH} = \sqrt{1-\rho_k}\left(\mathbf{h}_k^H \sum_{j=1}^K \mathbf{v}_j s_j + n_k\right).$$

Then, the harvested energy by the EH of the kth MS is obtained as

$$E_k = \zeta_k (1-\rho_k)\left(\sum_{j=1}^K |\mathbf{h}_k^H \mathbf{v}_j|^2 + \sigma_k^2\right)$$

where $\zeta_k \in (0\,1]$ is the constant that accounts for the energy conversion efficiency for the EH of the kth MS.

In this paper, we assume that the harvested power at each MS should be larger than a given threshold, and each DA port also needs to satisfy the per-DA port power constraint. Hence, our aim is to jointly optimize the transmit beamforming vector and the PS factor by maximizing the minimum SINR subject to the EH constraint and the per-DA power constraint. Then, by incorporating the norm-bounded channel uncertainty model in (1), the robust optimization problem is expressed as

$$\max_{\{\mathbf{v}_k\},\rho_k} \ \min_{\mathbf{h}_k \in \mathcal{H}_k} \mathrm{SINR}_k(\{\mathbf{v}_k\}, \rho_k) \tag{3a}$$

$$\text{s.t.}\ \zeta_k (1-\rho_k)\left(\sum_{j=1}^K |\mathbf{h}_k^H \mathbf{v}_j|^2 + \sigma_k^2\right) \geq e_k \quad \forall k \tag{3b}$$

$$\sum_{k=1}^K \mathrm{tr}(\mathbf{D}_m \mathbf{v}_k \mathbf{v}_k^H) \leq P_m \quad \forall m \tag{3c}$$

$$0 < \rho_k \leq 1 \quad \forall k \tag{3d}$$

where e_k represents the required harvested power of the kth MS. Problem (3) is nonconvex due to coupled variables $\{\rho_k\}$ and $\{\mathbf{v}_k\}$ in both the objective function and the EH constraint and, thus, is difficult to solve efficiently.

III. Proposed Robust Joint Designs

In this section, we propose two robust joint design algorithms for problem (3). First, we present a bisection search method, which generates a local optimal rank-one solution. To reduce the computational complexity, we then introduce an SCA-based algorithm to achieve a suboptimal solution.

A. Proposed Method Based on Bisection Search

To make problem (3) tractable, we decompose the problem into a set of the min–max per-DA port power balancing problems, one for each given SINR target $\Gamma > 0$ [15]. Using bisection search over Γ, the optimal solution to problem (3) can be obtained by solving the corresponding min–max per-DA port power balancing problem with different Γ. Then, for a given Γ, we focus on the following min–max per-DA port power balancing problem as

$$\min_{\{\mathbf{v}_k\},\rho_k} \ \max_{1\leq m\leq M} \frac{\sum_{k=1}^K \mathrm{tr}(\mathbf{D}_m \mathbf{v}_k \mathbf{v}_k^H)}{P_m} \tag{4a}$$

$$\text{s.t.}\ \zeta_k (1-\rho_k)\left(\sum_{j=1}^K |\mathbf{h}_k^H \mathbf{v}_j|^2 + \sigma_k^2\right) \geq e_k \quad \forall k \tag{4b}$$

$$\mathrm{SINR}_k(\{\mathbf{v}_k\}, \rho_k) \geq \Gamma \quad \forall k \tag{4c}$$

$$0 < \rho_k \leq 1 \quad \forall k. \tag{4d}$$

We represent $\alpha^*(\Gamma)$ as the optimal objective value of problem (4). Note that based on the equation $\alpha^*(\Gamma) = 1$ [22, Lemma 2], we can obtain the optimal beamforming solution for problem (3). Problem (4) is still nonconvex in terms of the nonconvex objective function (4a). First, we tackle the objective function (4a) by introducing an auxiliary variable α. Then, the min–max per-DA port power balancing problem (4) can be rewritten as

$$\min_{\{\mathbf{v}_k\},\rho_k,\alpha,\mathbf{h}_k\in\mathcal{H}_k} \alpha \tag{5a}$$

$$\text{s.t. } \sum_{k=1}^{K} \mathrm{tr}(\mathbf{D}_m \mathbf{v}_k \mathbf{v}_k^H) \le \alpha P_m \quad \forall m \tag{5b}$$

$$\text{(4b)–(4d).}$$

We can see that problem (5) has semi-infinite constraints (4b) and (4c), which are nonconvex. To make the constraint (4b) tractable, the following lemma is introduced to convert (4b) into a quadratic matrix inequality (QMI).

Lemma 1 (Schur complement [26]): Let $\mathbf{N}$ be a complex Hermitian matrix as

$$\mathbf{N} = \mathbf{N}^H = \begin{bmatrix} \mathbf{Y}_1 & \mathbf{Y}_2 \\ \mathbf{Y}_2^H & \mathbf{Y}_3 \end{bmatrix}.$$

Then, we have $\mathbf{N} \succ \mathbf{0}$ if and only if $\mathbf{Y}_1 - \mathbf{Y}_2^H \mathbf{Y}_3^{-1} \mathbf{Y}_2 \succeq \mathbf{0}$ with $\mathbf{Y}_3 \succ \mathbf{0}$, or $\mathbf{Y}_3 - \mathbf{Y}_2^H \mathbf{Y}_1^{-1} \mathbf{Y}_2 \succeq \mathbf{0}$ with $\mathbf{Y}_1 \succ \mathbf{0}$. ■

Let us define an $MN_T \times MN_T$ square matrix $\mathbf{V}_k$ as $\mathbf{V}_k = \mathbf{v}_k \mathbf{v}_k^H$. By utilizing Lemma 1, the constraint (4b) can be converted into

$$\begin{bmatrix} \zeta_k(1-\rho_k) & \sqrt{e_k} \\ \sqrt{e_k} & (\hat{\mathbf{h}}_k + \Delta\mathbf{h}_k)^H \mathbf{R} (\hat{\mathbf{h}}_k + \Delta\mathbf{h}_k) + \sigma_k^2 \end{bmatrix} \succeq \mathbf{0} \tag{6}$$

where $\mathbf{R} \triangleq \sum_{k=1}^{K} \mathbf{V}_k$. Note that (6) is still nonconvex. In order to remove the channel uncertainty in (6), the following lemma is required to convert the constraint (6) into LMI.

Lemma 2 [30, Th. 3.5]: Let us denote $\mathbf{U}_k \in \mathbb{C}$, for $k \in [1,6]$. If $\mathbf{T}_i \succeq \mathbf{0}$ for $i = 1, 2$, then the following QMIs

$$\begin{bmatrix} \mathbf{U}_1 & \mathbf{U}_2 + \mathbf{U}_3\mathbf{X} \\ (\mathbf{U}_2 + \mathbf{U}_3\mathbf{X})^H & \mathbf{U}_4 + \mathbf{X}^H\mathbf{U}_5 + \mathbf{U}_5^H\mathbf{X} + \mathbf{X}^H\mathbf{U}_6\mathbf{X} \end{bmatrix} \succeq \mathbf{0}$$

$$\mathbf{I} - \mathbf{X}^H \mathbf{T}_i \mathbf{X} \succeq \mathbf{0} \quad \forall \mathbf{X}$$

are equivalent to the LMI

$$\begin{bmatrix} \mathbf{U}_1 & \mathbf{U}_2 & \mathbf{U}_3 \\ \mathbf{U}_2^H & \mathbf{U}_4 & \mathbf{U}_5^H \\ \mathbf{U}_3^H & \mathbf{U}_5 & \mathbf{U}_6 \end{bmatrix} + \lambda_1 \begin{bmatrix} \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{I} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{T}_1 \end{bmatrix} + \lambda_2 \begin{bmatrix} \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{I} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{T}_2 \end{bmatrix} \succeq \mathbf{0}$$

where $\lambda_i \ge 0\,(i = 1, 2)$. ■

To proceed, we set $\mathbf{X} = \Delta\mathbf{h}_k$, $\mathbf{T}_1 = 1/\varepsilon_k^2\mathbf{I}$, $\mathbf{T}_2 = \mathbf{0}$, $\mathbf{U}_1 = 1 - \rho_k$, $\mathbf{U}_2 = \sqrt{e_k}$, $\mathbf{U}_3 = \mathbf{0}_{1\times MN_T}$, $\mathbf{U}_4 = \hat{\mathbf{h}}_k^H \mathbf{R} \hat{\mathbf{h}}_k + \sigma_k^2 - t_k$, and $\mathbf{U}_5 = \hat{\mathbf{h}}_k^H \mathbf{R}$, $\mathbf{U}_6 = \mathbf{R}$. Then, by exploiting Lemma 2, constraint (6) can be equivalently modified as the following convex LMI:

$$\mathbf{A}_k = \begin{bmatrix} \zeta_k(1-\rho_k) & \sqrt{e_k} & \mathbf{0}_{1\times MN_T} \\ \sqrt{e_k} & \hat{\mathbf{h}}_k^H \mathbf{R} \hat{\mathbf{h}}_k + \sigma_k^2 - t_k & \hat{\mathbf{h}}_k^H \mathbf{R} \\ \mathbf{0}_{MN_T\times 1} & \mathbf{R}\hat{\mathbf{h}}_k & \mathbf{R} + \frac{t_k}{\varepsilon_k^2}\mathbf{I} \end{bmatrix} \succeq \mathbf{0} \tag{7}$$

where $t_k \ge 0$ is a slack variable.

Next, we transform constraint (4c) to the convex one. Due to the definition of SINR_k and $\mathcal{H}_k$, constraint (4c) can be recast as

$$\rho_k \left| (\hat{\mathbf{h}}_k + \Delta\mathbf{h}_k)^H \mathbf{v}_k \right|^2 \ge \Gamma \left(\rho_k \sum_{j\ne k} \left| (\hat{\mathbf{h}}_k + \Delta\mathbf{h}_k)^H \mathbf{v}_j \right|^2 + \rho_k\sigma_k^2 + \delta_k^2 \right)$$

and thus, it follows that

$$\rho_k \left((\hat{\mathbf{h}}_k + \Delta\mathbf{h}_k)^H \mathbf{M}_k (\hat{\mathbf{h}}_k + \Delta\mathbf{h}_k) + \sigma_k^2 \right) \ge \delta_k^2 \tag{8}$$

where $\mathbf{M}_k = \frac{1}{\Gamma}\mathbf{V}_k - \sum_{j\ne k} \mathbf{V}_j$.

Also, we utilize a similar methodology for (8) as follows. By applying Lemma 1, constraint (8) can be changed into

$$\begin{bmatrix} \rho_k & \delta_k \\ \delta_k & (\hat{\mathbf{h}}_k + \Delta\mathbf{h}_k)^H \mathbf{M}_k (\hat{\mathbf{h}}_k + \Delta\mathbf{h}_k) + \sigma_k^2 \end{bmatrix} \succeq \mathbf{0}. \tag{9}$$

In order to get rid of the channel uncertainty $\Delta\mathbf{h}_k$ in (9), Lemma 2 is adopted, and constraint (9) is equivalently modified as

$$\mathbf{B}_k = \begin{bmatrix} \rho_k & \delta_k & \mathbf{0}_{1\times MN_T} \\ \delta_k & \hat{\mathbf{h}}_k^H \mathbf{M}_k \hat{\mathbf{h}}_k + \sigma_k^2 - r_k & \hat{\mathbf{h}}_k^H \mathbf{M}_k \\ \mathbf{0}_{MN_T\times 1} & \mathbf{M}_k \hat{\mathbf{h}}_k & \mathbf{M}_k + \frac{r_k}{\varepsilon_k^2}\mathbf{I} \end{bmatrix} \succeq \mathbf{0} \tag{10}$$

where $r_k \ge 0$ is a slack variable.

Defining $\hat{\mathbf{V}}_{m,k}$ as $\hat{\mathbf{V}}_{m,k} = \mathbf{D}_m \mathbf{V}_k$, problem (5) is thus reformulated as

$$\begin{aligned} &\min_{\{\mathbf{V}_k\},\rho_k,\alpha,t_k,r_k} \alpha \\ &\text{s.t. } \sum_{k=1}^{K} \mathrm{tr}(\hat{\mathbf{V}}_{m,k}) \le \alpha P_m \quad \forall m \\ &\qquad \mathbf{A}_k \succeq \mathbf{0},\ \mathbf{B}_k \succeq \mathbf{0},\ \mathbf{V}_k \succeq \mathbf{0}, \quad (4d) \\ &\qquad t_k \ge 0,\ r_k \ge 0,\ \mathrm{rank}(\mathbf{V}_k) = 1 \quad \forall k. \end{aligned} \tag{11}$$

The above optimization problem is difficult to solve in general due to the rank-one constraint. Therefore, we employ the semidefinite relaxation (SDR) technique [27], which simply drops the constraints $\mathrm{rank}(\mathbf{V}_k) = 1$ for all $\mathbf{V}_k$ s. Then, problem (11) becomes a convex problem, which can be solved efficiently by a convex programming solver such as CVX [28]. In the following theorem, we show that a solution $\mathbf{V}_k^*$ to problem (11) satisfies $\mathrm{rank}(\mathbf{V}_k^*) \le 2$.

Theorem 1: If problem (11) is feasible, the rank of a solution $\mathbf{V}_k^*$ to problem (11) via rank relaxation is less than or equal to 2.

Proof: See Appendix A. ■

After $\mathbf{V}_k^*$ is obtained, if $\text{rank}(\mathbf{V}_k^*) = 1$, we can compute an optimal transmit beamforming solution $\mathbf{v}_k$ by eigenvalue decomposition (EVD) of $\mathbf{V}_k^*$. If $\text{rank}(\mathbf{V}_k^*) = 2$, we use the conventional GR technique [27] to find $\mathbf{v}_k$ for $k = 1, ..., K$. In particular, the GR technique generates a suboptimal solution. Hence, when $\text{rank}(\mathbf{V}_k^*) = 2$, we will propose an iterative algorithm to recover the optimal rank-one solution by following the approach in [34].

First, since $\hat{\mathbf{V}}_{m,k}$ is always semipositive definite, we have $\text{tr}(\hat{\mathbf{V}}_{m,k}) \geq \lambda_{\max}(\hat{\mathbf{V}}_{m,k})$. Thus, we can prove that $\text{rank}(\hat{\mathbf{V}}_{m,k}) = 1$ if $\text{tr}(\hat{\mathbf{V}}_{m,k}) \leq \lambda_{\max}(\hat{\mathbf{V}}_{m,k})$. Then, we can transform the constraint $\text{rank}(\hat{\mathbf{V}}_{m,k}) = 1$ into the single reverse convex constraint as

$$\sum_{k=1}^{K} (\text{tr}(\hat{\mathbf{V}}_{m,k}) - \lambda_{\max}(\hat{\mathbf{V}}_{m,k})) \leq 0.$$

Note that the function $\lambda_{\max}(\hat{\mathbf{V}}_{m,k})$ on the set of Hermitian matrices is convex. When $\sum_{k=1}^{K} (\text{tr}(\hat{\mathbf{V}}_{m,k}) - \lambda_{\max}(\hat{\mathbf{V}}_{m,k}))$ is small enough, $\hat{\mathbf{V}}_{m,k}$ will approach $\lambda_{\max}(\hat{\mathbf{V}}_{m,k})\hat{\mathbf{v}}_{m,k}^{\max}(\hat{\mathbf{v}}_{m,k}^{\max})^H$, where $\hat{\mathbf{v}}_{m,k}^{\max}$ represents the eigenvector corresponding to the maximum eigenvalue $\lambda_{\max}(\hat{\mathbf{V}}_{m,k})$ with $\|\hat{\mathbf{v}}_{m,k}^{\max}\| = 1$. Then, the optimal transmit beamformer vector can be expressed by

$$\mathbf{v}_{m,k} = \sqrt{\lambda_{\max}(\hat{\mathbf{V}}_{m,k})}\hat{\mathbf{v}}_{m,k}^{\max} \tag{12}$$

which satisfies the rank-one constraint.

Thus, in order to make $\sum_{k=1}^{K} (\text{tr}(\hat{\mathbf{V}}_{m,k}) - \lambda_{\max}(\hat{\mathbf{V}}_{m,k}))$ as small as possible, we adopt the exact penalty method [26]. First, introducing a sufficiently large penalty ratio $\theta > 0$, the alternative formulation is considered as

$$\min_{\{\mathbf{V}_k\},\rho_k,\alpha,t_k,r_k} \quad \alpha \tag{13a}$$

$$\text{s.t. } \mathbf{A}_k \succeq \mathbf{0},\ \mathbf{B}_k \succeq \mathbf{0},\ \mathbf{V}_k \succeq \mathbf{0}, \quad (4d) \tag{13b}$$

$$\sum_{k=1}^{K} (\text{tr}(\hat{\mathbf{V}}_{m,k}) + \theta(\text{tr}(\hat{\mathbf{V}}_{m,k}) - \lambda_{\max}(\hat{\mathbf{V}}_{m,k}))) \leq \alpha P_m \tag{13c}$$

$$t_k \geq 0, r_k \geq 0 \quad \forall k. \tag{13d}$$

We can find from (13c) that the difference $\text{tr}(\hat{\mathbf{V}}_{m,k}) - \lambda_{\max}(\hat{\mathbf{V}}_{m,k})$ will be minimized when θ is large enough. Clearly, (13c) is set to minimize $\text{tr}(\hat{\mathbf{V}}_{m,k}) - \lambda_{\max}(\hat{\mathbf{V}}_{m,k})$. Note that (13c) is nonconvex due to the coupled θ and $\hat{\mathbf{V}}_{m,k}$. To eliminate the coupling between θ and $\hat{\mathbf{V}}_{m,k}$, we apply the following lemma to provide an effective approximation of (13c).

Lemma 3: Let us define $\mathbf{C} \in \mathbb{H}_+$ and $\mathbf{E} \in \mathbb{H}_+$. Then, it always follows $\lambda_{\max}(\mathbf{C}) - \lambda_{\max}(\mathbf{E}) \geq \boldsymbol{e}_{\max}^H(\mathbf{C} - \mathbf{E})\boldsymbol{e}_{\max}$, where $\boldsymbol{e}_{\max}$ denotes the eigenvector corresponding to the maximum eigenvalue of $\mathbf{E}$. ■

According to Lemma 3, we propose an iterative algorithm to recover a local optimal solution. For given some feasible $\{\hat{\mathbf{V}}_{m,k}^{(n)}\}$ to problem (13), we get

$$\begin{aligned}
&\text{tr}\left(\hat{\mathbf{V}}_{m,k}^{(n+1)}\right) + \theta\Big[\text{tr}\left(\hat{\mathbf{V}}_{m,k}^{(n+1)}\right) - \lambda_{\max}\left(\hat{\mathbf{V}}_{m,k}^{(n)}\right) \\
&\qquad - \left(\hat{\mathbf{v}}_{m,k}^{\max,(n)}\right)^H \left(\hat{\mathbf{V}}_{m,k}^{(n+1)} - \hat{\mathbf{V}}_{m,k}^{(n)}\right)\hat{\mathbf{v}}_{m,k}^{\max,(n)}\Big] \\
&\leq \text{tr}\left(\hat{\mathbf{V}}_{m,k}^{(n)}\right) + \theta\left(\text{tr}\left(\hat{\mathbf{V}}_{m,k}^{(n)}\right) - \lambda_{\max}\left(\hat{\mathbf{V}}_{m,k}^{(n)}\right)\right)
\end{aligned} \tag{14}$$

where the superscript n represents the nth iteration.

Hence, the following SDP problem generates an optimal solution $\mathbf{V}_{m,k}^{(n+1)}$ that is better than $\mathbf{V}_{m,k}^{(n)}$ to problem (13) as

$$\min_{\{\mathbf{V}_k\},\rho_k,\alpha,t_k,r_k} \quad \alpha \tag{15a}$$

$$\text{s.t. (13b), (13d)} \tag{15b}$$

$$\begin{aligned}
&\sum_{k=1}^{K}\Big\{\text{tr}(\hat{\mathbf{V}}_{m,k}) + \theta\Big[\text{tr}(\hat{\mathbf{V}}_{m,k}) - \lambda_{\max}(\hat{\mathbf{V}}_{m,k}^{(n)}) \\
&\qquad - (\hat{\mathbf{v}}_{m,k}^{\max,(n)})^H\big(\hat{\mathbf{V}}_{m,k} \\
&\qquad\qquad - \hat{\mathbf{V}}_{m,k}^{(n)}\big)\hat{\mathbf{v}}_{m,k}^{\max,(n)}\Big]\Big\} \\
&\leq \alpha P_m.
\end{aligned} \tag{15c}$$

Now, problem (15) can be further simplified to

$$\min_{\{\mathbf{V}_k\},\rho_k,\alpha,t_k,r_k} \quad \alpha \tag{16a}$$

$$\text{s.t. (13b), (13d)} \tag{16b}$$

$$\begin{aligned}
&\sum_{k=1}^{K}\Big\{\text{tr}(\hat{\mathbf{V}}_{m,k}) + \theta\Big[\text{tr}(\hat{\mathbf{V}}_{m,k}) \\
&\qquad - \left(\hat{\mathbf{v}}_{m,k}^{\max,(n)}\right)^H \hat{\mathbf{V}}_{m,k}\hat{\mathbf{v}}_{m,k}^{\max,(n)}\Big]\Big\} \\
&\leq \alpha P_m \quad \forall m.
\end{aligned} \tag{16c}$$

To summarize, we can solve problem (3) with a given Γ, and a bisection search algorithm is applied to update Γ for the objective value $\alpha^* = 1$. Then, this process is repeated until convergence. For the bisection method, we need to determine an upper bound $\Gamma_{\max}$ as $0 < \Gamma < \Gamma_{\max}$. Then, we can see that

$$\begin{aligned}
\text{SINR}_k(\{\mathbf{v}_k\}, \rho_k) &= \frac{\rho_k |\mathbf{h}_k^H \mathbf{v}_k|^2}{\rho_k \sum_{j\neq k} |\mathbf{h}_k^H \mathbf{v}_j|^2 + \rho_k \sigma_k^2 + \delta_k^2} \\
&\leq \frac{\rho_k |\mathbf{h}_k^H \mathbf{v}_k|^2}{\rho_k \sigma_k^2 + \delta_k^2} \\
&\leq \frac{\rho_k \|\mathbf{h}_k\|^2 \sum_{j=1}^{M} P_m}{\rho_k \sigma_k^2 + \delta_k^2} \\
&\leq \frac{\|\mathbf{h}_k\|^2 \sum_{j=1}^{M} P_m}{\sigma_k^2 + \delta_k^2}.
\end{aligned}$$

From this, we can set $\Gamma_{\max}$ as $\max_k\{\frac{\|\mathbf{h}_k\|^2 \sum_{j=1}^{M} P_m}{\sigma_k^2 + \delta_k^2}\}$. Due to monotonicity of α, the bisection search algorithm needs

Algorithm 1: Proposed Algorithm Based on Bisection Search.

Set $\Gamma_{\min} = 0$, $\Gamma_{\max} = \max_k \{\frac{\|\mathbf{h}_k\|^2 \sum_{j=1}^M P_m}{\sigma_k^2+\delta_k^2}\}$, $n = 0$, $\theta > 0$, a prescribed accuracy tolerance $\epsilon > 0$ and $\eta > 0$.
Randomly generate an initial value $\{\mathbf{V}_k^{(0)}, \rho_k^{(0)}\}, \forall k$ in (16).
Repeat
  Set $\Gamma_{\mathrm{mid}} = (\Gamma_{\min} + \Gamma_{\max})/2$.
  Repeat
    Solve problem (16) with Γ_{mid} to obtain a solution $\mathbf{V}_k^{(n+1)}$ and $\rho_k^{(n+1)}$.
    If $\hat{\mathbf{V}}_{m,k}^{(n+1)} = \hat{\mathbf{V}}_{m,k}^{(n)}$, set $\theta \leftarrow 2\theta$.
    Update $n \leftarrow n+1$.
  Until $|\mathrm{tr}(\hat{\mathbf{V}}_{m,k}^{(n)}) - \lambda_{\max}(\hat{\mathbf{V}}_{m,k}^{(n)})| < \epsilon$
  Set $\mathbf{V}_k^{(0)} = \mathbf{V}_k^{(n)}$, $\rho_k^{(0)} = \rho_k^{(n)}$, and $n = 0$.
  Repeat
    Solve problem (16) with Γ_{mid} to obtain a solution $\mathbf{V}_k^{(n+1)}$, $\rho_k^{(n+1)}$, and $\alpha^{(n+1)}$.
    Update $n \leftarrow n+1$.
  Until $|\mathrm{tr}(\hat{\mathbf{V}}_{m,k}^{(n)}) - \lambda_{\max}(\hat{\mathbf{V}}_{m,k}^{(n)})| < \epsilon$
  If $\alpha^{(n+1)} < 1$,
    set $\Gamma_{\min} = \Gamma_{\mathrm{mid}}$.
  else
    set $\Gamma_{\max} = \Gamma_{\mathrm{mid}}$.
Until $|\Gamma_{\max} - \Gamma_{\min}| < \eta$
Calculate $\mathbf{v}_k$ according to (12).

$\mathcal{O}(\log_2 \frac{\Gamma_{\max}}{\eta})$ iterations, where η is a small positive constant, which controls the accuracy of the bisection search algorithm. It is noted that this bisection search algorithm converges to the optimal solution $\mathbf{v}_k^*$ for problem (3). The proposed algorithm based on bisection search is summarized in Algorithm 1.[1]

B. Robust Iterative Algorithm Based on the SCA

To reduce the computational complexity of Algorithm 1, we consider another formulation for the minimum SINR maximization problem. Based on the SCA method, the optimization can also be reformulated into a convex form with linear constraints. Thus, the robust SINR maximization problem can be rewritten as

$$\min_{\{\mathbf{v}_k\},\rho_k} \max_{\mathbf{h}_k\in\mathcal{H}_k} \frac{|\mathbf{h}_k^H\mathbf{v}_k|^2}{\sum_{j\neq k}|\mathbf{h}_k^H\mathbf{v}_j|^2 + \sigma_k^2 + \frac{\delta_k^2}{\rho_k}} \tag{17a}$$

$$\text{s.t.} \quad \min_{\mathbf{h}_k\in\mathcal{H}_k} \zeta_k(1-\rho_k)\left(\sum_{j=1}^K |\mathbf{h}_k^H\mathbf{v}_j|^2 + \sigma_k^2\right) \geq e_k \quad \forall k,$$

$$\text{(3c), (3d).} \tag{17b}$$

[1]The proposed optimization algorithm is performed by the MPU. Then, the MPU can send the beamforming solutions to individual transmitters through fiber optics or an exclusive RF link. Also, it can transmit the PS factor solution to individual receivers through the estimated instantaneous channel.

In this problem, we minimize the numerator of the SINR while maximizing the denominator of the SINR [9]. Based on a tight approximation, the minimum and the maximum for each term can be determined by employing the Lagrangian multiplier method. In addition, to equivalently convert the objective function (17a), we introduce the exponential variables e^{x_k} and e^{y_k} as

$$e^{x_k} \leq \min_{\mathbf{h}_k\in\mathcal{H}_k} |\mathbf{h}_k^H\mathbf{v}_k|^2 \tag{18a}$$

$$e^{y_k} \geq \max_{\mathbf{h}_k\in\mathcal{H}_k} \sum_{j\neq k}|\mathbf{h}_k^H\mathbf{v}_j|^2 + \sigma_k^2 + \frac{\delta_k^2}{\rho_k}. \tag{18b}$$

Thus, in order to circumvent the nonconvex objective function (17a), problem (17) is expressed by introducing a slack variable τ as

$$\min_{\{\mathbf{v}_k\},\rho_k,\tau,x_k,y_k} \tau$$

$$\text{s.t.} \quad e^{x_k - y_k} \leq \tau, \tag{19a}$$

$$\text{(3c), (3d), (17b), (18a), (18b).} \tag{19b}$$

Note that (18b) is in concave form. Defining $y_k^{(n)}$ as the variables y_k at the nth iteration for an SCA iterative algorithm, a Taylor series expansion $e^{z_k^{(n)}}(z_k - z_k^{(n)} + 1) \leq e^{z_k}$ is adopted to linearize (18b) as

$$e^{y_k^{(n)}}\left(y_k - y_k^{(n)} + 1\right) \geq \max_{\mathbf{h}_k\in\mathcal{H}_k} \sum_{j\neq k}|\mathbf{h}_k^H\mathbf{v}_j|^2 + \sigma_k^2 + \frac{\delta_k^2}{\rho_k}. \tag{20}$$

When computing the EH constraint in (17b) and the SINR constraint in (20), we need to calculate $|\mathbf{h}_k^H\mathbf{v}_j|^2$. Using $\mathbf{x}^H\mathbf{A}\mathbf{x} = \mathrm{tr}\left(\mathbf{A}\mathbf{x}\mathbf{x}^H\right)$, we can write this as

$$\begin{aligned}
|\mathbf{h}_k^H\mathbf{v}_j|^2 &= |(\hat{\mathbf{h}}_k + \Delta\mathbf{h}_k)^H\mathbf{v}_j|^2 \\
&= \mathbf{v}_j^H(\hat{\mathbf{h}}_k + \Delta\mathbf{h}_k)(\hat{\mathbf{h}}_k + \Delta\mathbf{h}_k)^H\mathbf{v}_j \\
&= \mathrm{tr}\big((\hat{\mathbf{h}}_k + \Delta\mathbf{h}_k)(\hat{\mathbf{h}}_k + \Delta\mathbf{h}_k)^H\mathbf{v}_j\mathbf{v}_j^H\big) \\
&= \mathrm{tr}\big((\hat{\mathbf{H}}_k + \Delta_k)\mathbf{V}_j\big)
\end{aligned}$$

where $\hat{\mathbf{H}}_k$ is defined as $\hat{\mathbf{H}}_k \triangleq \hat{\mathbf{h}}_k\hat{\mathbf{h}}_k^H$, and $\Delta_k \triangleq \hat{\mathbf{h}}_k\Delta\mathbf{h}_k^H + \Delta\mathbf{h}_k\hat{\mathbf{h}}_k^H + \Delta\mathbf{h}_k\Delta\mathbf{h}_k^H$ represents the uncertainty in the matrix $\hat{\mathbf{H}}_k$.

It is noted that Δ_k is a norm-bounded matrix as $\|\Delta_k\|_F \leq \xi_k$. We can straightforwardly find the following relation [27]:

$$\begin{aligned}
\|\Delta_k\|_F &= \|\hat{\mathbf{h}}_k\Delta\mathbf{h}_k^H + \Delta\mathbf{h}_k\hat{\mathbf{h}}_k^H + \Delta\mathbf{h}_k\Delta\mathbf{h}_k^H\|_F \\
&\leq \|\hat{\mathbf{h}}_k\Delta\mathbf{h}_k^H\|_F + \|\Delta\mathbf{h}_k\hat{\mathbf{h}}_k^H\|_F + \|\Delta\mathbf{h}_k\Delta\mathbf{h}_k^H\|_F \\
&\leq \|\hat{\mathbf{h}}_k\|\|\Delta\mathbf{h}_k^H\| + \|\Delta\mathbf{h}_k\|\|\hat{\mathbf{h}}_k^H\| + \|\Delta\mathbf{h}_k\|^2 \\
&= \varepsilon_k^2 + 2\varepsilon_k\|\hat{\mathbf{h}}_k\|
\end{aligned}$$

where the first inequality is based on the triangle inequality, and the second inequality come from the Cauchy–Schwarz inequality. It is possible to choose $\xi_k \triangleq \varepsilon_k^2 + 2\varepsilon_k\|\hat{\mathbf{h}}_k\|$. It is noted that the bounds of this uncertainty are derived by the triangle inequality, the Cauchy–Schwarz inequality, and the multiplicity of the second norm, which are tight enough.

Adopting the preceding notations, we can rewrite (19) at the nth iteration as

$$\begin{aligned}
&\min_{\{\mathbf{V}_k\},\rho_k,\tau,x_k,y_k} \tau\\
&\text{s.t.} \min_{\|\Delta_k\|_F\le\xi_k} \mathrm{tr}\big((\hat{\mathbf{H}}_k+\Delta_k)\mathbf{V}_k\big)\ge e^{x_k}\\
&\max_{\|\Delta_k\|_F\le\xi_k} \sum_{j\neq k}\mathrm{tr}\big((\hat{\mathbf{H}}_k+\Delta_k)\mathbf{V}_j\big)+\sigma_k^2+\frac{\delta_k^2}{\rho_k}\\
&\qquad\le e^{y_k^{(n)}}\left(y_k-y_k^{(n)}+1\right)\\
&\min_{\|\Delta_k\|_F\le\xi_k} \sum\nolimits_{j=1}^{K}\mathrm{tr}\big((\hat{\mathbf{H}}_k+\Delta_k)\mathbf{V}_j\big)\ge\frac{e_k}{\zeta_k(1-\rho_k)}-\sigma_k^2\\
&\text{(3c), (3d), (19a)},\ \mathbf{V}_k\succeq\mathbf{0},\ \mathrm{rank}(\mathbf{V}_k)=1.
\end{aligned}\tag{21}$$

Note that problem (21) is nonconvex due to the existence of $\mathrm{tr}((\hat{\mathbf{H}}_k+\Delta_k)\mathbf{V}_k)$ in both the SINR and EH constraints. For computing $\mathrm{tr}((\hat{\mathbf{H}}_k+\Delta_k)\mathbf{V}_k)$, we have the following proposition.

Proposition 1: Let us denote $\Delta_k^{\min}$ and $\Delta_k^{\max}$ as the minimizer and the maximizer of $\mathrm{tr}((\hat{\mathbf{H}}_k+\Delta_k)\mathbf{V}_k)$, respectively. Then, $\Delta_k^{\min}$ and $\Delta_k^{\max}$ are expressed as

$$\Delta_k^{\min}=-\xi_k\frac{\mathbf{V}_k^H}{\|\mathbf{V}_k\|_F}\quad \Delta_k^{\max}=\xi_k\frac{\mathbf{V}_k^H}{\|\mathbf{V}_k\|_F}.\tag{22}$$

Proof: See Appendix B. ■

Using these results in (22) to remove the channel uncertainty Δ_k, we get the following convex form:

$$\begin{aligned}
&\min_{\|\Delta_k\|_F\le\xi_k}\sum_{j=1}^{K}\mathrm{tr}\big((\hat{\mathbf{H}}_k+\Delta_k)\mathbf{V}_j\big)\\
&\quad=\sum_{j=1}^{K}\big(\mathrm{tr}(\hat{\mathbf{H}}_k\mathbf{V}_j)-\xi_k\|\mathbf{V}_j\|_F\big)\\
&\max_{\|\Delta_k\|_F\le\xi_k}\sum_{j\neq k}\mathrm{tr}\big((\hat{\mathbf{H}}_k+\Delta_k)\mathbf{V}_j\big)\\
&\quad=\sum_{j\neq k}\big(\mathrm{tr}(\hat{\mathbf{H}}_k\mathbf{V}_j)+\xi_k\|\mathbf{V}_j\|_F\big).
\end{aligned}$$

Thus, by removing the rank-one constraint, the associated SINR maximization problem can be rewritten as

$$\min_{\{\mathbf{V}_k\},\rho_k,\tau,x_k,y_k}\tau$$

$$\text{s.t. } \mathrm{tr}(\hat{\mathbf{H}}_k\mathbf{V}_k)-\xi_k\|\mathbf{V}_k\|_F\ge e^{x_k}\tag{23a}$$

$$\sum_{j\neq k}\big(\mathrm{tr}(\hat{\mathbf{H}}_k\mathbf{V}_j)+\xi_k\|\mathbf{V}_j\|_F\big)+\sigma_k^2+\frac{\delta_k^2}{\rho_k}\le e^{y_k^{(n)}}\left(y_k-y_k^{(n)}+1\right)\tag{23b}$$

$$\sum_{j=1}^{K}\big(\mathrm{tr}(\hat{\mathbf{H}}_k\mathbf{V}_j)-\xi_k\|\mathbf{V}_j\|_F\big)\ge\frac{e_k}{\zeta_k(1-\rho_k)}-\sigma_k^2,\tag{23c}$$

$$\text{(3c), (3d), (19a)},\ \mathbf{V}_k\succeq\mathbf{0}\quad\forall k.$$

Algorithm 2: Robust Iterative Algorithm Based on the SCA.

Initialize $\{y_k^{(n)}\}$ and set $n=0$.
Repeat
  Solve problem (23) with $\{y_k^{(n)}\}$ to obtain $\mathbf{V}_k^{*(n)}$ and $\tau^{*(n)}$ for $k=1,\dots,K$.
  Set $y_k{}^{(n+1)}=y_k^{(n)}$ for $k=1,\dots K$.
  Update $n\leftarrow n+1$.
Until Convergence
If $\mathrm{rank}(\mathbf{V}_k^{*(n)})=1$,
  compute $\{\mathbf{v}_k^*\}$ by EVD of $\mathbf{V}_k^*(n)$.
else
  use the GR technique to find $\{\mathbf{v}_k^*\}$ for $k=1,\dots,K$.

Problem (23) becomes a convex form for a given $\{y_k^{(n)}\}$, which can be solved by using CVX [28]. In the SCA approach, the approximation with the current optimal solution can be updated iteratively until constraint (23b) holds with equality. The SCA algorithm is outlined in Algorithm 2. In Algorithm 2, the optimal solution to problem (23) at the nth iteration is defined as $\{\mathbf{V}_k^{*(n)}\}$, which achieves a stable point when the SCA algorithm converges.

IV. Computational Complexity

In this section, we evaluate the computational complexity of the proposed robust design methods. As will be shown in Section V, the proposed algorithms exhibit gains in terms of both computational complexity and performance compared to the conventional SDP scheme in [22], which employs local search. Now, we will present the complexity comparison by adopting the analysis in [31] and [32]. The complexities of the proposed algorithms are shown in Table I. Here, we denote n, $L^{\max}=\log_2\frac{\Gamma_{\max}}{\eta}$, $Q^{\max}$, and $D^{\max}$ as the number of decision variables, the bisection search number, the SCA iteration number, and the local search number in [22], respectively.

1) Algorithm 1 in problem (16) involves $2K$ LMI constraints of size MN_T+2, K LMI constraints of size MN_T, and $4K+M$ linear constraints.

2) Algorithm 2 in problem (23) has K second-order cones (SOC) constraints of dimension $M^2N_T^2+1$, K SOC constraints of dimension $(K-1)M^2N_T^2+1$, K SOC constraints of dimension $KM^2N_T^2+1$, K LMI constraints of size MN_T, and $3K+M$ linear constraints.

3) The conventional scheme in [22] consists of $2K$ LMI constraints of size MN_T+1, K LMI constraints of size MN_T, and $2K+M$ linear constraints.

For example, for a system with $M=3, K=2, N_T=3$, $L^{\max}=Q^{\max}=6$, and $D^{\max}=100$, the complexities of the proposed Algorithm 1, Algorithm 2, and the conventional scheme [22] are $\mathcal{O}(1.96\times10^9)$, $\mathcal{O}(3.41\times10^8)$, and $\mathcal{O}(4.31\times$

This article has been accepted for inclusion in a future issue of this journal. Content is final as presented, with the exception of pagination.

TABLE I
COMPLEXITY ANALYSIS OF DIFFERENT ALGORITHMS

Algorithms	Complexity order
Algorithm 1	$\mathcal{O}\Big(nL^{\max}Q^{\max}\sqrt{2K(MN_T+2)+KMN_T+4K+M}\Big\{2K(MN_T+2)^3+K(MN_T)^3+n[2K(MN_T+2)^2+K(MN_T)^2]+4K+M+n^2\Big\}\Big)$, where $n=\mathcal{O}(M^2N_T^2+3K+1)$
Algorithm 2	$\mathcal{O}\Big(nQ^{\max}\sqrt{6K+KMN_T+3K+M}\Big\{K[(M^2N_T^2+1)^2+((K-1)M^2N_T^2+1)^2+(KM^2N_T^2+1)^2]+K[(MN_T)^3+n(MN_T)^2]+3K+M+n^2\Big\}\Big)$, where $n=\mathcal{O}(M^2N_T^2+3K+1)$
Conventional scheme [22]	$\mathcal{O}\Big(nD^{\max}\sqrt{K(3MN_T+2)+2K+M}[2K(MN_T+1)^3+KM^3N_T^3+n(2K(MN_T+1)^2+KM^2N_T^2+2K+M)+n^2]\Big)$, where $n=\mathcal{O}(M^2N_T^2+2K+1)$

10^{10}), respectively. Thus, the complexity of the proposed Algorithms 1 and 2 are only 4.5% and 0.8% of that of the conventional scheme in [22], respectively.

V. SIMULATION RESULTS

In this section, we numerically compare the performance of the proposed algorithms for multiuser DAS SWIPT systems. Throughout the simulation, we consider DAS with a circular antenna layout and set $M=3$, $K=3$, and $N_T=4$. The power of each DA port is set to $P_1=\frac{P}{6}$, $P_2=\frac{P}{3}$, and $P_3=\frac{P}{2}$ as in [22]. Three DA ports form an equilateral triangle, while all MSs are uniformly distributed inside a disc with the cell radius $R=\sqrt{\frac{112}{3}}$ m centered at the centroid of the triangle. The jth DA port is located at $(r\cos\frac{2\pi(j-1)}{M}, r\sin\frac{2\pi(j-1)}{M})$ for $j=1,\ldots,M$ with $r=\sqrt{\frac{3}{7}}R$ as in [4]. The pathloss exponent γ is set to be 3. According to this setting, a received signal-to-noise ratio loss of 23.5 dB is observed at cell edge users compared to cell center users. All channel coefficients $\bar{\mathbf{h}}_{m,k}\in\mathbb{C}^{N_T\times 1}$ are modeled as Rician fading. The channel vector $\bar{\mathbf{h}}_{m,k}$ is given as $\bar{\mathbf{h}}_{m,k}=\sqrt{\frac{K_R}{1+K_R}}\bar{\mathbf{h}}_{m,k}^{\text{LOS}}+\sqrt{\frac{1}{1+K_R}}\bar{\mathbf{h}}_{m,k}^{\text{NLOS}}$, where $\bar{\mathbf{h}}_{m,k}^{\text{LOS}}$ indicates the line-of-sight (LOS) component with $\|\bar{\mathbf{h}}_{m,k}^{\text{LOS}}\|^2=d_{m,k}^{-\gamma/2}$, $\bar{\mathbf{h}}_{m,k}^{\text{NLOS}}$ represents the Rayleigh fading component as $\bar{\mathbf{h}}_{m,k}^{\text{NLOS}}\sim\mathcal{CN}(0,d_{m,k}^{-\gamma/2}\mathbf{I})$, and K_R is the Rician factor equal to 3. For the LOS component, we apply the far-field uniform linear antenna array to model the channels in [33]. For simplicity, it is assumed that all MSs have the same set of parameters, i.e., $\zeta_k=\zeta, \delta_k^2=\delta^2, \sigma_k^2=\sigma^2$, and $e_k=e$ for $k=1,\ldots,K$. In addition, we set $\sigma^2=-50$ dBm, $\delta^2=-30$ dBm, and $\zeta=0.3$. Also, all the channel uncertainties are chosen to be the same as $\varepsilon_k=\varepsilon, \forall k$. In the simulation, the worst-case rate in all the ID users $\min_{\forall j}\min_{\Delta\mathbf{h}_j\in\mathcal{H}_j}\log_2(1+\text{SINR}_j)$ is plotted by taking an average over 1000 randomly generated channel realizations.

Fig. 2 investigates the convergence performance of the proposed algorithms with $e=3$ dBm and $\varepsilon=0.01$. It is clear that the proposed iterative algorithms indeed converge in all cases. We can see that after seven iterations, the steady average worst-case rate is achieved for all P.

In Fig. 3, we present the average worst-case rate versus the number of DA ports M with various channel uncertainty ε with $P=60$ dBm, $e=5$ dBm, and $\varepsilon=0.01$. It is found that our proposed robust algorithms attain substantial worst-case rate improvements over the conventional scheme in [22]. It is observed that there is about 0.3 b/s/Hz difference between the curves of $\varepsilon=0.01$ and 0.1 for the proposed algorithms. Furthermore, our proposed Algorithm 2 achieves about 0.5 b/s/Hz and 0.7 b/s/Hz gain compared to the conventional scheme [22] for $\varepsilon=0.01$ and 0.1, respectively. We also see that our proposed

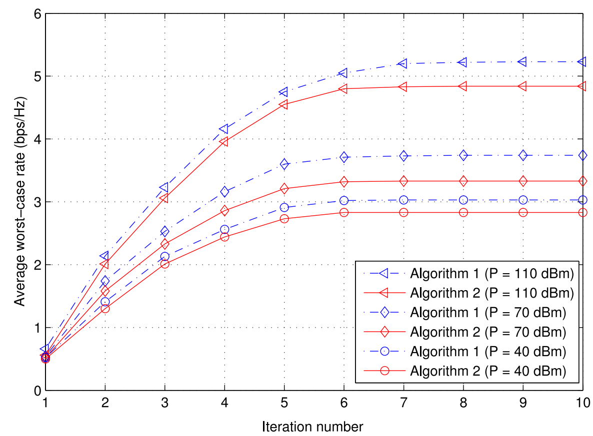

Fig. 2. Convergence performance of the proposed iterative algorithm for various P.

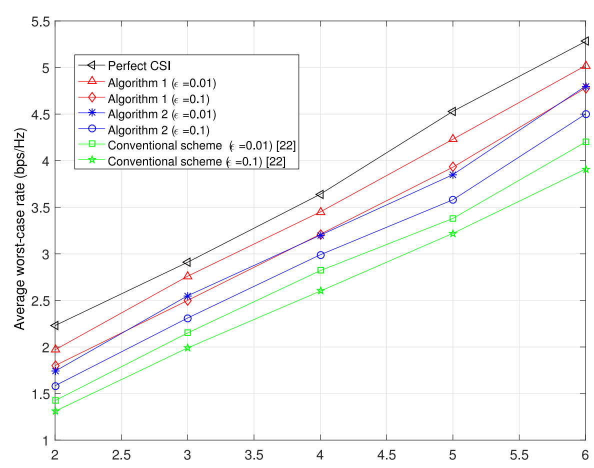

Fig. 3. Average worst-case rate versus the number of DA ports.

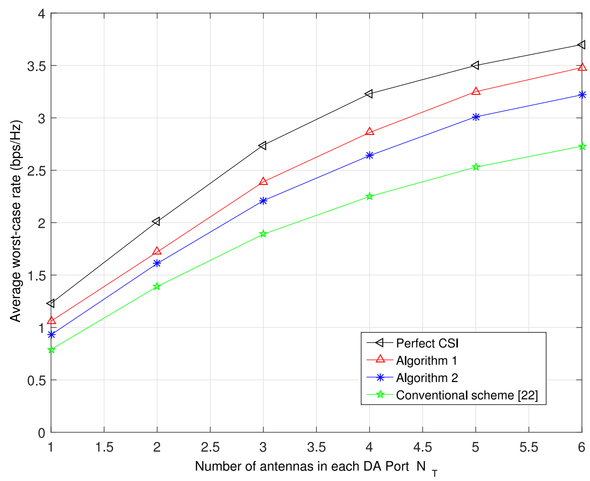

Fig. 4. Average worst-case rate versus the number of antennas in each DA port.

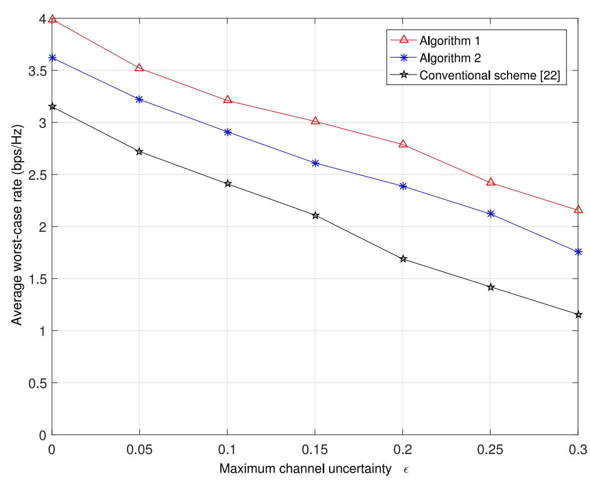

Fig. 5. Average worst-case rate versus channel uncertainty ε.

Algorithm 1 outperforms Algorithm 2 at the expense of increased complexity.

Fig. 4 shows the performance comparison among robust algorithms for different number of antennas in each DA port with $e = 5$ dBm and $P = 80$ dBm. One can see that the conventional algorithm [22] requires more antennas than our proposed robust algorithms. The performance gap between our proposed Algorithms 1 and 2 curves is about 0.3 b/s/Hz. Moreover, as N_T increases, the performance gap between our proposed algorithms and the conventional scheme becomes bigger.

Fig. 5 depicts the effect of the channel uncertainty ε on the average worst-case rate with $e = 0$ dBm and $P = 50$ dBm. We can check that as the maximum channel uncertainty ε decreases, the average worst-case rate becomes enhanced. Clearly, the proposed robust algorithms outperform the conventional scheme [22].

Finally, in Fig. 6, we exhibit the average worst-case rate versus the total transmit power target P for various ε with $e = 3$ dBm. Compared to our proposed Algorithm 1, Algorithm 2 achieves

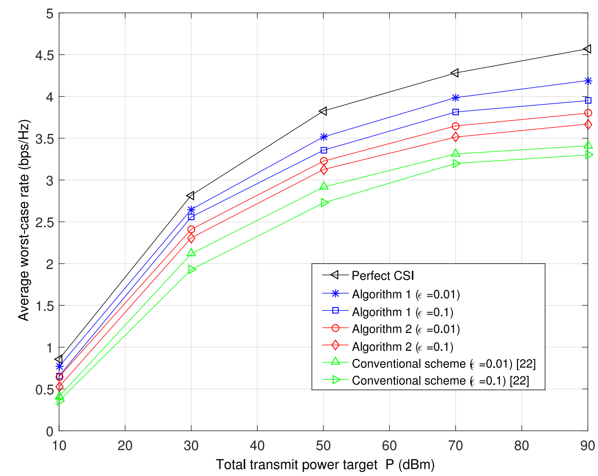

Fig. 6. Average worst-case rate versus P for various ε.

a complexity reduction at the expense of a performance loss. It is observed that as ε increases, the performance gap between our proposed algorithms and the conventional scheme becomes larger.

VI. Conclusion

In this paper, we have studied a design of robust transmit beamforming and PS in multiuser DAS SWIPT downlink systems under the per-DA port power constraint and the EH constraint. Assuming imperfect CSIT, the uncertainty of the channel is modeled by an Euclidean ball. We have developed an algorithm to find a robust beamforming solution for maximizing the worst-case SINR by addressing a set of convex per-DA port power balancing problems. The reformulated problem can be solved by applying the SDR technique. Also, given the beamforming solution, the PS factor has been calculated. We have proposed an iterative algorithm and a low-complexity algorithm for the worst-case SINR maximization problem. Simulation results have demonstrated the validity of the proposed algorithms.

Appendix A
Proof of Theorem 1

If the rank-one constraint is ignored, problem (11) becomes convex and satisfies Slater's condition. Thus, its duality gap is zero [26]. Assume that the dual variables $\{\mathbf{C}_k\} \in \mathbb{H}_+, \{\mathbf{Q}_k\} \in \mathbb{H}_+, \{\mathbf{S}_k\} \in \mathbb{H}_+$ and $\{\mu_m\} \geq 0$ correspond to the constraint $\mathbf{A}_k \succeq \mathbf{0}, \mathbf{B}_k \succeq \mathbf{0}, \mathbf{V}_k \succeq \mathbf{0}$ and $\sum_{k=1}^{K} \mathrm{tr}(\mathbf{D}_m \mathbf{V}_k) \leq \alpha P_m$ in (11), respectively. Then, the Lagrangian dual function of the primal problem (11) is given by

$$\begin{aligned}\mathcal{L} = \alpha - \sum_{k=1}^{K} \left(\mathrm{tr}\left(\mathbf{C}_k \mathbf{A}_k\right) + \mathrm{tr}\left(\mathbf{Q}_k \mathbf{B}_k\right) + \mathrm{tr}\left(\mathbf{S}_k \mathbf{V}_k\right)\right) \\ + \sum_{m=1}^{M} \mu_m \left(\sum_{k=1}^{K} \mathrm{tr}(\mathbf{D}_m \mathbf{V}_k) - \alpha P_m\right). \quad (24)\end{aligned}$$

Since $\mathbf{C}_k$ and $\mathbf{T}_k$ are Hermitian matrices, we have

$$\mathrm{tr}(\mathbf{C}_k\mathbf{A}_k) = \mathrm{tr}(\mathbf{C}_k\mathbf{G}_k^H\mathbf{T}\mathbf{G}_k) + \mathrm{tr}(\mathbf{C}_k\mathbf{F}_k)$$
$$\mathrm{tr}(\mathbf{Q}_k\mathbf{B}_k) = \mathrm{tr}(\mathbf{Q}_k\mathbf{G}_k^H\mathbf{M}_k\mathbf{G}_k) + \mathrm{tr}(\mathbf{Q}_k\mathbf{E}_k)$$

where

$$\mathbf{E}_k = \begin{bmatrix} \rho_k & \delta_k & \mathbf{0}_{1\times MN_T} \\ \delta_k & \sigma_k^2 - r_k & \mathbf{0}_{1\times MN_T} \\ \mathbf{0}_{MN_T\times 1} & \mathbf{0}_{MN_T\times 1} & \frac{r_k}{\varepsilon_k^2}\mathbf{I} \end{bmatrix}$$
$$\mathbf{F}_k = \begin{bmatrix} \zeta_k(1-\rho_k) & \sqrt{e_k} & \mathbf{0}_{1\times MN_T} \\ \sqrt{e_k} & \sigma_k^2 - t_k & \mathbf{0}_{1\times MN_T} \\ \mathbf{0}_{MN_T\times 1} & \mathbf{0}_{MN_T\times 1} & \frac{t_k}{\varepsilon_k^2}\mathbf{I} \end{bmatrix}$$
$$\mathbf{G}_k = [\mathbf{0} \quad \hat{\mathbf{h}}_k \quad \mathbf{I}].$$

Taking a partial derivative of (24) with respect to $\mathbf{V}_k$ and applying the Karush–Kuhn–Tucker conditions [26], it follows that

$$\sum_{m=1}^{M} \mu_m\mathbf{D}_m - \left(\mathbf{G}_k\mathbf{C}_k\mathbf{G}_k^H + \tfrac{1}{\Gamma}\mathbf{G}_k\mathbf{Q}_k\mathbf{G}_k^H + \mathbf{S}_k\right) = 0. \quad (25)$$

Let $\{\mathbf{C}_k^*\}, \{\mathbf{Q}_k^*\}, \{\mathbf{S}_k^*\}$, and $\{\mu_m^*\}$ be the optimal dual solution to problem (11). Note that $\mathbf{Q}_k^*\mathbf{B}_k^* = \mathbf{0}$ from the complementary slackness conditions of problem (11). Since the size of $\mathbf{Q}_k^*$ and $\mathbf{B}_k^*$ is $(MN_T+2)\times(MN_T+2)$, we have $\mathrm{rank}(\mathbf{Q}_k^*) + \mathrm{rank}(\mathbf{B}_k^*) \le MN_T + 2$. Denoting r_k^* as the optimal solution to problem (11), r_k^* in $\mathbf{B}_k^*$ in (11) is nonnegative. If $r_k^* > 0$, $r_k^*\mathbf{I} + \mathbf{M}_k^*$ has full rank. We will prove that $r_k^* \neq 0$ by contradiction.

If $r_k^* = 0$, the constraint $\|\Delta\mathbf{h}_k\|^2 \le \varepsilon_k^2$ does not hold since r_k^* is the dual variable for (10). Note that the condition $\|\Delta\mathbf{h}_k\|^2 \le \varepsilon_k^2$ is the only constraint on $\Delta\mathbf{h}_k$. If $\Delta\mathbf{h}_k$ is the worst channel uncertainty, which minimizes $q \triangleq \rho_k|\mathbf{h}_k^H\mathbf{v}_k|^2/(\rho_k\sum_{j\neq k}|\mathbf{h}_k^H\mathbf{v}_j|^2 + \rho_k\sigma_k^2 + \delta_k^2)$, we can always find a scalar $\omega > 1$, which satisfies $\|\Delta\mathbf{h}_k\|^2 = \varepsilon_k^2$. Substituting the channel uncertainty $\omega\Delta\mathbf{h}_k$ in q, we can find an SINR lower than that obtained by $\Delta\mathbf{h}_k^*$. This is contradictory to the assumption that $\Delta\mathbf{h}_k^*$ minimizes the SINR. Thus, it follows $r_k^* \neq 0$, which leads to $r_k^* > 0$. As a result, $r_k^*\mathbf{I} + \mathbf{M}_k^*$ becomes full rank, and we have $\mathrm{rank}(\mathbf{B}_k^*) \ge N$. Furthermore, since $\mathrm{rank}(\mathbf{Q}_k^*)$ is nonzero. Thus, the rank of $\mathbf{Q}_k^*$ equals 1. Similarly, we can show that $\mathrm{rank}(\mathbf{C}_k^*) = 1$. Then, it follows $\mathrm{rank}\big(\mathbf{G}_k^H(\mathbf{C}_k^* + \frac{1}{\Gamma}\mathbf{Q}_k^*)\mathbf{G}_k\big) \le \mathrm{rank}\big(\mathbf{G}_k^H\mathbf{C}_k^*\mathbf{G}_k\big) + \frac{1}{\Gamma}\mathrm{rank}\big(\mathbf{G}_k^H\mathbf{Q}_k^*\mathbf{G}_k\big) = 2$.

Thus, multiplying both sides of (25) with $\mathbf{V}_k^*$ yields

$$\left(\sum_{m=1}^{M}\mu_m^*\mathbf{D}_m\right)\mathbf{V}_k^* = \left(\mathbf{G}_k\left(\mathbf{C}_k^* + \tfrac{1}{\Gamma}\mathbf{Q}_k^*\right)\mathbf{G}_k^H + \mathbf{S}_k^*\right)\mathbf{V}_k^*$$

where it is noted that $\mathbf{S}_k^*\mathbf{V}_k^* = \mathbf{0}$. Since $\sum_{m=1}^{M}\mu_m^*\mathbf{D}_m$ has full rank, following the rank inequality $\mathrm{rank}(\mathbf{AB}) \le \min(\mathrm{rank}(\mathbf{A}), \mathrm{rank}(\mathbf{B}))$, we can finally prove that

$$\mathrm{rank}\left\{\left(\sum_{m=1}^{M}\mu_m^*\mathbf{D}_m\right)\mathbf{V}_k^*\right\} = \mathrm{rank}\left(\mathbf{V}_k^*\right)$$
$$\le \mathrm{rank}\left(\mathbf{G}_k\left(\mathbf{C}_k^* + \frac{1}{\lambda}\mathbf{Q}_k^*\right)\mathbf{G}_k^H\right) \le 2.$$

Appendix B
Proof of Proposition 1

By introducing an arbitrary positive multiplier $\theta \ge 0$, the Lagrangian function is given by

$$\mathrm{L}\left(\Delta_k, \theta\right) = \mathrm{tr}\big((\hat{\mathbf{H}}_k + \Delta_k)\mathbf{V}_k\big) + \theta\big(\|\Delta_k\|^2 - \xi_k^2\big).$$

We differentiate the Lagrangian function with respect to Δ_k^* and equate it to zero [29] as

$$\nabla_{\Delta_k^*}\mathrm{L}\left(\Delta_k, \theta\right) = \mathbf{V}_k^H + \theta\Delta_k = 0.$$

Then, we can find the optimal solution $\Delta_k^{\mathrm{opt}} = -\frac{1}{\theta}\mathbf{V}_k^H$. In order to remove the role of an arbitrary parameter of θ, the Lagrangian function is differentiated with respect to θ and set to zero as

$$\nabla_\theta\mathrm{L}\left(\Delta_k, \theta\right) = \left\|\Delta_k^{\mathrm{opt}}\right\|^2 - \xi_k^2 = 0.$$

Thus, the optimal solution for θ is obtained as $\theta^{\mathrm{opt}} = \frac{\|\mathbf{V}_k^H\|}{\xi_k}$.

By combining the above results, we finally get

$$\Delta_k^{\mathrm{opt}} = \pm\,\xi_k\frac{\mathbf{V}_k^H}{\|\mathbf{V}_k\|}.$$

Accordingly, the minimum and maximum of Δ_k can be expressed as

$$\Delta_k^{\min} = -\,\xi_k\frac{\mathbf{V}_k^H}{\|\mathbf{V}_k\|},\ \Delta_k^{\max} = \xi_k\frac{\mathbf{V}_k^H}{\|\mathbf{V}_k\|}.$$

To check if this optimal solution is a minimum, we confirm that the second derivative at the optimal solution point Δ_k^{opt} is PSD as

$$\nabla^2_{\Delta_k^*}\mathrm{L}\left(\Delta_k^{\mathrm{opt}}, \theta^{\mathrm{opt}}\right) = \theta^{\mathrm{opt}}\left(\mathrm{vec}\left\{\mathbf{I}_{MN_T}\right\}\mathrm{vec}\left\{\mathbf{I}_{MN_T}\right\}\right)^T \succeq 0.$$

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