Superposition Signaling in Broadcast Interference Networks

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5 authors, including:

Tuan Hoang
University of Technology Sydney

Ho Huu Minh Tam
University of Technology Sydney

Ha H Nguyen
University of Saskatchewan

Trung Q. Duong
Queen's University Belfast

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H. D. Tuan, H. H. M. Tam, H. H. Nguyen, T. Q. Duong and H. V. Poor

Abstract—**It is known that superposition signaling in Gaussian interference networks is capable of improving the achievable rate region. However, the problem of maximizing the rate gain offered by superposition signaling is numerically prohibitive, even in the simplest case of two-user single-input single-output interference networks. This paper examines superposition signaling for the general networks of multiple-input multiple-output (MIMO) broadcast Gaussian interference networks. The problem of maximizing either the sum rate or the minimal user's rate under superposition signaling and dirty paper coding is solved by a computationally-efficient path-following procedure, which requires only a convex quadratic program for each iteration but ensures convergence at least to a locally-optimal solution. Numerical results demonstrate the substantial performance advantage of the proposed approach.**

Index Terms—**Gaussian interference networks, multi-user MIMO, superposition signaling, convex quadratic programming.**

I. Introduction

A wireless multi-cell system can be modeled as an interference network with multiple cells and multiple users (e.g. mobile terminals) in each cell. In the two-user case, it is known that using Gaussian inputs and treating the residual interference as noise in Gaussian interference networks (GINs) can achieve the sum rate capacity only for certain scenarios, including the low interference regime (see [1] and references therein), or under certain sufficient conditions in terms of matrix equations [2], [3]. Superposition signaling refers to splitting signals intended for users to form various signal combinations at the transmitters. This facilitates partial interference decoding to improve the network's achievable rate region.

The achievable rate region for two-user single-input single-output (SISO) GINs has been investigated in [4]–[14] and [15]. The Han-Kobayashi (H-K) superposition signalling scheme [4] achieves the best known rate region. With H-K signalling, the signal sent by each transmitter is a superposition of two components: (i) a private message that is decoded by the intended receiver only, and (ii) a common message that is decoded by both receivers. The optimal signal superposition scheme to realize the advantage of H-K signalling is computationally prohibitive in the domain of arbitrary input distributions and time sharing. Reference [7] was the first to develop a simplified H-K signalling scheme, which uses independent and identically distributed (i.i.d.) Gaussian input distributions and does not require time sharing. As such, the achievable rate region is defined explicitly via computationally tractable functions of input powers. Since optimization for these functions is still computationally difficult, [7] proposed a simple power allocation, which achieves the capacity region to within one bit. For some special weak interference classes, the optimal power allocations for maximizing the sum rate have been given in [9], [10] and [14].

Inspired by [7], references [16] and [17] derived the covariances of private and common Gaussian messages for H-K signalling, which achieve the capacity region of two-user multiple-input multiple-output (MIMO) GINs to within a constant gap. A similar result for the K-user cyclic GIN was obtained in [18]. It was also shown in [19]–[21] that using non-Gaussian inputs (or in [22] with Gaussian inputs) and treating interference as noise achieves the capacity region of some special SISO GINs within a constant gap. The within-constant-gap results have a merit in the high signal-to-noise ratio (SNR) regime only, where the achievable rate region is sufficiently large. As analyzed in [23], under practical SNR conditions, such results are not better than what is achieved by treating interference as noise. In fact, it is still not known what rate gain H-K superposition signalling with Gaussian inputs can offer even for two-user SISO GINs. Furthermore, it is still not known what gain using non-Gaussian inputs and treating interference as noise can offer for GINs.

It has been noted that, in the high SNR regime, interference alignment [24] may achieve a better achievable region. However, a better achievable rate region does not necessarily yield a better sum rate or better minimal user rate. This issue has not been treated in depth in previous work, and thus, our focus on H-K signalling scheme for optimization is based on the premise that it is computable and offers a meaningful rate gain in MIMO interference networks.

Reference [25] was the first to apply the H-K signalling in multiple-input single-output (MISO) broadcast GINs. The common and private messages are *sequentially decoded* at

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H. D. Tuan is with the School of Electrical and Data Engineering, University of Technology, Sydney, NSW 2007, Australia; Email: tuan.hoang@uts.edu.au

H. H. M. Tam was with the Faculty of Engineering and Information Technology, University of Technology, Sydney, NSW 2007, Australia. He is now with Thinxtra Solution Pty., Sydney, Australia; Email: thomas.ho@thinxtra.com

H. H. Nguyen is with the Department of Electrical and Computer Engineering, University of Saskatchewan, Saskatoon, Canada; Email: ha.nguyen@usask.ca.

T. Q. Duong is with Queen's University Belfast, Belfast BT7 1NN, UK; Email: trung.q.duong@qub.ac.uk.

H. V. Poor is with the Department of Electrical Engineering, Princeton University, Princeton, NJ 08544, USA; Email: poor@princeton.edu.

the users to improve the users' minimum rate. Inspired by [25], our previous works [23], [26] also examined sequential decoding of common and private messages in H-K signalling to maximize either the sum rate or the minimal user's rate for MIMO broadcast GINs. Such design problems for the MIMO GINs were recast as optimization of d.c. (difference of two concave) functions over convex quadratic constraints, which were then solved by the so called d.c. iterations (DCI) of d.c. programming (see e.g. [27]–[31]). However, under the optimal jointly decoding as originally considered in H-K signalling, the nonconvex constraints are unavoidable. As such, the design of covariances of private messages and common messages to maximize either the sum rate or user's minimum rate in a broadcast GIN is a very difficult nonconvex constrained optimization problem. Popular approaches such as Lagrangian multiplier or convex relaxation are unable even to locate feasible solutions.

The contribution of the present paper is twofold:

- Developing an efficient convex quadratic-based path-following computation procedure for maximizing the sum rate and minimal user's rate by H-K signalling in broadcast MIMO GINs under practical SNRs, which generates a sequence of feasible and improved points and ensures convergence to at least a locally optimum point. Unlike [25], [26] and [23], dirty paper coding (DPC) [32] is employed to improve the achievable rate regions.
- Numerically demonstrating the benefit of H-K superposition signalling and DPC in MIMO broadcast GINs.

The rest of the paper is organized as follows. Section II formulates the optimization problem considered in this paper and discusses the challenges in finding solutions. Section III proposes a new solution method. Section IV provides simulation results. Section V concludes the paper.

Notation. Deterministic variables are boldfaced. The notation $\langle A\rangle$ means the trace of matrix A, while $|A|$ is its determinant. The inner product $\langle X,Y\rangle$ between matrices X and Y is therefore defined as $\langle X^HY\rangle$. The inner product between vectors x and y is defined as $\langle x,y\rangle = x^Hy$. $A\succ B$ ($A\succeq B$, resp.) for Hermitian symmetric matrices A and B means that $A-B$ is positive definite (semi-definite, resp.). For notational simplicity, $[X]^2$ refers to XX^H, which is positive semi-definite ($[X]^2\succeq 0\ \forall\ X$). The following properties are used in the paper.

(P1) $A\succeq B\succ 0$ implies $|A|\geq|B|$ and $B^{-1}\succeq A^{-1}\succ 0$.
(P2) $\langle[\boldsymbol{X}]^2A\rangle = \langle\boldsymbol{X}^HA\boldsymbol{X}\rangle$, which is a convex quadratic function in $\boldsymbol{X}$ whenever $A\succeq 0$. Also define $||\boldsymbol{X}||^2=\langle[\boldsymbol{X}]^2\rangle$.
(P3) $\sum_{i=1}^n[X_i]^2 = [X]^2$ and $\langle(\sum_{i=1}^n[X_i]^2)A\rangle = \langle X^HAX\rangle$ for $X=[X_1\quad X_2\quad\dots\quad X_n]$.

II. Problem Formulation and Solution

Consider a communication network consisting of N transmitters as illustrated in Fig. 1. Each transmitter (Tx) is equipped with $N_t\geq 1$ antennas to serve its K users, each of which is equipped with $N_r\geq 1$ antennas. Define $\mathcal{I}:=\{1,2,\dots,N\}$ and $\mathcal{J}:=\{1,2,\dots,K\}$. User j who is served by the ith Tx is referred to as user (i,j). Let $H_{m,i,j}\in\mathbb{C}^{N_r\times N_t}$ be the channel matrix from Tx m to user (i,j). Accordingly, $H_{i,i,j}$ and $H_{m,i,j}$ for $m\neq i$ are the direct and interfering channels with respect to user (i,j). The complex baseband signal $y_{i,j}\in\mathbb{C}^{N_r}$ received by user (i,j) is

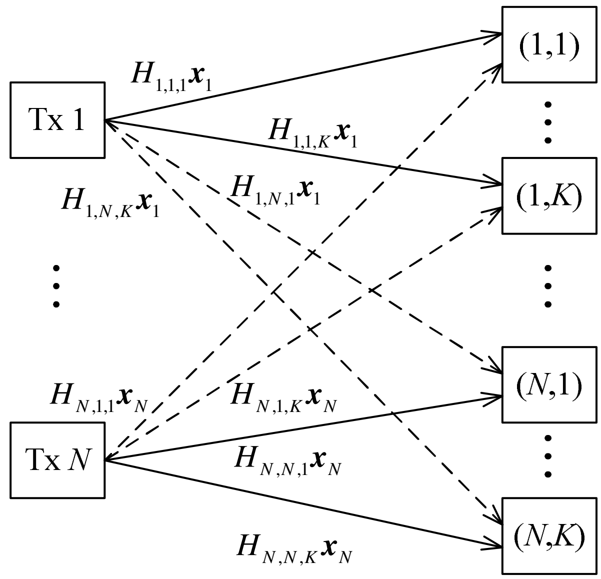


Fig. 1: Illustration of an interference network.

$$\begin{aligned} y_{i,j} &= \sum_{m=1}^{N} H_{m,i,j}\boldsymbol{x}_m + n_{i,j}\\ &= H_{i,i,j}\boldsymbol{x}_i + \sum_{m\in\mathcal{I}\setminus\{i\}} H_{m,i,j}\boldsymbol{x}_m + n_{i,j}\\ &= H_{i,i,j}\left(\sum_{k=1}^{K}\boldsymbol{x}_{i,k}\right) + \sum_{m\in\mathcal{I}\setminus\{i\}} H_{m,i,j}\left(\sum_{k=1}^{K}\boldsymbol{x}_{m,k}\right)\\ &\quad +n_{i,j}\\ &= \sum_{k=1}^{K} H_{i,i,j}\boldsymbol{x}_{i,k} + \sum_{m\in\mathcal{I}\setminus\{i\}}\sum_{k=1}^{K} H_{m,i,j}\boldsymbol{x}_{m,k}\\ &\quad +n_{i,j}, \end{aligned} \tag{1}$$

where

- $\boldsymbol{x}_m$ is the signal transmitted from Tx m, which is the superposition of signals $\boldsymbol{x}_{m,k}\in\mathbb{C}^{N_t}$ intended for all users (m,k):
$$\boldsymbol{x}_m = \sum_{k=1}^{K}\boldsymbol{x}_{m,k}.$$
- $n_{i,j}\in\mathbb{C}^{N_r}$ and its entries are i.i.d. Gaussian noise samples with zero-means and variances σ^2.

The H-K signalling involves a pairing operator $a(i,j)$ that describes which other user, beside user (i,j), decodes the common message of user (i,j). When user (i,j) has no common message, then $a(i,j)$ is an empty set. Formally, it is a mapping

$$a:\mathcal{I}\times\mathcal{J}\to(\mathcal{I}\times\mathcal{J})\cup\{\emptyset\}$$

with the restriction that $a(i,j)=(\tilde{i},\tilde{j})$ always has $\tilde{i}\neq i$ and $a^{-1}(\tilde{i},\tilde{j})=\{(i,j)\ :a(i,j)=(\tilde{i},\tilde{j})\}$ has cardinality no more than one.

With $\emptyset\neq a(i,j)=(\tilde{i},\tilde{j})$, $\tilde{i}\neq i$, signal $\boldsymbol{x}_{i,j}$ intended for user (i,j) is a superposition of private message $x^{\mathsf{p}}_{i,j}\in\mathbb{C}^{N_t}$ with covariance $\boldsymbol{Q}^{\mathsf{p}}_{i,j}$ and a common message $x^{\mathsf{c}}_{i,j}\in\mathbb{C}^{N_t}$ with covariance $\boldsymbol{Q}^{\mathsf{p}}_{i,j}$, i.e.,

$$\boldsymbol{x}_{i,j}=x^{\mathsf{p}}_{i,j}+x^{\mathsf{c}}_{i,j}$$

The user (i,j)'s common message $x^{\mathsf{c}}_{i,j}$ is to be decoded by user (i,j), and also by user $(\tilde{i},\tilde{j})$. On the other hand, if $(i,j)=a(\hat{i},\hat{j})$ for some $\hat{i}\neq i$, then users (i,j) and $(\hat{i},\hat{j})$ decode the common message $x^{\mathsf{c}}_{\hat{i},\hat{j}}$ of user $(\hat{i},\hat{j})$.

For simplicity, the following transmit power constraints are considered (although other power constraints can be easily incorporated):

$$\begin{aligned}\mathcal{W} &= \{\boldsymbol{Q}:=(\boldsymbol{Q}^{\mathsf{p}}_{i,j}\quad \boldsymbol{Q}^{\mathsf{c}}_{i,j})_{(i,j)\in\mathcal{I}\times\mathcal{J}}\ :\ \boldsymbol{Q}^{\mathsf{p}}_{i,j}\succeq 0,\\ &\quad \boldsymbol{Q}^{\mathsf{c}}_{i,j}\succeq 0, \sum_{j\in\mathcal{J}}\langle \boldsymbol{Q}^{\mathsf{p}}_{i,j}+\boldsymbol{Q}^{\mathsf{c}}_{i,j}\rangle\leq P_B, i\in\mathcal{I}\}, \end{aligned}\tag{2}$$

Note that $x^{\mathsf{c}}_{i,j}\equiv 0$ in (1) and thus $\boldsymbol{Q}^{\mathsf{c}}_{i,j}\equiv 0$ in (2) whenever $a(i,j)=\emptyset$.

With dirty-paper coding (DPC) and decoding [32] in a broadcast network, user (i,j) views the term $\sum_{k\leq i}H_{i,i,j}\boldsymbol{x}_{i,k}$ as known non-causally and thus reduces it from the interference in (1) [33, Lemma 1]. As such, the $N_r\times N_r$ covariance matrix of the interference plus noise at user (i,j) is given as

$$\begin{aligned}\mathcal{M}_{i,j}(\boldsymbol{Q}) &:= \sum_{(n,k)\in\mathcal{I}\times\mathcal{J}}H_{n,i,j}(\boldsymbol{Q}^{\mathsf{p}}_{n,k}+\boldsymbol{Q}^{\mathsf{c}}_{n,k})H^H_{n,i,j}\\ &\quad +\sigma^2 I_{N_r}-\sum_{k\geq j}H_{i,i,j}(\boldsymbol{Q}^{\mathsf{p}}_{i,k}+\boldsymbol{Q}^{\mathsf{c}}_{i,k})H^H_{i,i,j}\\ &\quad -H_{\hat{i},i,j}\boldsymbol{Q}^{\mathsf{c}}_{\hat{i},\hat{j}}H^H_{\hat{i},i,j}.\end{aligned}\tag{3}$$

Under nonorthogonal multiple access (NOMA) [34], [35] a message intended for a user with a worse channel condition is not only decoded by itself but also by another user (served by the same transmitter) with a better channel condition. The latter then cancels that message for the former from the interference in decoding its own message. In H-K signalling, all three messages $\boldsymbol{x}^{\mathsf{p}}_{i,j}$, $\boldsymbol{x}^{\mathsf{c}}_{i,j}$ and $\boldsymbol{x}_{a^{-1}(i,j)}$ are jointly decoded and the corresponding achievable rates $\boldsymbol{r}^{\mathsf{p}}_{i,j}$, $\boldsymbol{r}^{\mathsf{c}}_{i,j}$ and $\boldsymbol{r}^{\mathsf{c}}_{a^{-1}(i,j)}$ satisfy

$$\begin{aligned}f^{\mathsf{p}}_{i,j}(\boldsymbol{Q}^{\mathsf{p}}_{i,j},\mathcal{M}_{i,j}(\boldsymbol{Q})) &:=\\ \ln\left|I_{N_r}+H_{i,i,j}\boldsymbol{Q}^{\mathsf{p}}_{i,j}H^H_{i,i,j}(\mathcal{M}_{i,j}(\boldsymbol{Q}))^{-1}\right| &\geq \boldsymbol{r}^{\mathsf{p}}_{i,j},\end{aligned}\tag{4}$$

$$\begin{aligned}f^{\mathsf{c}}_{i,j}(\boldsymbol{Q}^{\mathsf{c}}_{i,j},\mathcal{M}_{i,j}(\boldsymbol{Q})) &:=\\ \ln\left|I_{N_r}+H_{i,i,j}\boldsymbol{Q}^{\mathsf{c}}_{i,j}H^H_{i,i,j}(\mathcal{M}_{i,j}(\boldsymbol{Q}))^{-1}\right| &\geq \boldsymbol{r}^{\mathsf{c}}_{i,j},\end{aligned}\tag{5}$$

$$\begin{aligned}f^{\mathsf{a}}_{i,j}(\boldsymbol{Q}^{\mathsf{c}}_{\hat{i},\hat{j}},\mathcal{M}_{i,j}(\boldsymbol{Q})) &:=\\ \ln\left|I_{N_r}+H_{\hat{i},i,j}\boldsymbol{Q}^{\mathsf{c}}_{\hat{i},\hat{j}}H^H_{\hat{i},i,j}(\mathcal{M}_{i,j}(\boldsymbol{Q}))^{-1}\right| &\geq \boldsymbol{r}^{\mathsf{c}}_{\hat{i},\hat{j}},\end{aligned}\tag{6}$$

$$\begin{aligned}f^{\mathsf{pc}}_{i,j}(\boldsymbol{Q}^{\mathsf{p}}_{i,j},\boldsymbol{Q}^{\mathsf{c}}_{i,j},\mathcal{M}_{i,j}(\boldsymbol{Q})) &:=\\ \ln\big|I_{N_r}+(H_{i,i,j}\boldsymbol{Q}^{\mathsf{p}}_{i,j}H^H_{i,i,j}&\\ +H_{i,i,j}\boldsymbol{Q}^{\mathsf{c}}_{i,j}H^H_{i,i,j})(\mathcal{M}_{i,j}(\boldsymbol{Q}))^{-1}\big| &\geq \boldsymbol{r}^{\mathsf{p}}_{i,j}+\boldsymbol{r}^{\mathsf{c}}_{i,j},\end{aligned}\tag{7}$$

$$\begin{aligned}f^{\mathsf{pa}}_{i,j}(\boldsymbol{Q}^{\mathsf{p}}_{i,j},\boldsymbol{Q}^{\mathsf{c}}_{\hat{i},\hat{j}},\mathcal{M}_{i,j}(\boldsymbol{Q})) &:=\\ \ln\big|I_{N_r}+(H_{i,i,j}\boldsymbol{Q}^{\mathsf{p}}_{i,j}H^H_{i,i,j}&\\ +H_{\hat{i},i,j}\boldsymbol{Q}^{\mathsf{c}}_{\hat{i},\hat{j}}H^H_{\hat{i},i,j})(\mathcal{M}_{i,j}(\boldsymbol{Q}))^{-1}\big| &\geq \boldsymbol{r}^{\mathsf{p}}_{i,j}+\boldsymbol{r}^{\mathsf{c}}_{\hat{i},\hat{j}},\end{aligned}\tag{8}$$

$$\begin{aligned}f^{\mathsf{ca}}_{i,j}(\boldsymbol{Q}^{\mathsf{c}}_{i,j},\boldsymbol{Q}^{\mathsf{c}}_{\hat{i},\hat{j}},\mathcal{M}_{i,j}(\boldsymbol{Q})) &:=\\ \ln\big|I_{N_r}+(H_{i,i,j}\boldsymbol{Q}^{\mathsf{c}}_{i,j}H^H_{i,i,j}&\\ +H_{\hat{i},i,j}\boldsymbol{Q}^{\mathsf{c}}_{\hat{i},\hat{j}}H^H_{\hat{i},i,j})(\mathcal{M}_{i,j}(\boldsymbol{Q}))^{-1}\big| &\geq \boldsymbol{r}^{\mathsf{c}}_{i,j}+\boldsymbol{r}^{\mathsf{c}}_{\hat{i},\hat{j}},\end{aligned}\tag{9}$$

$$\begin{aligned}f^{\mathsf{pca}}_{i,j}(\boldsymbol{Q}^{\mathsf{p}}_{i,j},\boldsymbol{Q}^{\mathsf{c}}_{i,j},\boldsymbol{Q}^{\mathsf{c}}_{\hat{i},\hat{j}},\mathcal{M}_{i,j}(\boldsymbol{Q})) &:=\\ \ln\big|I_{N_r}+(H_{i,i,j}\boldsymbol{Q}^{\mathsf{p}}_{i,j}H^H_{i,i,j}+H_{i,i,j}\boldsymbol{Q}^{\mathsf{c}}_{i,j}H^H_{i,i,j}&\\ +H_{\hat{i},i,j}\boldsymbol{Q}^{\mathsf{c}}_{\hat{i},\hat{j}}H^H_{\hat{i},i,j})(\mathcal{M}_{i,j}(\boldsymbol{Q}))^{-1}\big| &\geq\\ \boldsymbol{r}^{\mathsf{p}}_{i,j}+\boldsymbol{r}^{\mathsf{c}}_{i,j}+\boldsymbol{r}^{\mathsf{c}}_{\hat{i},\hat{j}}.&\end{aligned}\tag{10}$$

It should be noted that the constraint (5) in $\boldsymbol{r}^{\mathsf{c}}_{i,j}\neq 0$ assigns the following constraint for user $(\tilde{i},\tilde{j})=a(i,j)$:

$$f^{\mathsf{a}}_{\tilde{i},\tilde{j}}(\boldsymbol{Q}^{\mathsf{c}}_{i,j},\mathcal{M}_{\tilde{i},\tilde{j}}(\boldsymbol{Q}))\geq \boldsymbol{r}^{\mathsf{c}}_{i,j}.\tag{11}$$

On the other hand, the constraint (6) in $\boldsymbol{r}^{\mathsf{c}}_{\hat{i},\hat{j}}$ with $a^{-1}(i,j)=(\hat{i},\hat{j})\neq\emptyset$ results from the following constraint for user $(\hat{i},\hat{j})=a^{-1}(i,j)$:

$$f^{\mathsf{c}}_{\hat{i},\hat{j}}(\boldsymbol{Q}^{\mathsf{c}}_{\hat{i},\hat{j}},\mathcal{M}_{\hat{i},\hat{j}}(\boldsymbol{Q}))\geq \boldsymbol{r}^{\mathsf{c}}_{\hat{i},\hat{j}}.\tag{12}$$

For $\mathbf{r}^{\mathsf{p}}=[\mathbf{r}^{\mathsf{p}}_{i,j}]_{(i,j)\in\mathcal{I}\times J}$, $\mathbf{r}^{\mathsf{c}}=[\mathbf{r}^{\mathsf{c}}_{i,j}]_{(i,j)\in\mathcal{I}\times J}$ and $\mathbf{r}=(\mathbf{r}^{\mathsf{p}},\mathbf{r}^{\mathsf{c}})$, the *sum rare maximization problem* is thus

$$\max_{\boldsymbol{Q},\boldsymbol{r}}\sum_{(i,j)\in\mathcal{I}\times\mathcal{J}}(\boldsymbol{r}^{\mathsf{p}}_{i,j}+\boldsymbol{r}^{\mathsf{c}}_{i,j})\ :\ (2),(4)-(10).\tag{13}$$

While constraint (2) in (13) is (convex) semi-definite, other constraints (4)-(10) are highly nonconvex. Therefore, problem (13) is maximization of a linear objective function subject to nonconvex constraints.

To the authors' best knowledge there is no available method to handle nonconvex constraints (4)-(10). To understand the complexity of these nonconvex constraints, let us revisit the simplest case of two-user MIMO interference channels considered in [36]:

$$\begin{aligned}y_{1,1} &= H_{1,1,1}(\boldsymbol{x}^{\mathsf{p}}_{1,1}+\boldsymbol{x}^{\mathsf{c}}_{1,1})+H_{2,1,1}(\boldsymbol{x}^{\mathsf{p}}_{2,1}+\boldsymbol{x}^{\mathsf{c}}_{2,1})\\ &\quad +n_{1,1}\\ y_{2,1} &= H_{1,2,1}(\boldsymbol{x}^{\mathsf{p}}_{1,1}+\boldsymbol{x}^{\mathsf{c}}_{1,1})+H_{2,2,1}(\boldsymbol{x}^{\mathsf{p}}_{2,1}+\boldsymbol{x}^{\mathsf{c}}_{2,1})\\ &\quad +n_{2,1}.\end{aligned}\tag{14}$$

The authors of [36] considered a two-stage scheme, which decodes the common messages in the first stage and then decodes the private messages in the second stage. The sum achievable rate maximization problem under this scheme is addressed by performing the following optimization steps for each grind point $(\alpha_1,\alpha_2)\in(0,1)\times(0,1)$ of the power allocation factors:

- Solve the private sum-rate maximization [36, (eq. (7)]:

$$\max_{\boldsymbol{Q}^{\mathsf{p}}_{i,1},i=1,2} \ln\left|I_{N_r}+H_{1,1,1}\boldsymbol{Q}^{\mathsf{p}}_{1,1}H^H_{1,1,1}(\sigma I_{N_r} +H_{2,1,1}\boldsymbol{Q}^{\mathsf{p}}_{2,1}H^H_{2,1,1})^{-1}\right| +\ln\left|I_{N_r}+H_{2,2,1}\boldsymbol{Q}^{\mathsf{p}}_{2,1}H^H_{2,2,1}(\sigma I_{N_r} +H_{1,2,1}\boldsymbol{Q}^{\mathsf{p}}_{1,1}H^H_{1,2,1})^{-1}\right| \ : \quad (15)$$

$$\boldsymbol{Q}^{\mathsf{p}}_{i,1}\succeq 0, \langle \boldsymbol{Q}^{\mathsf{p}}_{i,1}\rangle\leq (1-\alpha_i)P_B, i=1,2. \quad (16)$$

- Suppose $Q^{\mathsf{p}}_{i,1}(\alpha_1,\alpha_2)=(Q^{\mathsf{p}}_{1,1}(\alpha_1,\alpha_2),Q^{\mathsf{p}}_{2,1}(\alpha_1,\alpha_2))$ is a solution found from solving (15)-(16). Then solve the common sum-rate maximization [36, eq. (13)]:

$$\max_{\boldsymbol{Q}^{c}_{i,1},\boldsymbol{r}^{\mathsf{c}}_{i,1},i=1,2} \boldsymbol{r}^{\mathsf{c}}_{1,1}+\boldsymbol{r}^{\mathsf{c}}_{2,1} \ : \quad (17)$$

$$\boldsymbol{Q}^{\mathsf{c}}_{i,1}\succeq 0, \langle \boldsymbol{Q}^{\mathsf{c}}_{i,1}\rangle\leq \alpha_i P_B, i=1,2, \quad (18)$$

$$\ln\left|I_{N_r}+H_{1,1,1}\boldsymbol{Q}^{\mathsf{c}}_{1,1}H^H_{1,1,1} \times(\mathcal{M}_{1,1}(Q^{\mathsf{p}}(\alpha_1,\alpha_2))^{-1}\right| \geq \boldsymbol{r}^{\mathsf{c}}_{1,1}, \quad (19)$$

$$\ln\left|I_{N_r}+H_{1,2,1}\boldsymbol{Q}^{\mathsf{c}}_{1,1}H^H_{1,2,1} \times(\mathcal{M}_{2,1}(Q^{\mathsf{p}}(\alpha_1,\alpha_2))^{-1}\right| \geq \boldsymbol{r}^{\mathsf{c}}_{1,1}, \quad (20)$$

$$\ln\left|I_{N_r}+H_{2,1,1}\boldsymbol{Q}^{\mathsf{c}}_{2,1}H^H_{2,1,1} \times(\mathcal{M}_{1,1}(Q^{\mathsf{p}}(\alpha_1,\alpha_2))^{-1}\right| \geq \boldsymbol{r}^{\mathsf{c}}_{2,1}, \quad (21)$$

$$\ln\left|I_{N_r}+H_{2,2,1}\boldsymbol{Q}^{\mathsf{c}}_{2,1}H^H_{2,2,1} \times(\mathcal{M}_{2,1}(Q^{\mathsf{p}}(\alpha_1,\alpha_2)))^{-1}\right| \geq \boldsymbol{r}^{\mathsf{c}}_{2,1}, \quad (22)$$

$$\ln\left|I_{N_r}+(H_{1,1,1}\boldsymbol{Q}^{\mathsf{c}}_{1,1}H^H_{1,1,1}+H_{2,1,1}\boldsymbol{Q}^{\mathsf{c}}_{2,1}H^H_{2,1,1}) \times(\mathcal{M}_{1,1}(Q^{\mathsf{p}}(\alpha_1,\alpha_2)))^{-1}\right| \geq \boldsymbol{r}^{\mathsf{c}}_{1,1}+\boldsymbol{r}^{\mathsf{c}}_{2,1}, \quad (23)$$

$$\ln\left|I_{N_r}+(H_{1,2,1}\boldsymbol{Q}^{\mathsf{c}}_{1,1}H^H_{1,2,1}+H_{2,2,1}\boldsymbol{Q}^{\mathsf{c}}_{2,1}H^H_{2,2,1}) \times(\mathcal{M}_{2,1}(Q^{\mathsf{p}}(\alpha_1,\alpha_2)))^{-1}\right| \geq \boldsymbol{r}^{\mathsf{c}}_{2,1}+\boldsymbol{r}^{\mathsf{c}}_{2,1}, \quad (24)$$

where

$$\mathcal{M}_{1,1}(Q^{\mathsf{p}}(\alpha_1,\alpha_2)) = \sigma I_{N_r}+H_{1,1,1}Q^{\mathsf{p}}_{1,1}(\alpha_1,\alpha_2)H^H_{1,1,1} +H_{2,1,1}Q^{\mathsf{p}}_{2,1}(\alpha_1,\alpha_2)H^H_{2,1,1},$$

$$\mathcal{M}_{2,1}(Q^{\mathsf{p}}(\alpha_1,\alpha_2)) = \sigma I_{N_r}+H_{1,2,1}Q^{\mathsf{p}}_{1,1}(\alpha_1,\alpha_2)H^H_{1,2,1} +H_{2,2,1}Q^{\mathsf{p}}_{2,1}(\alpha_1,\alpha_2)H^H_{2,2,1}.$$

As the private sum-rate maximization (15)-(16) is highly nonconvex in $\boldsymbol{Q}^{\mathsf{p}}_{i,1}$, the authors of [36] proposed to solve it by alternating optimization between $\boldsymbol{Q}^{\mathsf{p}}_{1,1}$ and $\boldsymbol{Q}^{\mathsf{p}}_{1,1}$, which is still a difficult nonconvex problem and computationally prohibitive. Although the sum common rate optimization (17)-(24) is convex log-det function optimization, it is also computationally difficult. Again, the authors in [36] proposed to solve it by alternating optimization between $\boldsymbol{Q}^{\mathsf{c}}_{1,1}$ and $\boldsymbol{Q}^{\mathsf{c}}_{1,1}$, which is still a convex log-det function optimization and computationally demanding. In summary, the proposed method in [36] for separate private sum-rate maximization (15)-(16) and common sum-rate maximization (17)-(24) is already very computationally demanding for each $(\alpha_1,\alpha_2)\in(0,1)\times(0,1)$.

III. Proposed Solution

We return to the optimization problem in (13). To give some insight into its computational challenge, let us rewrite constraints (4)-(10) as

$$\ln\left|\mathcal{M}_{i,j}(\boldsymbol{Q})+H_{i,i,j}\boldsymbol{Q}^{\mathsf{p}}_{i,j}H^H_{i,i,j}\right|-\ln|\mathcal{M}_{i,j}(\boldsymbol{Q})|\geq \boldsymbol{r}^{\mathsf{p}}_{i,j}, \quad (25)$$

$$\ln\left|\mathcal{M}_{i,j}(\boldsymbol{Q})+H_{i,i,j}\boldsymbol{Q}^{\mathsf{c}}_{i,j}H^H_{i,i,j}\right|-\ln|\mathcal{M}_{i,j}(\boldsymbol{Q})|\geq \boldsymbol{r}^{\mathsf{c}}_{i,j}, \quad (26)$$

$$\ln\left|\mathcal{M}_{i,j}(\boldsymbol{Q})+H_{\hat{i},i,j}\boldsymbol{Q}^{\mathsf{c}}_{\hat{i},\hat{j}}H^H_{\hat{i},i,j}\right|-\ln|\mathcal{M}_{i,j}(\boldsymbol{Q})|\geq \boldsymbol{r}^{\mathsf{c}}_{\hat{i},\hat{j}}, \quad (27)$$

$$\ln\left|\mathcal{M}_{i,j}(\boldsymbol{Q})+H_{i,i,j}\boldsymbol{Q}^{\mathsf{p}}_{i,j}H^H_{i,i,j}+H_{i,i,j}\boldsymbol{Q}^{\mathsf{c}}_{i,j}H^H_{i,i,j}\right| -\ln|\mathcal{M}_{i,j}(\boldsymbol{Q})|\geq \boldsymbol{r}^{\mathsf{p}}_{i,j}+\boldsymbol{r}^{\mathsf{c}}_{i,j}, \quad (28)$$

$$\ln\left|\mathcal{M}_{i,j}(\boldsymbol{Q})+H_{i,i,j}\boldsymbol{Q}^{\mathsf{p}}_{i,j}H^H_{i,i,j}+H_{\hat{i},i,j}\boldsymbol{Q}^{\mathsf{c}}_{\hat{i},\hat{j}}H^H_{\hat{i},i,j}\right| -\ln|\mathcal{M}_{i,j}(\boldsymbol{Q})|\geq \boldsymbol{r}^{\mathsf{p}}_{i,j}+\boldsymbol{r}^{\mathsf{c}}_{\hat{i},\hat{j}}, \quad (29)$$

$$\ln\left|\mathcal{M}_{i,j}(\boldsymbol{Q})+H_{i,i,j}\boldsymbol{Q}^{\mathsf{c}}_{i,j}H^H_{i,i,j}+H_{\hat{i},i,j}\boldsymbol{Q}^{\mathsf{c}}_{\hat{i},\hat{j}}H^H_{\hat{i},i,j}\right| -\ln|\mathcal{M}_{i,j}(\boldsymbol{Q})|\geq \boldsymbol{r}^{\mathsf{c}}_{i,j}+\boldsymbol{r}^{\mathsf{c}}_{\hat{i},\hat{j}}, \quad (30)$$

$$\ln\left|\mathcal{M}_{i,j}(\boldsymbol{Q})+H_{i,i,j}\boldsymbol{Q}^{\mathsf{p}}_{i,j}H^H_{i,i,j}+H_{i,i,j}\boldsymbol{Q}^{\mathsf{c}}_{i,j}H^H_{i,i,j} +H_{\hat{i},i,j}\boldsymbol{Q}^{\mathsf{c}}_{\hat{i},\hat{j}}H^H_{\hat{i},i,j}\right|-\ln|\mathcal{M}_{i,j}(\boldsymbol{Q})|\geq \boldsymbol{r}^{\mathsf{p}}_{i,j}+\boldsymbol{r}^{\mathsf{c}}_{i,j}+\boldsymbol{r}^{\mathsf{c}}_{\hat{i},\hat{j}}. \quad (31)$$

In principle, all these nonconvex constraints can be successively and innerly approximated by convex constraints by linearizing the nonconvex function $\ln|\mathcal{M}_{i,j}(\boldsymbol{Q})|$ in (25)-(31) [31]. As a consequence, the nonconvex program (13) can be successively solved by a sequence of convex programs. However, these convex programs involve log-det function constraints (the first term in (25)-(31)), which are although convex but still cannot be handled by the present convex solvers.[1]

Next, we present a technique to equivalently express the semi-definite constraint (2) by a simple convex quadratic function and to successively approximate nonconvex constraints (4)-(10) by convex quadratic constraints. To this end, factorize each $\boldsymbol{Q}^s_{i,j}$, $s\in\{\mathsf{p},\mathsf{c}\}$ as

$$\boldsymbol{Q}^s_{i,j}=[\boldsymbol{V}^s_{i,j}]^2,\ \boldsymbol{V}^s_{i,j}\in\mathbb{C}^{N_t\times N_t}. \quad (32)$$

The semi-definite constraint (2) in $\boldsymbol{Q}$ becomes the convex quadratic constraint in $\boldsymbol{V}$:

$$\mathcal{W}_B=\Big\{\boldsymbol{V}:=[\boldsymbol{V}^{\mathsf{p}}_{i,j}\quad \boldsymbol{V}^{\mathsf{c}}_{i,j}]_{(i,j)\in\mathcal{I}\times\mathcal{J}} \ : \sum_{j\in\mathcal{J}}(||\boldsymbol{V}^{\mathsf{p}}_{i,j}||^2+||\boldsymbol{V}^{\mathsf{c}}_{i,j}||^2)\leq P_B, i\in\mathcal{I}\Big\}, \quad (33)$$

while $\mathcal{M}_{i,j}(\boldsymbol{Q})$ defined by (3), which is a linear map in $\boldsymbol{Q}$, becomes a quadratic map in $\boldsymbol{V}$. For notational simplicity, we

[1] For convex programs involving log-det functions in their objectives only, there is still no available solver of polynomial-time.

use the same notation $\mathcal{M}_{i,j}(\boldsymbol{V})$ for

$$\begin{aligned}\mathcal{M}_{i,j}(\boldsymbol{V}) \quad := \quad & \sum_{(n,k)\in\mathcal{I}\times\mathcal{J}} H_{n,i,j}([\boldsymbol{V}^{\mathsf{p}}_{n,k}]^2+[\boldsymbol{V}^{\mathsf{c}}_{n,k}]^2)H^H_{n,i,j}\\ & +\sigma^2 I_{N_r}-\sum_{k\geq j} H_{i,i,j}([\boldsymbol{V}^{\mathsf{p}}_{i,k}]^2+[\boldsymbol{V}^{\mathsf{c}}_{i,k}]^2)H^H_{i,i,j}\\ & -H_{\hat{i},i,j}[\boldsymbol{V}^{\mathsf{c}}_{\hat{i},\hat{j}}]^2H^H_{\hat{i},i,j}. \end{aligned} \tag{34}$$

The constraints (4)-(10) in $\boldsymbol{Q}$ are equivalently expressed as the following constraints in $\boldsymbol{V}$

$$\begin{aligned} F^{\mathsf{p}}_{i,j}(\boldsymbol{V}^{\mathsf{p}}_{i,j},\mathcal{M}_{i,j}(\boldsymbol{V})) & := \\ \ln\left|I_{N_r}+[H_{i,i,j}\boldsymbol{V}^{\mathsf{p}}_{i,j}]^2(\mathcal{M}_{i,j}(\boldsymbol{V}))^{-1}\right| & \geq \boldsymbol{r}^{\mathsf{p}}_{i,j}, \end{aligned} \tag{35}$$

$$\begin{aligned} F^{\mathsf{c}}_{i,j}(\boldsymbol{V}^{\mathsf{c}}_{i,j},\mathcal{M}_{i,j}(\boldsymbol{V})) & := \\ \ln\left|I_{N_r}+[H_{i,i,j}\boldsymbol{V}^{\mathsf{c}}_{i,j}]^2(\mathcal{M}_{i,j}(\boldsymbol{V}))^{-1}\right| & \geq \boldsymbol{r}^{\mathsf{c}}_{i,j}, \end{aligned} \tag{36}$$

$$\begin{aligned} F^{\mathsf{a}}_{i,j}(\boldsymbol{V}^{\mathsf{c}}_{\hat{i},\hat{j}},\mathcal{M}_{i,j}(\boldsymbol{V})) & := \\ \ln\left|I_{N_r}+[H_{\hat{i},i,j}\boldsymbol{V}^{\mathsf{c}}_{\hat{i},\hat{j}}]^2(\mathcal{M}_{i,j}(\boldsymbol{V}))^{-1}\right| & \geq \boldsymbol{r}^{\mathsf{c}}_{\hat{i},\hat{j}}, \end{aligned} \tag{37}$$

$$\begin{aligned} F^{\mathsf{pc}}_{i,j}(\boldsymbol{V}^{\mathsf{p}}_{i,j},\boldsymbol{V}^{\mathsf{c}}_{i,j},\mathcal{M}_{i,j}(\boldsymbol{V})) & := \\ \ln\left|I_{N_r}+([H_{i,i,j}\boldsymbol{V}^{\mathsf{p}}_{i,j}]^2+[H_{i,i,j}\boldsymbol{V}^{\mathsf{c}}_{i,j}]^2)(\mathcal{M}_{i,j}(\boldsymbol{V}))^{-1}\right| & \geq \\ \boldsymbol{r}^{\mathsf{p}}_{i,j}+\boldsymbol{r}^{\mathsf{c}}_{i,j}, & \end{aligned} \tag{38}$$

$$\begin{aligned} F^{\mathsf{pa}}_{i,j}(\boldsymbol{V}^{\mathsf{p}}_{i,j},\boldsymbol{V}^{\mathsf{c}}_{\hat{i},\hat{j}},\mathcal{M}_{i,j}(\boldsymbol{V})) & := \\ \ln\left|I_{N_r}+([H_{i,i,j}\boldsymbol{V}^{\mathsf{p}}_{i,j}]^2+[H_{\hat{i},i,j}\boldsymbol{V}^{\mathsf{c}}_{\hat{i},\hat{j}}]^2)(\mathcal{M}_{i,j}(\boldsymbol{V}))^{-1}\right| & \geq \\ \boldsymbol{r}^{\mathsf{p}}_{i,j}+\boldsymbol{r}^{\mathsf{c}}_{\hat{i},\hat{j}}, & \end{aligned} \tag{39}$$

$$\begin{aligned} F^{\mathsf{ca}}_{i,j}(\boldsymbol{V}^{\mathsf{c}}_{i,j},\boldsymbol{V}^{\mathsf{c}}_{\hat{i},\hat{j}},\mathcal{M}_{i,j}(\boldsymbol{V})) & := \\ \ln\left|I_{N_r}+([H_{i,i,j}\boldsymbol{V}^{\mathsf{c}}_{i,j}]^2+[H_{\hat{i},i,j}\boldsymbol{V}^{\mathsf{c}}_{\hat{i},\hat{j}}]^2)(\mathcal{M}_{i,j}(\boldsymbol{V}))^{-1}\right| & \geq \\ \boldsymbol{r}^{\mathsf{c}}_{i,j}+\boldsymbol{r}^{\mathsf{c}}_{\hat{i},\hat{j}}, & \end{aligned} \tag{40}$$

$$\begin{aligned} F^{\mathsf{pca}}_{i,j}(\boldsymbol{V}^{\mathsf{p}}_{i,j},\boldsymbol{V}^{\mathsf{c}}_{i,j},\boldsymbol{V}^{\mathsf{c}}_{\hat{i},\hat{j}},\mathcal{M}_{i,j}(\boldsymbol{V})) & := \\ \ln\big|I_{N_r}+([H_{i,i,j}\boldsymbol{V}^{\mathsf{p}}_{i,j}]^2+[H_{i,i,j}\boldsymbol{V}^{\mathsf{c}}_{i,j}]^2 & \\ +[H_{\hat{i},i,j}\boldsymbol{V}^{\mathsf{c}}_{\hat{i},\hat{j}}]^2)(\mathcal{M}_{i,j}(\boldsymbol{V}))^{-1}\big| & \geq \\ \boldsymbol{r}^{\mathsf{p}}_{i,j}+\boldsymbol{r}^{\mathsf{c}}_{i,j}+\boldsymbol{r}^{\mathsf{c}}_{\hat{i},\hat{j}}. & \end{aligned} \tag{41}$$

With the above developments, the problem in (13) is equivalently reformulated as

$$\max_{\boldsymbol{V},\boldsymbol{r}}\ \mathcal{P}(\boldsymbol{r}):=\sum_{(i,j)\in\mathcal{I}\times\mathcal{J}}(\boldsymbol{r}^{\mathsf{p}}_{i,j}+\boldsymbol{r}^{\mathsf{c}}_{i,j})\ :\ (33),(35)-(41). \tag{42}$$

It is pointed out that all functions in (35)-(41) are highly nonlinear, nonconcave in variable $\boldsymbol{V}$. As such it is useful to find their lower bounds, that are global to guarantee the richness of the feasibility region but also sufficiently local for a tight approximation. Our bounding technique is based on the following result, whose proof is given in Appendix A.

Theorem 1: The following inequality holds true for all matrices $\boldsymbol{X}_i\in\mathbb{C}^{N_r\times N_t}, X_i^{(\kappa)}\in\mathbb{C}^{N_r\times N_t}$, $i=1,\ldots,L$ and $0\prec\boldsymbol{M}\in\mathbb{C}^{N_r\times N_r}$, $0\prec M^{(\kappa)}\in\mathbb{C}^{N_r\times N_r}$:

$$\begin{aligned} \ln|I_{N_r}+(\sum_{i=1}^L[\boldsymbol{X}_i]^2)\boldsymbol{M}^{-1}| \quad \geq & \\ \ln|I_{N_r}+(\sum_{i=1}^L[\boldsymbol{X}_i^{(\kappa)}]^2)(M^{(\kappa)})^{-1}| & \\ -\langle(\sum_{i=1}^L[X_i^{(\kappa)}]^2)(M^{(\kappa)})^{-1}\rangle & \\ +2\sum_{i=1}^L\Re\{\langle(X_i^{(\kappa)})^H(M^{(\kappa)})^{-1}\boldsymbol{X}_i\rangle\} & \\ +\langle(M^{(\kappa)}+\sum_{i=1}^L[X^{(\kappa)}]^2)^{-1} & \\ -(M^{(\kappa)})^{-1},\boldsymbol{M}+\sum_{i=1}^L[\boldsymbol{X}_i]^2\rangle. & \end{aligned} \tag{43}$$

Next, as

$$M^{(\kappa)}+\sum_{i=1}^L[X_i^{(\kappa)}]^2\succeq M^{(\kappa)}\succ 0,$$

it follows from **(P1)** that

$$(M^{(\kappa)}+\sum_{i=1}^L[X_i^{(\kappa)}]^2)^{-1}-(M^{(\kappa)})^{-1}\preceq 0.$$

Thus, it follows from (P2) that the right hand side (RHS) of (43) is concave quadratic in $\boldsymbol{X}\triangleq[\boldsymbol{X}_i]_{i=1,\ldots,L}$. Obviously the RHS of (43) is still concave quadratic in $\mathbf{X}$ for

$$\boldsymbol{M}=\sum_{i=1}^L H_i[\mathbf{X}_i]^2H_i^H+A, A\succ 0,$$

and accordingly, $M^{(\kappa)}=\sum_{i=1}^L H_i[X_i^{(\kappa)}]^2H_i^H+A$.

Now, define the following positive combination of $[\boldsymbol{V}^x_{i,j}]^2$, $x\in\{\mathsf{p},\mathsf{c}\}$:

$$\begin{aligned} \mathcal{M}^{\mathsf{p}}_{i,j}(\boldsymbol{V}) &= \mathcal{M}_{i,j}(\boldsymbol{V})+[H_{i,i,j}\boldsymbol{V}^{\mathsf{p}}_{i,j}]^2,\\ \mathcal{M}^{\mathsf{c}}_{i,j}(\boldsymbol{V}) &= \mathcal{M}_{i,j}(\boldsymbol{V})+[H_{i,i,j}\boldsymbol{V}^{\mathsf{c}}_{i,j}]^2,\\ \mathcal{M}^{\mathsf{a}}_{i,j}(\boldsymbol{V}) &= \mathcal{M}_{i,j}(\boldsymbol{V})+[H_{\hat{i},i,j}\boldsymbol{V}^{\mathsf{c}}_{\hat{i},\hat{j}}]^2. \end{aligned}$$

Applying Theorem 1 at $V^{(\kappa)}=[V^{\mathsf{p},(\kappa)}_{i,j}\quad V^{\mathsf{c},(\kappa)}_{i,j}]_{(i,j)\in\mathcal{I}\times\mathcal{J}}$ gives

$$\begin{aligned} F^{\mathsf{p}}_{i,j}(\boldsymbol{V}^{\mathsf{p}}_{i,j},\mathcal{M}_{i,j}(\boldsymbol{V})) &\geq \mathcal{F}^{\mathsf{p},(\kappa)}_{i,j}(\boldsymbol{V}),\\ F^{\mathsf{c}}_{i,j}(\boldsymbol{V}^{\mathsf{c}}_{i,j},\mathcal{M}_{i,j}(\boldsymbol{V})) &\geq \mathcal{F}^{c(\kappa)}_{i,j}(\boldsymbol{V}),\\ F^{\mathsf{a}}_{i,j}(\boldsymbol{V}^{\mathsf{c}}_{\hat{i},\hat{j}},\mathcal{M}^{\mathsf{a}}_{i,j}(\boldsymbol{V})) &\geq \mathcal{F}^{\mathsf{a},(\kappa)}_{i,j}(\boldsymbol{V}) \end{aligned} \tag{44}$$

with the following concave quadratic functions in $\boldsymbol{V}$

$$\begin{aligned} \mathcal{F}^{\mathsf{p},(\kappa)}_{i,j}(\boldsymbol{V}) \quad := \quad & a^{\mathsf{p},(\kappa)}_{i,j}+2\Re\{\langle B^{\mathsf{p},(\kappa)}_{i,j}\boldsymbol{V}^{\mathsf{p}}_{i,j}\rangle\}\\ & +\langle C^{\mathsf{p},(\kappa)}_{i,j},\mathcal{M}^{\mathsf{p}}_{i,j}(\boldsymbol{V})\rangle, \end{aligned} \tag{45}$$

$$\begin{aligned} \mathcal{F}^{c(\kappa)}_{i,j}(\boldsymbol{V}) \quad := \quad & a^{\mathsf{c},(\kappa)}_{i,j}+2\Re\{\langle B^{\mathsf{c},(\kappa)}_{i,j}\boldsymbol{V}^{\mathsf{c}}_{i,j}\rangle\}\\ & +\langle C^{\mathsf{c},(\kappa)}_{i,j},\mathcal{M}^{\mathsf{c}}_{i,j}(\boldsymbol{V})\rangle, \end{aligned} \tag{46}$$

$$\begin{aligned} \mathcal{F}^{\mathsf{a},(\kappa)}_{i,j}(\boldsymbol{V}) \quad := \quad & a^{\mathsf{a},(\kappa)}_{i,j}+2\Re\{\langle B^{\mathsf{a},(\kappa)}_{i,j}\boldsymbol{V}^{\mathsf{c}}_{\hat{i},\hat{j}}\rangle\}\\ & +\langle C^{\mathsf{a},(\kappa)}_{i,j},\mathcal{M}^{\mathsf{a}}_{i,j}(\boldsymbol{V})\rangle, \end{aligned} \tag{47}$$

where

$$\begin{aligned} 0>a^{\mathsf{p},(\kappa)}_{i,j} \quad = \quad & F^{\mathsf{p}}_{i,j}(V^{\mathsf{p},(\kappa)}_{i,j},\mathcal{M}_{i,j}(V^{(\kappa)}))\\ & -\langle[H_{i,i,j}V^{\mathsf{p},(\kappa)}_{i,j}]^2(\mathcal{M}_{i,j}(V^{(\kappa)}))^{-1}\rangle, \end{aligned} \tag{48}$$

$$0 > a^{\mathsf{c},(\kappa)}_{i,j} = F^{\mathsf{c}}_{i,j}(V^{\mathsf{c},(\kappa)}_{i,j}, \mathcal{M}_{i,j}(V^{(\kappa)})) - \langle [H_{i,i,j}V^{\mathsf{c},(\kappa)}_{i,j}]^2(\mathcal{M}_{i,j}(V^{(\kappa)}))^{-1}\rangle, \quad (49)$$

$$0 > a^{\mathsf{a},(\kappa)}_{i,j} = F^{\mathsf{a}}_{i,j}(V^{\mathsf{c},(\kappa)}_{\hat{i},\hat{j}}, \mathcal{M}^{\mathsf{a}}_{i,j}(V^{(\kappa)})) - \langle [H_{\hat{i},i,j}V^{\mathsf{c},(\kappa)}_{\hat{i},\hat{j}}]^2(\mathcal{M}_{i,j}(V^{(\kappa)}))^{-1}\rangle, \quad (50)$$

and

$$B^{\mathsf{p},(\kappa)}_{i,j} = (V^{\mathsf{p},(\kappa)}_{i,j})^H H^H_{i,i,j}(\mathcal{M}_{i,j}(V^{(\kappa)}))^{-1}H_{i,i,j}, \quad (51)$$

$$B^{\mathsf{c},(\kappa)}_{i,j} = (V^{\mathsf{c},(\kappa)}_{i,j})^H H^H_{i,i,j}(\mathcal{M}_{i,j}(V^{(\kappa)}))^{-1}H_{i,i,j}, \quad (52)$$

$$B^{a(\kappa)}_{i,j} = (V^{\mathsf{c},(\kappa)}_{\hat{i},\hat{j}})^H H^H_{\hat{i},i,j}(\mathcal{M}_{i,j}(V^{(\kappa)}))^{-1}H_{\hat{i},i,j}, \quad (53)$$

and

$$0 \succeq C^{\mathsf{p},(\kappa)}_{i,j} = \mathcal{M}^{\mathsf{p}}_{i,j}(V^{(\kappa)}))^{-1} - (\mathcal{M}_{i,j}(V^{(\kappa)}))^{-1}, \quad (54)$$

$$0 \succeq C^{\mathsf{c},(\kappa)}_{i,j} = \mathcal{M}^{\mathsf{c}}_{i,j}(V^{(\kappa)}))^{-1} - (\mathcal{M}_{i,j}(V^{(\kappa)}))^{-1}, \quad (55)$$

$$0 \succeq C^{\mathsf{a},(\kappa)}_{i,j} = \mathcal{M}^{\mathsf{a}}_{i,j}(V^{(\kappa)}))^{-1} - (\mathcal{M}_{i,j}(V^{(\kappa)}))^{-1}. \quad (56)$$

Analogously, under the following definitions of the positive combinations of $[\boldsymbol{V}]^2$

$$\begin{array}{rcl}\mathcal{M}^{\mathsf{pc}}_{i,j}(\boldsymbol{V}) &=& \mathcal{M}_{i,j}(\boldsymbol{V}) + [H_{i,i,j}\boldsymbol{V}^{\mathsf{p}}_{i,j}]^2 + [H_{i,i,j}\boldsymbol{V}^{\mathsf{c}}_{i,j}]^2,\\ \mathcal{M}^{\mathsf{pa}}_{i,j}(\boldsymbol{V}) &=& \mathcal{M}_{i,j}(\boldsymbol{V}) + [H_{i,i,j}\boldsymbol{V}^{\mathsf{p}}_{i,j}]^2 + [H_{\hat{i},i,j}\boldsymbol{V}^{\mathsf{c}}_{\hat{i},\hat{j}}]^2,\\ \mathcal{M}^{\mathsf{ca}}_{i,j}(\boldsymbol{V}) &=& \mathcal{M}_{i,j}(\boldsymbol{V}) + [H_{\hat{i},i,j}\boldsymbol{V}^{\mathsf{c}}_{\hat{i},\hat{j}}]^2 + [H_{\hat{i},i,j}\boldsymbol{V}^{\mathsf{c}}_{\hat{i},\hat{j}}]^2,\\ \mathcal{M}^{\mathsf{pca}}_{i,j}(\boldsymbol{V}) &=& \mathcal{M}_{i,j}(\boldsymbol{V}) + [H_{i,i,j}\boldsymbol{V}^{\mathsf{p}}_{i,j}]^2 + [H_{i,i,j}\boldsymbol{V}^{\mathsf{c}}_{i,j}]^2\\ && +[H_{\hat{i},i,j}\boldsymbol{V}^{\mathsf{c}}_{\hat{i},\hat{j}}]^2\end{array}$$

and by applying Theorem 1, one has

$$\begin{array}{rcl}F^{\mathsf{pc}}_{i,j}(\boldsymbol{V}^{\mathsf{p}}_{i,j}, \boldsymbol{V}^{\mathsf{c}}_{i,j}, \mathcal{M}_{i,j}(\boldsymbol{V})) &\geq& \mathcal{F}^{\mathsf{pc},(\kappa)}_{i,j}(\boldsymbol{V}),\\ F^{\mathsf{pa}}_{i,j}(\boldsymbol{V}^{\mathsf{p}}_{i,j}, \boldsymbol{V}^{\mathsf{c}}_{\hat{i},\hat{j}}, \mathcal{M}_{i,j}(\boldsymbol{V})) &\geq& \mathcal{F}^{\mathsf{pa},(\kappa)}_{i,j}(\boldsymbol{V}),\\ F^{\mathsf{ca}}_{i,j}(\boldsymbol{V}^{\mathsf{c}}_{i,j}, \boldsymbol{V}^{\mathsf{c}}_{\hat{i},\hat{j}}, \mathcal{M}_{i,j}(\boldsymbol{V})) &\geq& \mathcal{F}^{\mathsf{ca},(\kappa)}_{i,j}(\boldsymbol{V}),\\ F^{\mathsf{pca}}_{i,j}(\boldsymbol{V}^{\mathsf{p}}_{i,j}, \boldsymbol{V}^{\mathsf{c}}_{i,j}, \boldsymbol{V}^{\mathsf{c}}_{\hat{i},\hat{j}}, \mathcal{M}_{i,j}(\boldsymbol{V})) &\geq& \mathcal{F}^{\mathsf{pca},(\kappa)}_{i,j}(\boldsymbol{V}).\end{array} \quad (57)$$

The various concave quadratic functions in (57) are given as:

$$\mathcal{F}^{\mathsf{pc},(\kappa)}_{i,j}(\boldsymbol{V}) := a^{\mathsf{pc},(\kappa)}_{i,j} + 2\Re\{\langle B^{\mathsf{p},(\kappa)}_{i,j}\boldsymbol{V}^{\mathsf{p}}_{i,j}\rangle\} + 2\Re\{\langle B^{\mathsf{c},(\kappa)}_{i,j}\boldsymbol{V}^{\mathsf{c}}_{i,j}\rangle\} + \langle C^{\mathsf{pc},(\kappa)}_{i,j}, \mathcal{M}^{\mathsf{pc}}_{i,j}(\boldsymbol{V})\rangle, \quad (58)$$

$$\mathcal{F}^{\mathsf{pa},(\kappa)}_{i,j}(\boldsymbol{V}) := a^{\mathsf{pa},(\kappa)}_{i,j} + 2\Re\{\langle B^{\mathsf{p},(\kappa)}_{i,j}\boldsymbol{V}^{\mathsf{p}}_{i,j}\rangle\} + 2\Re\{\langle B^{\mathsf{a},(\kappa)}_{i,j}\boldsymbol{V}^{\mathsf{c}}_{\hat{i},\hat{j}}\rangle\} + \langle C^{\mathsf{pa},(\kappa)}_{i,j}, \mathcal{M}^{\mathsf{pa}}_{i,j}(\boldsymbol{V})\rangle, \quad (59)$$

$$\mathcal{F}^{\mathsf{ca},(\kappa)}_{i,j}(\boldsymbol{V}) := a^{\mathsf{ca},(\kappa)}_{i,j} + 2\Re\{\langle B^{\mathsf{c},(\kappa)}_{i,j}\boldsymbol{V}^{\mathsf{c}}_{i,j}\rangle\} + 2\Re\{\langle B^{\mathsf{a},(\kappa)}_{i,j}\boldsymbol{V}^{\mathsf{c}}_{\hat{i},\hat{j}}\rangle\} + \langle C^{\mathsf{ca},(\kappa)}_{i,j}, \mathcal{M}^{\mathsf{ca}}_{i,j}(\boldsymbol{V})\rangle, \quad (60)$$

$$\mathcal{F}^{\mathsf{pca},(\kappa)}_{i,j}(\boldsymbol{V}) := a^{\mathsf{pca},(\kappa)}_{i,j} + 2\Re\{\langle B^{\mathsf{p},(\kappa)}_{i,j}\boldsymbol{V}^{\mathsf{p}}_{i,j}\rangle\} + 2\Re\{\langle B^{\mathsf{c},(\kappa)}_{i,j}\boldsymbol{V}^{\mathsf{c}}_{i,j}\rangle\} + 2\Re\{\langle B^{\mathsf{a},(\kappa)}_{i,j}\boldsymbol{V}^{\mathsf{c}}_{\hat{i},\hat{j}}\rangle\} + \langle C^{\mathsf{pca},(\kappa)}_{i,j}, \mathcal{M}^{\mathsf{pca}}_{i,j}(\boldsymbol{V})\rangle, \quad (61)$$

where

$$0 > a^{\mathsf{pc},(\kappa)}_{i,j} = F^{\mathsf{pc}}_{i,j}(V^{\mathsf{p},(\kappa)}_{i,j}, V^{\mathsf{c},(\kappa)}_{i,j}, \mathcal{M}_{i,j}(V^{(\kappa)})) - \langle([H_{i,i,j}V^{\mathsf{p},(\kappa)}_{i,j}]^2 + [H_{i,i,j}V^{\mathsf{c},(\kappa)}_{i,j}]^2) \times(\mathcal{M}_{i,j}(V^{(\kappa)}))^{-1}\rangle, \quad (62)$$

$$0 > a^{\mathsf{pa},(\kappa)}_{i,j} = F^{\mathsf{pa}}_{i,j}(V^{p(\kappa)}_{i,j}, V^{c(\kappa)}_{\hat{i},\hat{j}}, \mathcal{M}_{i,j}(V^{(\kappa)})) - \langle([H_{i,i,j}V^{\mathsf{p},(\kappa)}_{i,j}]^2 + [H_{\hat{i},i,j}V^{\mathsf{c},(\kappa)}_{\hat{i},\hat{j}}]^2) \times(\mathcal{M}_{i,j}(V^{(\kappa)})^{-1}\rangle, \quad (63)$$

$$0 > a^{\mathsf{ca},(\kappa)}_{i,j} = F^{\mathsf{ca}}_{i,j}(V^{\mathsf{c},(\kappa)}_{i,j}, V^{\mathsf{c},(\kappa)}_{\hat{i},\hat{j}}, \mathcal{M}_{i,j}(V^{(\kappa)})) - \langle([H_{i,i,j}V^{\mathsf{c},(\kappa)}_{i,j}]^2 + [H_{\hat{i},i,j}V^{\mathsf{c},(\kappa)}_{\hat{i},\hat{j}}]^2) \times(\mathcal{M}_{i,j}(V^{(\kappa)}))^{-1}\rangle, \quad (64)$$

$$0 > a^{\mathsf{pca},(\kappa)}_{i,j} = F^{\mathsf{pca}}_{i,j}(V^{\mathsf{p},(\kappa)}_{i,j}, V^{\mathsf{c},(\kappa)}_{i,j}, V^{\mathsf{c},(\kappa)}_{\hat{i},\hat{j}}, \mathcal{M}_{i,j}(V^{(\kappa)})) - \langle([H_{i,i,j}V^{\mathsf{p},(\kappa)}_{i,j}]^2 + [H_{i,i,j}V^{\mathsf{c},(\kappa)}_{i,j}]^2 + [H_{\hat{i},i,j}V^{\mathsf{c},(\kappa)}_{\hat{i},\hat{j}}]^2)(\mathcal{M}_{i,j}(V^{(\kappa)}))^{-1}\rangle, \quad (65)$$

and

$$0 \succeq C^{\mathsf{pc},(\kappa)}_{i,j} = \mathcal{M}^{\mathsf{pc}}_{i,j}(V^{(\kappa)}))^{-1} - (\mathcal{M}_{i,j}(V^{(\kappa)}))^{-1}, \quad (66)$$

$$0 \succeq C^{\mathsf{pa},(\kappa)}_{i,j} = \mathcal{M}^{\mathsf{pa}}_{i,j}(V^{(\kappa)}))^{-1} - (\mathcal{M}_{i,j}(V^{(\kappa)}))^{-1}, \quad (67)$$

$$0 \succeq C^{\mathsf{ca},(\kappa)}_{i,j} = \mathcal{M}^{\mathsf{ca}}_{i,j}(V^{(\kappa)}))^{-1} - (\mathcal{M}_{i,j}(V^{(\kappa)}))^{-1}, \quad (68)$$

$$0 \succeq C^{\mathsf{pca},(\kappa)}_{i,j} = \mathcal{M}^{\mathsf{pca}}_{i,j}(V^{(\kappa)}))^{-1} - (\mathcal{M}_{i,j}(V^{(\kappa)}))^{-1}. \quad (69)$$

We now propose the following path-following procedure based on convex quadratic programming for solving (13).

- *Initialization:* Initialize any feasible solution $V^{(0)} = (V^{\mathsf{p},(0)}_{i,j} \quad V^{\mathsf{c},(0)}_{i,j})_{(i,j)\in\mathcal{I}\times\mathcal{J}}$ to the convex power constraint (33). Set $Q^{\mathsf{p},(0)}_{i,j} = V^{\mathsf{p},(0)}_{i,j}(V^{\mathsf{p},(0)}_{i,j})^H$, $Q^{\mathsf{c},(0)}_{i,j} = V^{\mathsf{c},(0)}_{i,j}(V^{\mathsf{c},(0)}_{i,j})^H$, $Q^{(0)} = [Q^{\mathsf{p},(0)}_{i,j} \quad Q^{\mathsf{c},(0)}_{i,j}]_{(i,j)\in\mathcal{I}\times J}$ and solve the linear program

$$\max_{\boldsymbol{r}^{\mathsf{p}}=[\boldsymbol{r}^{\mathsf{p}}_{i,j}], \boldsymbol{r}^{\mathsf{c}}=[\boldsymbol{r}^{\mathsf{c}}_{i,j}]} \sum_{(i,j)\in\mathcal{I}\times\mathcal{J}} (\boldsymbol{r}^{\mathsf{p}}_{i,j} + \boldsymbol{r}^{\mathsf{c}}_{i,j}) \;:\; (4)-(10) \quad \text{for} \quad \mathbf{Q} = Q^{(0)} \quad (70)$$

  to find the optimal solution $r^{(0)}$.
- κ*-th* iteration is to generate $V^{(\kappa+1)} := (V^{\mathsf{p},(\kappa+1)}_{i,j} \quad V^{\mathsf{c},(\kappa+1)}_{i,j})_{(i,j)\in\mathcal{I}\times\mathcal{J}}$ and $r^{(\kappa+1)} := (r^{\mathsf{p},(\kappa+1)}_{i,j} \quad r^{\mathsf{c},(\kappa+1)}_{i,j})_{(i,j)\in\mathcal{I}\times\mathcal{J}}$ from $(V^{(\kappa)}, r^{(\kappa)})$ by the optimal solution of the convex quadratic program

$$\max_{\boldsymbol{V},\boldsymbol{r}} \mathcal{P}(\boldsymbol{r}) := \sum_{(i,j)\in\mathcal{I}\times\mathcal{J}} (\boldsymbol{r}^{\mathsf{p}}_{i,j} + \boldsymbol{r}^{\mathsf{c}}_{i,j}) \;:\; (33), \quad (71a)$$

$$\mathcal{F}^{\mathsf{p},(\kappa)}_{i,j}(\boldsymbol{V}) \geq \boldsymbol{r}^{\mathsf{p}}_{i,j}, \mathcal{F}^{\mathsf{c},(\kappa)}_{i,j}(\boldsymbol{V}) \geq \boldsymbol{r}^{\mathsf{c}}_{i,j}, \quad (71b)$$

$$\mathcal{F}^{\mathsf{a},(\kappa)}_{i,j}(\boldsymbol{V}) \geq \boldsymbol{r}^{\mathsf{c}}_{\hat{i},\hat{j}}, \mathcal{F}^{\mathsf{pc},(\kappa)}_{i,j}(\boldsymbol{V}) \geq \boldsymbol{r}^{\mathsf{p}}_{i,j} + \boldsymbol{r}^{\mathsf{c}}_{i,j}, \quad (71c)$$

$$\mathcal{F}^{\mathsf{pa},(\kappa)}_{i,j}(\boldsymbol{V}) \geq \boldsymbol{r}^{\mathsf{p}}_{i,j} + \boldsymbol{r}^{\mathsf{c}}_{\hat{i},\hat{j}}, \mathcal{F}^{\mathsf{ca},(\kappa)}_{i,j}(\boldsymbol{V}) \geq \boldsymbol{r}^{\mathsf{c}}_{i,j} + \boldsymbol{r}^{\mathsf{c}}_{\hat{i},\hat{j}}, \quad (71d)$$

$$\mathcal{F}^{\mathsf{pca},(\kappa)}_{i,j}(\boldsymbol{V}) \geq \boldsymbol{r}^{\mathsf{p}}_{i,j} + \boldsymbol{r}^{\mathsf{c}}_{i,j} + \boldsymbol{r}^{\mathsf{c}}_{\hat{i},\hat{j}}, \quad (71e)$$

$$(i,j)\in\mathcal{I}\times\mathcal{J}, (\hat{i},\hat{j}) = a^{-1}(i,j) \quad (71f)$$

Algorithm 1 QP-based path-following algorithm for solving (13)

Initialize $\kappa := 0$.
Initialize any feasible solution $V^{(0)} = (V^{\mathsf{p},(0)}_{i,j} \quad V^{\mathsf{c},(0)}_{i,j})_{(i,j)\in\mathcal{I}\times\mathcal{J}}$ to the convex power constraint (33). Solve linear program (70) to find the optimal solution $r^{(0)}$.
repeat
    Solve quadratic program (71) for $(V^{(\kappa+1)}, r^{(\kappa+1)})$.
    Set $\kappa := \kappa + 1$.
until convergence of the objective in (42), i.e., $(\mathcal{P}(r^{(\kappa+1)}) - \mathcal{P}(r^{(\kappa)}))/\mathcal{P}(r^{(\kappa)}) \le \epsilon$ for a given computational tolerance ϵ.

For $\Delta \triangleq |\cup_{(i,j)\in\mathcal{I}\times\mathcal{J}} a(i,j)|$, the number of quadratic constraints in (71) is bounded by $m = 3N + 7\Delta + (NK - \Delta)$ while the variable number is $n = NKM_t^2/2 + \Delta M_t^2/2 + NK + (NK - \Delta)$. So the computational complexity of (71) is upper bounded by $O(n^2m^{2.5} + m^{3.5})$.

It is pointed out that (71b)-(71e) are employed when both $a(i,j) \neq \emptyset$ and $a^{-1}(i,j) \neq \emptyset$. Other three possible cases are

- $a(i,j) \neq \emptyset$ but $a^{-1}(i,j) = \emptyset$: In this case user (i,j) needs to decode $s^{\mathsf{p}}_{i,j}$ and $s^{\mathsf{c}}_{i,j}$ only. Hence replace (71b)-(71e) with

$$\begin{aligned} \mathcal{F}^{\mathsf{p},(\kappa)}_{i,j}(\boldsymbol{V}) \ge \boldsymbol{r}^{\mathsf{p}}_{i,j}, \mathcal{F}^{\mathsf{c},(\kappa)}_{i,j}(\boldsymbol{V}) \ge \boldsymbol{r}^{\mathsf{c}}_{i,j}, \\ \mathcal{F}^{\mathsf{pc},(\kappa)}_{i,j}(\boldsymbol{V}) \ge \boldsymbol{r}^{\mathsf{p}}_{i,j} + \boldsymbol{r}^{\mathsf{c}}_{i,j}. \end{aligned} \tag{72}$$

- $a(i,j) = \emptyset$ but $a^{-1}(i,j) = (\hat{i},\hat{j}) \neq \emptyset$: In this case user (i,j) needs to decode $s^{\mathsf{p}}_{i,j}$ and $s^{\mathsf{c}}_{\hat{i},\hat{j}}$ only. Hence replace (71b)-(71e) with

$$\begin{aligned} \mathcal{F}^{\mathsf{p},(\kappa)}_{i,j}(\boldsymbol{V}) \ge \boldsymbol{r}^{\mathsf{p}}_{i,j}, \mathcal{F}^{\mathsf{a},(\kappa)}_{i,j}(\boldsymbol{V}) \ge \boldsymbol{r}^{\mathsf{c}}_{\hat{i},\hat{j}}, \\ \mathcal{F}^{\mathsf{pa},(\kappa)}_{i,j}(\boldsymbol{V}) \ge \boldsymbol{r}^{\mathsf{p}}_{i,j} + \boldsymbol{r}^{\mathsf{c}}_{\hat{i},\hat{j}}. \end{aligned} \tag{73}$$

- Both $a(i,j) = \emptyset$ and $a^{-1}(i,j) = \emptyset$: In this case user (i,j) needs to decode its private message $s^{\mathsf{p}}_{i,j}$ only. Then, replace (71b)-(71e) with

$$\mathcal{F}^{\mathsf{p},(\kappa)}_{i,j}(\boldsymbol{V}) \ge \boldsymbol{r}^{\mathsf{p}}_{i,j}. \tag{74}$$

Algorithm 1 recaps the above a QP-based path-following procedure for solving the sum rate maximization problem (13). The convergence property of the proposed algorithm is established in the following proposition.

Proposition 1: Algorithm 1 generates a sequence $\{(V^{(\kappa)}, r^{(\kappa)})\}$ of feasible and improved solutions of the original nonconvex program (42) in the sense that

$$\mathcal{P}(r^{(\kappa+1)}) > \mathcal{P}(r^{(\kappa)}) \tag{75}$$

as far as $(Q^{(\kappa+1)}, r^{(\kappa+1)}) \neq (Q^{(\kappa)}, r^{(\kappa)})$, which converges at least to a solution satisfying the KKT condition for optimality of (13).

Proof: By (44) and (57), every feasible solution to (71) is also feasible to (42). Then (75) is true because $(V^{(\kappa)}, r^{(\kappa)})$ is also feasible to (71), while $(V^{(\kappa+1)}, r^{(\kappa+1)})$ is its optimal solution. Furthermore, the sequence $\{(V^{(\kappa)}, r^{(\kappa)})\}$ is bounded by constraint (33). By Cauchy's theorem there is a convergent subsequence $\{(V^{(\kappa_\nu)}, r^{(\kappa_\nu)})\}$ so

$$\lim_{\nu\to+\infty}(\mathcal{P}(r^{(\kappa_{\nu+1})}) - \mathcal{P}(r^{(\kappa_\nu)})) = 0.$$

For every κ, there is ν such that $\kappa_\nu \le \kappa$ and $\kappa + 1 \le \kappa_\nu$. Therefore

$$\begin{aligned} 0 &\le \lim_{\kappa\to+\infty}(\mathcal{P}(r^{(\kappa+1)}) - \mathcal{P}(r^{(\kappa)})) \\ &\le \lim_{\kappa\to+\infty}(\mathcal{P}(r^{(\kappa_{\nu+1})}) - \mathcal{P}(r^{(\kappa_\nu)})) \\ &= 0, \end{aligned}$$

showing that $\lim_{\kappa\to+\infty}(\mathcal{P}(r^{(\kappa+1)}) - \mathcal{P}(r^{(\kappa)})) = 0$. Each accumulation point $\{(\bar{V}, \bar{r})\}$ of the sequence $\{(V^{(\kappa)}, r^{(\kappa)})\}$ obviously satisfies the KKT condition for optimality [37]. $\square$

Remark. The maximin rate optimization problem, formulated as

$$\max_{\boldsymbol{Q},\boldsymbol{r}} \min_{(i,j)\in\mathcal{I}\times\mathcal{J}} (\boldsymbol{r}^{\mathsf{p}}_{i,j} + \boldsymbol{r}^{\mathsf{c}}_{i,j}) \ : \ (2), (4) - (10), \tag{76}$$

can also be solved by the proposed path-following algorithm when replacing the objective in (70) and (71) with $\min_{(i,j)\in\mathcal{I}\times\mathcal{J}}(\boldsymbol{r}^{\mathsf{p}}_{i,j} + \boldsymbol{r}^{\mathsf{c}}_{i,j})$.

IV. Numerical Results

In this section, numerical results are presented to show the rate performances achieved by different signalling schemes. For ease of discussion, the conventional signalling involving only private messages is referred to as "private only", while the proposed H-K signalling is referred to as "H-K". The computational tolerance in Algorithm 1 is set as $\epsilon = 10^{-5}$. Each point plotted for the Monte Carlo simulations is based on 100 random network realizations.

For convenience, set $H_{m,i,j} = \sqrt{\eta_{m,i,j}}h_{m,i,j}$ for $m \neq i$. The entries $h_{m,i,j}$ are independent and identically distributed complex Gaussian variables with zero mean and unit variance, which represent the small-scaling fading, whereas $\eta_{m,i,j}$ captures the path loss and large-scale fading.

Obviously, the effectiveness of the H-K signalling strongly depends on the pairing operator a. Unfortunately optimization of the pairing operator is an intractable combinatorial problem. It is pointed out that a heuristic rule for choosing a based on the performance of "private only" messaging was proposed in [25] and further developed in [23].

A. $N = 2$, $K = 1$ *with* $N_t = N_r \in \{1, 2, 4, 6, 8\}$*, as in [36, Fig. 3]*

In this study, the direct channel strengths $\eta_{1,1,1} = \eta_{2,2,1} = 0$ dB and the inferring channel strengths $\eta_{1,2,1} = \eta_{2,1,1} = -4.7712$ dB are selected as in [36, p. 4317]. Fig. 2 plots the sum rate performance versus the number of antennas, under a per-Tx power budget $P_B = 30$ dB. For comparison, also included is the performance of the two-stage scheme in [36], which is extremely computationally demanding. Its performance plotted in Fig. 2 based on only 225 sampled points already took hours of computer simulation to obtain.

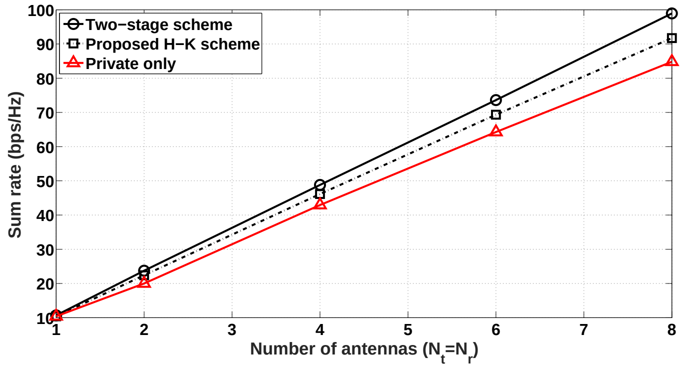
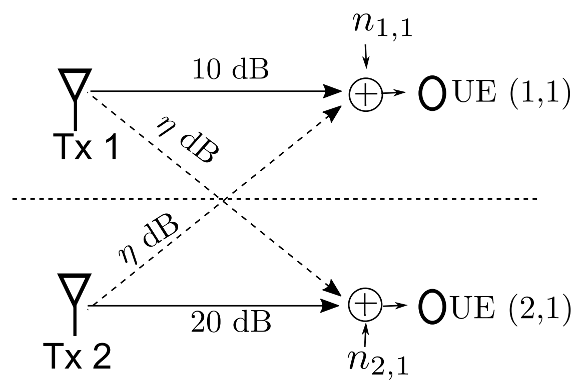
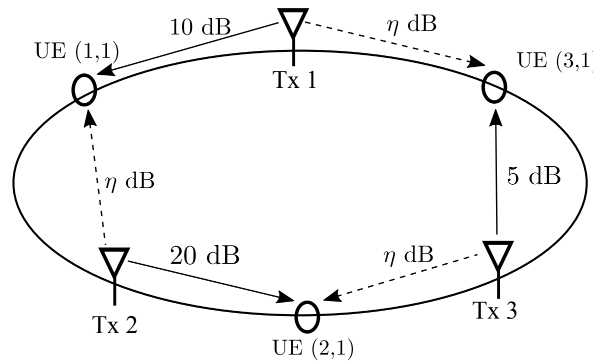


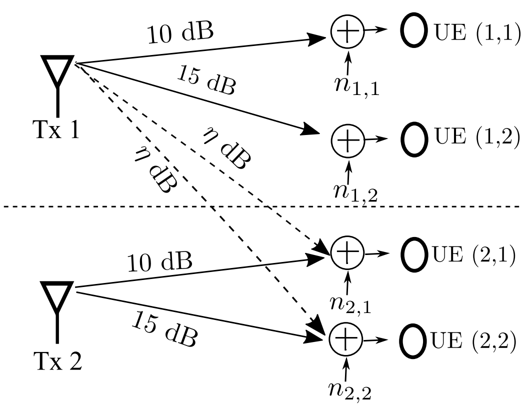
Fig. 2: Plots of the sum rate versus the number of antennas.



(a) $N = 2,\ K = 1$.



(b) Cyclic $N = 3,\ K = 1$



(c) $N = 2,\ K = 2$

Fig. 3: Different interference networks considered in simulation.

B. $N = 2,\ K = 1,\ N_t = 4,\ N_r = 2$

Here, the statistical performance of MIMO interference networks depicted as in Fig. 3a is analyzed. Following [7], [38], the direct channel strengths are fixed at $(\eta_{1,1,1}, \eta_{2,2,1}) = (10, 20)$ (in dB), while the interfering channel strengths $\eta_{1,2,1} = \eta_{2,1,1}$ are increased from -5 dB to 20 dB. These values cover a wide range of channels effects, such as path loss and shadowing, which may be environment-dependent. The simulation scenarios thus vary from weak MIMO GINs to mixed MIMO GINs. The upper and lower bounds on the sum or minimal rates can be obtained by solving the linear inequality [17, (52a)-(52i)] and [17, (11)- (17)], respectively. Fig. 4 show that both of these bounds are quite loose. The performance of the conventional scheme degrades significantly as the interference channel strength η increases. This is in a sharp contrast to the improved performance behavior of the H-K signalling.

C. Three-user cyclic GIN with $N_t = 4,\ N_r = 2$

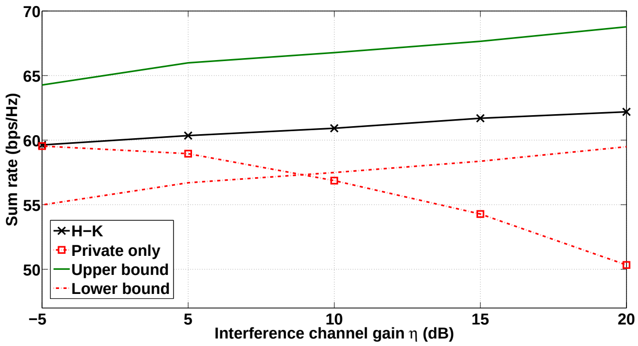
Fig. 3b depicts a three-user cyclic GIN. The direct channel strengths $(\eta_{1,1,1}, \eta_{2,2,1}, \eta_{3,3,1})$ are fixed at $(10, 20, 5)$ (in dB), while the interfering channel strengths $\eta_{2,1,1} = \eta_{3,2,1} = \eta_{1,3,1}$ are increased from -10 dB to 30 dB for testing different scenarios. Fig. 5 shows a profound performance improvement achieved by using H-K signalling, especially when the interference channel gain η is large. In contrast, the performance of the conventional scheme is severely deteriorated.

D. $N = 2,\ K = 2,\ N_t = 4,\ N_r = 2$

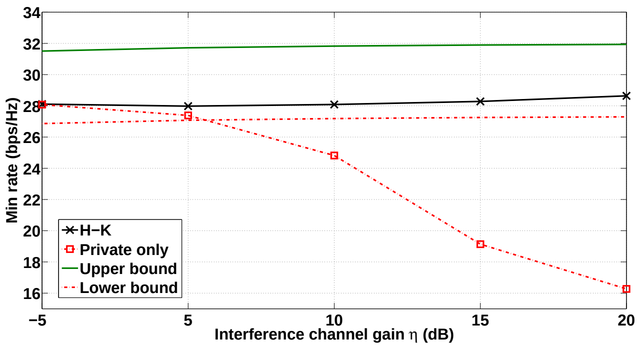
As shown in Fig. 3c, the direct channel strengths $\eta_{1,1,1} = \eta_{2,2,1}$ and $\eta_{1,1,2} = \eta_{2,2,2}$ are, respectively, fixed at 10 dB and 15 dB, and the interfering channel strengths $\eta_{2,1,1}$ and $\eta_{2,1,2}$ are set to -50 dB (thus these interfering channels are basically disabled). The interfering channel strengths $\eta_{1,2,1} = \eta_{1,2,2}$ are increased from -10 dB to 50 dB. There are two users per cell so the DPC (which results in the covariance of the interference-plus-noise as in (3)) is expected to be beneficial. To confirm this fact, we also compare the performance of the H-K signalling with a signalling scheme that does not implement DPC. For the latter, the interference-plus-noise covariance is conventionally calculated as

$$\mathcal{M}_{i,j}(\boldsymbol{Q}) := \sum_{(n,k)\in\mathcal{I}\times\mathcal{J}} H_{n,i,j}(\boldsymbol{Q}^{\mathsf{p}}_{n,k} + \boldsymbol{Q}^{\mathsf{c}}_{n,k})H^H_{n,i,j} + \sigma^2 I_{N_r} - H_{i,i,j}(\boldsymbol{Q}^{\mathsf{p}}_{i,j} + \boldsymbol{Q}^{\mathsf{c}}_{i,j})H^H_{i,i,j} - H_{\hat{i},i,j}\boldsymbol{Q}^{\mathsf{c}}_{\hat{i},\hat{j}}H^H_{\hat{i},i,j}. \tag{77}$$

Fig. 6 shows the superior performance of the H-K signalling with and without DPC. As expected, a more profound enhancement in the performance of the H-K signalling is observed when the intercell interference channel gain is high (e.g., $\eta > 15$ dB).

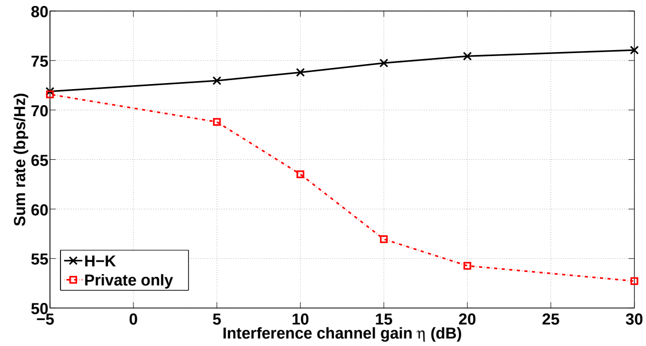


(a) Sum rate.

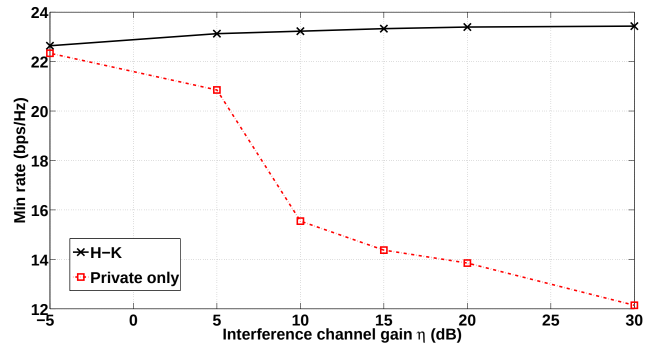


(b) Minimum rate.

Fig. 4: Rate performance versus interfering channel strength for $N = 2$, $K = 1$.



(a) Sum rate.



(b) Minimum rate.

Fig. 5: Rate performance versus interfering channel strength for a cyclic channel GIN, $N = 3$, $K = 1$.

V. Conclusions

In this paper, we have studied the H-K superposition signalling strategy for multi-user MIMO broadcast interference networks. The ability of the H-K signalling to increase the achievable rate region of a multi-user MIMO Gaussian interference network has been previously demonstrated, but its optimization has never been adequately addressed. The main contribution of this paper is to show that such an optimization problem can be solved by a path-following procedure based on convex quadratic programming of low computational complexity. In the presence of mild-to-strong interference, simulation results demonstrated significant rate gains obtained by our optimized H-K signalling.

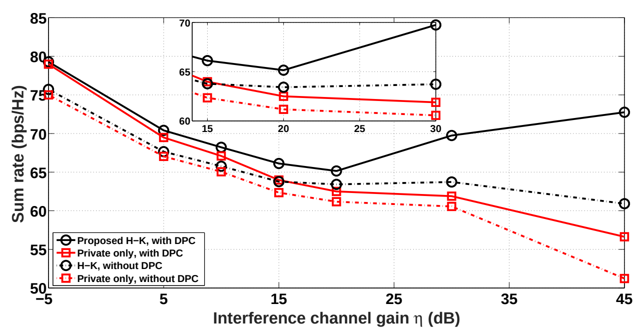
Appendix A: Proof of Theorem 1

Lemma 1: The following inequality holds for all $\boldsymbol{X}$, $X^{(\kappa)}$ and $\mathbf{Y} \succ [\mathbf{X}]^2$, $Y^{(\kappa)} \succ [X^{(\kappa)}]^2$ of appropriate sizes:

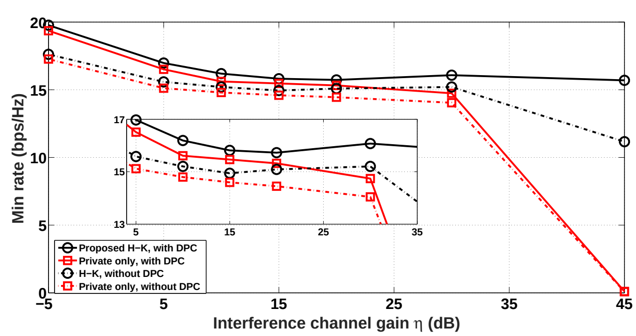
$$\begin{array}{rl}\ln|I_{N_r} - [\mathbf{X}]^2\mathbf{Y}^{-1}| & \leq \\ \ln|I_{N_r} - [X^{(\kappa)}]^2(Y^{(\kappa)})^{-1}| & \\ +\langle [X^{(\kappa)}]^2(Y^{(\kappa)} - [X^{(\kappa)}]^2)^{-1}\rangle & \\ -2\Re\{\langle (X^{(\kappa)})^H(Y^{(\kappa)} - [X^{(\kappa)}]^2)^{-1}\mathbf{X}\rangle\} & \\ +\langle (Y^{(\kappa)} - [X^{(\kappa)}]^2)^{-1} - (Y^{(\kappa)})^{-1}, \mathbf{Y}\rangle. & \end{array} \quad (78)$$

Proof: Define the function

$$g(\mathbf{X}, \mathbf{Y}) := \ln|I_{N_r} - [\mathbf{X}]^2\mathbf{Y}^{-1}| \quad \text{on} \quad \{\mathbf{Y} \succ [\mathbf{X}]^2\}$$



(a) Sum rate.



(b) Minimum rate.

Fig. 6: Rate performance versus interfering channel strength for $N = 2,\ K = 2,\ N_t = 4,\ N_r = 2$.

and mapping

$$h(\mathbf{X},\mathbf{Y}) := \mathbf{X}^H\mathbf{Y}^{-1}\mathbf{X} \quad \text{on} \quad \{\mathbf{Y}\succ 0\}.$$

By [39, Appendix C], whenever $\alpha \geq 0,\ \beta \geq 0,\ \alpha+\beta=1$, the following matrix inequality holds true

$$h(\alpha(\mathbf{X},\mathbf{Y})+\beta(X^{(\kappa)},Y^{(\kappa)})) \preceq \alpha h(\mathbf{X},\mathbf{Y})+\beta h(X^{(\kappa)},Y^{(\kappa)}).$$

It then follows that

$$\begin{array}{rl} I_{N_r}-h(\alpha(\mathbf{X},\mathbf{Y})+\beta(X^{(\kappa)},Y^{(\kappa)})) & \succeq \\ I_{N_r}-\alpha h(\mathbf{X},\mathbf{Y})-\beta h(X^{(\kappa)},Y^{(\kappa)}). & \end{array}$$

Therefore

$$\begin{array}{rl} g(\alpha(\mathbf{X},\mathbf{Y})+\beta(X^{(\kappa)},Y^{(\kappa)})) & = \\ \ln|I_{N_r}-h(\alpha(\mathbf{X},\mathbf{Y})+\beta(X^{(\kappa)},Y^{(\kappa)}))| & \geq \\ \ln|I_{N_r}-\alpha h(\mathbf{X},\mathbf{Y})-\beta h(X^{(\kappa)},Y^{(\kappa)})| & \geq \\ \alpha\ln|I_{N_r}-h(\mathbf{X},\mathbf{Y})|+\beta\ln|I_{N_r}-h(X^{(\kappa)},Y^{(\kappa)})| & = \\ \alpha g(\mathbf{X},\mathbf{Y})+\beta g(X^{(\kappa)},Y^{(\kappa)}), & \end{array} \tag{79}$$

showing that $g(\cdot)$ is a concave function. Note that (79) is based on the fact that function $\ln|Z|$ is concave in $Z\succ 0$.

For such a concave function, it is true [40] that

$$\begin{array}{rl} g(\mathbf{X},\mathbf{Y}) & \leq \\ g(X^{(\kappa)},Y^{(\kappa)})+\langle\nabla g(X^{(\kappa)},Y^{(\kappa)}),(\mathbf{X},\mathbf{Y}) & \\ -(X^{(\kappa)},Y^{(\kappa)})\rangle & = \\ \ln|I_{N_r}-[X^{(\kappa)}]^2(Y^{(\kappa)})^{-1}|-2\Re\{\langle(X^{(\kappa)})^H(Y^{(\kappa)} & \\ -[X^{(\kappa)}]^2)^{-1}(\mathbf{X}-X^{(\kappa)})\rangle\} & \\ +\langle(Y^{(\kappa)}-[X^{(\kappa)}]^2)^{-1}-(Y^{(\kappa)})^{-1},\mathbf{Y}-Y^{(\kappa)}\rangle & = \\ \ln|I_{N_r}-[X^{(\kappa)}]^2(Y^{(\kappa)})^{-1}|-2\Re\{\langle(X^{(\kappa)})^H(Y^{(\kappa)} & \\ -[X^{(\kappa)}]^2)^{-1}\mathbf{X}\rangle\} & \\ +2\langle(X^{(\kappa)})^H(Y^{(\kappa)}-[X^{(\kappa)}]^2)^{-1}X^{(\kappa)})\rangle & \\ +\langle(Y^{(\kappa)}-[X^{(\kappa)}]^2)^{-1}-(Y^{(\kappa)})^{-1},\mathbf{Y}\rangle & \\ -\langle(Y^{(\kappa)}-[X^{(\kappa)}]^2)^{-1}-(Y^{(\kappa)})^{-1},Y^{(\kappa)}\rangle. & \end{array}$$

The right hand side (RHS) of the last inequality is the RHS of (78) because

$$\begin{array}{rl} 2\langle(X^{(\kappa)})^H(Y^{(\kappa)}-[X^{(\kappa)}]^2)^{-1}X^{(\kappa)})\rangle & \\ -\langle(Y^{(\kappa)}-[X^{(\kappa)}]^2)^{-1}-(Y^{(\kappa)})^{-1},Y^{(\kappa)}\rangle & = \\ \langle[X^{(\kappa)}]^2(Y^{(\kappa)}-[X^{(\kappa)}]^2)^{-1}\rangle. & \end{array}$$

This completes the proof of Lemma 1. □

Now, the proof of Theorem 1 is as follows. By defining

$$\boldsymbol{X}=[\boldsymbol{X}_1\ \ \boldsymbol{X}_2\ \ldots\ \boldsymbol{X}_L]$$

and using (P3) to rewrite

$$\begin{array}{rl} \ln|I_{N_r}+(\sum_{i=1}^{L}[\boldsymbol{X}_i]^2)\boldsymbol{M}^{-1}| & = \\ -\ln|I_{N_r}-[\boldsymbol{X}]^2(\boldsymbol{M}+[\boldsymbol{X}]^2)^{-1}|. & \end{array}$$

The inequality (43) then follows from (78) by substituting

$$\begin{array}{c} \boldsymbol{X}\leftarrow\boldsymbol{X},\ \boldsymbol{M}+[\boldsymbol{X}]^2\leftarrow\mathbf{Y}, \\ X^{(\kappa)}\leftarrow X^{(\kappa)},\ M^{(\kappa)}+[X^{(\kappa)}]^2\leftarrow Y^{(\kappa)}. \end{array}$$

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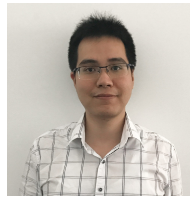
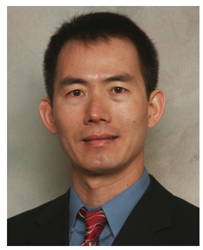
Hoang Duong Tuan received the Diploma (Hons.) and Ph.D. degrees in applied mathematics from Odessa State University, Ukraine, in 1987 and 1991, respectively. He spent nine academic years in Japan as an Assistant Professor in the Department of Electronic-Mechanical Engineering, Nagoya University, from 1994 to 1999, and then as an Associate Professor in the Department of Electrical and Computer Engineering, Toyota Technological Institute, Nagoya, from 1999 to 2003. He was a Professor with the School of Electrical Engineering and Telecommunications, University of New South Wales, from 2003 to 2011. He is currently a Professor with the Faculty of Engineering and Information Technology, University of Technology Sydney. He has been involved in research with the areas of optimization, control, signal processing, wireless communication, and biomedical engineering for more than 20 years.



Ho Huu Minh Tam was born in Ho Chi Minh City, Vietnam. He received the B.S. degree in electrical engineering and telecommunications from the Ho Chi Minh City University of Technology, Vietnam, in 2012, the Ph.D. degree in electrical engineering from the University of Technology Sydney, NSW, Australia, in 2016. He is now with Thinxtra Solution Pty., Sydney, Australia His research interest is in optimization techniques in signal processing for wireless communications and internet of things.



H a H. Nguyen (M'01, SM'05) received the B.Eng. degree from the Hanoi University of Technology (HUT), Hanoi, Vietnam, in 1995, the M.Eng. degree from the Asian Institute of Technology (AIT), Bangkok, Thailand, in 1997, and the Ph.D. degree from the University of Manitoba, Winnipeg, MB, Canada, in 2001, all in electrical engineering. He joined the Department of Electrical and Computer Engineering, University of Saskatchewan, Saskatoon, SK, Canada, in 2001, and became a full Professor in 2007. He currently holds the position of Cisco Systems Research Chair. His research interests fall into broad areas of Communication Theory, Wireless Communications, and Statistical Signal Processing. Dr. Nguyen was an Associate Editor for the IEEE Transactions on Wireless Communications and IEEE Wireless Communications Letters during 2007-2011 and 2011-2016, respectively. He currently serves as an Associate Editor for the IEEE Transactions on Vehicular Technology. He was a Co-chair for the Multiple Antenna Systems and Space-Time Processing Track, IEEE Vehicular Technology Conferences (Fall 2010, Ottawa, ON, Canada and Fall 2012, Quebec, QC, Canada), Lead Co-chair for the Wireless Access Track, IEEE Vehicular Technology Conferences (Fall 2014, Vancouver, BC, Canada), Lead Co-chair for the Multiple Antenna Systems and Cooperative Communications Track, IEEE Vehicular Technology Conference (Fall 2016, Montreal, QC, Canada), and Technical Program Co-chair for Canadian Workshop on Information Theory (2015, St. John's, NL, Canada). He is a coauthor, with Ed Shwedyk, of the textbook "A First Course in Digital Communications" (published by Cambridge University Press). Dr. Nguyen is a Fellow of the Engineering Institute of Canada (EIC) and a Registered Member of the Association of Professional Engineers and Geoscientists of Saskatchewan (APEGS).

Trung Q. Duong (S'05, M'12, SM'13) received his Ph.D. degree in Telecommunications Systems from Blekinge Institute of Technology (BTH), Sweden in 2012. Since 2013, he has joined Queen's University Belfast, UK as a Lecturer (Assistant Professor). His current research interests include small-cell networks, physical layer security, energy-harvesting communications, cognitive relay networks. He is the author or co-author of more than 260 technical papers published in scientific journals (142 articles) and presented at international conferences (121 papers).

Dr. Duong currently serves as an Editor for the IEEE Transactions on Wireless Communications, IEEE Transactions on Communications, IET Communications, and a Senior Editor for IEEE Communications Letters. He was awarded the Best Paper Award at the IEEE Vehicular Technology Conference (VTC-Spring) in 2013, IEEE International Conference on Communications (ICC) 2014, and IEEE Global Communications Conference (GLOBECOM) 2016. He is the recipient of prestigious Royal Academy of Engineering Research Fellowship (2016-2021).

H. Vincent Poor (S72, M77, SM82, F87) received the Ph.D. degree in EECS from Princeton University in 1977. From 1977 until 1990, he was on the faculty of the University of Illinois at Urbana-Champaign. Since 1990 he has been on the faculty at Princeton, where he is currently the Michael Henry Strater University Professor of Electrical Engineering. During 2006 to 2016, he served as Dean of Princetons School of Engineering and Applied Science. His research interests are in the areas of information theory, statistical signal processing and stochastic analysis, and their applications in wireless networks and related fields such as smart grid and social networks. Among his publications in these areas is the book *Mechanisms and Games for Dynamic Spectrum Allocation* (Cambridge University Press, 2014).

Dr. Poor is a member of the National Academy of Engineering, the National Academy of Sciences, and is a foreign member of the Royal Society. He is also a fellow of the American Academy of Arts and Sciences, the National Academy of Inventors, and other national and international academies. He received the Marconi and Armstrong Awards of the IEEE Communications Society in 2007 and 2009, respectively. Recent recognition of his work includes the 2016 John Fritz Medal, the 2017 IEEE Alexander Graham Bell Medal, Honorary Professorships at Peking University and Tsinghua University, both conferred in 2016, and a D.Sc. *honoris causa* from Syracuse University awarded in 2017.