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Intelligent Reflect Surface Aided Secure Transmission in MIMO Channel With SWIPT

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ABSTRACT This paper considers a multiple-input multiple-output (MIMO) secure simultaneous wireless information and power transfer (SWIPT) system aided by the intelligent reflecting surface (IRS), where the transmitter (T), the information receiver (IR) and energy receiver (ER) are all equipped with multiple antennas. Assuming that the ER may be potential eavesdropper (Eve), we aim to maximize the secrecy rate via jointly designing the precoding matrix, the artificial noise (AN) covariance, and the phase shift matrix, subject to the harvested energy and unit modulus reflect coefficient (RC) constraints. The formulated secrecy rate maximization (SRM) problem is non-convex with multiple coupled variables. To tackle it, an inexact block coordinate descent (IBCD) method is proposed, where the unit modulus constraint is handled by the penalty majorization-minimization (MM) and the complex circle manifold (CCM) methods. Finally, simulation results validate the effectiveness of IRS in enhancing the security.

INDEX TERMS Intelligent reflecting surface, unit modulus reflect coefficient, majorization-minimization, complex circle manifold.

I. INTRODUCTION

A. MOTIVATION

Radio frequency (RF) transmission enabled simultaneous wireless information and power transfer (SWIPT) is a promising solution for future energy-efficient communication system. SWIPT has attracted growing research interests in recent years as a viable technique to provide simultaneous data and energy access for massive low-power devices [1]. In order to make SWIPT reality, how to improve the energy transmission efficiency, and how to efficiently balance the performance conflicts between energy harvesting (EH) and information decoding (ID) are challenging tasks to be tackled. To deal with these issues, various techniques such as adaptive power control, multi-antenna beamforming, and large antenna array have been proposed [2].

Recently, the newly proposed intelligent reflecting surface (IRS) has drawn wide attention in wireless communication systems [3]. An IRS comprises an array of reflecting elements, which can reflect and alter the phase of the electromagnetic (EM) wave passively [4]. Hence, by smartly tuning the phase shifts with a programmable controller, the direct signals from the transmitter and the reflected signals from the IRS can be combined constructively or destructively according to different requirements [5]. Furthermore, the IRS reflecting elements are generally made of small and low-cost components, which efficiently reflect the received signal without a dedicated RF processing, or re-transmission [6]. Due to these appealing virtues, IRS has been introduced into various wireless communication systems, such as the downlink multiuser network in [7] and [8], the SWIPT network in [9]–[11], the multigroup multicast network in [12] and relay network in [13], etc.

Due to the openness of wireless transmission medium, wireless information is susceptible to be eavesdropped. Thus, the secure communication is a critical issue for wireless systems. Physical layer security (PLS) is a newly emerging secrecy communication technique [14]. In comparison with several existing PLS schemes, e.g., jammer-aided secure communication or the relay-aided secure communication, the IRS-aided secure transmission does not employ an additional transmitter to generate certain signal or interference, thus, no extra power consumption is need [15]. Besides, since operate in the full duplex (FD) mode, the IRS-aided scheme achieves higher spectrum efficiency than the half duplex (HD) relay scheme [16].

Due to these advantages, the research about IRS-aided PLS has attracted increasingly attention. Specifically, in [17], the authors investigated the problem of maximizing the secrecy rate in a secure multiple-input single-output (MISO) channel aided by IRS. Furthermore, the secure IRS-aided design in multiple-input multiple-output (MIMO) system was

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investigated in [18] and [19]. While, in [20], the authors investigated the secure transmission for IRS-assisted millimeter-wave communication systems. Recently, in [21] and [22], the authors investigated the robust transmission by an IRS with considering imperfect channel state information (CSI).

However, considering simultaneously secrecy information and energy transmission, the IRS-aided secure MIMO SWIPT design has not been investigated yet. Motivated by this, in this paper, we focus on the IRS aided secure SWIPT design in MIMO wiretap channel. Specifically, a secrecy rate maximization (SRM) problem is formulated by jointly optimizing the precoding matrix, the artificial noise (AN) covariance, and the IRS phase shifters, subject to multiply non-convex constraints. We decoupled the original problem into several subproblems and proposed an inexact block coordinate descent (IBCD) based algorithm, in which the unit modulus constraint is solved by the majorization-minimization (MM) and the complex circle manifold (CCM) method. Simulation results confirm that IRS can improve the secrecy performance of a MIMO SWIPT system.

B. RELATED WORKS

In this subsection, we discuss the similarity and difference of our work with several related works. From the view of system model and methodology, the most related work are [11] and [13], however, this work has several difference with them. Firstly, the work in [11] was not security concerned, thus, the objective in [11] is quiet differently with this work. Besides, the MM and CCM methods in [13] can not be directly applied in our problem, since the MM and CCM methods are only feasible when there exists only unit modulus constraint in the conditions. To overcome the obstacle, we introduce the penalty method to move this constraint into the objective. While for the security concerned literatures in MIMO channel such as [18], [19] and [23], both the methods in [18] and [19] are not suitable when considering AN, while the work in [23] was not considering IRS. Thus, our work is different with these related works.

Particularly, the precoding matrix, the AN covariance, and the phase shifts at the IRS are jointly optimized in this work. The formulated SRM problem is non-convex, while the most challenging part is the unit modulus constraint of the reflect coefficient (RC). To handle this obstacle, we decoupled the original problem into two subproblems and proposed an IBCD based algorithm. Firstly, with fixed phase shifters of IRS, the optimal precoding matrix and AN covariance are obtained in an alternating method. Then, given the precoding matrix and AN covariance, the harvested energy and unit modulus constraints are solved by the penalty MM and CCM methods.

C. CONTRIBUTIONS

The contributions of this work is summarized as follows:

- In this work, we aim to utilize an IRS to improve the security in MIMO SWIPT network. To the best of our knowledge, such problem has not been investigated yet. The objective function (OF) of this work is the difference of two information rate expressions, thus is not jointly concave over these coupled variables. To handle it, the IBCD method is used to reformulate the SRM objective into a linear formulation.
- Specifically, given the phase shifts of IRS, the optimal precoding matrix and AN covariance are obtained in an alternating optimization (AO) method. Then, given the precoding matrix and AN covariance, the optimization of IRS phase shifts is transformed into a quadratically constrained quadratic program QCQP) problem with non-convex harvested energy and unit modulus constraints. To solve it, the penalty MM and CCM methods are proposed, where the phase shifts are derived in closed form iteratively.
- The simulation results confirm the convergence of the proposed IBCD method. Besides, the simulation results show that on the one hand, the IRS can greatly enhance the security of an AN aided MIMO SWIPT system, on the other hand, larger IRS element number and more transmit power are beneficial to the security.

D. ORGANIZATION AND NOTATIONS

The rest of this paper is organized as follows. The system model and problem statement are given in Section II. Section III investigates the IBCD algorithm with penalty MM and CCM methods. Simulation results are provided in Section IV. Section V concludes this paper.

The main notations are as follows. Throughout this paper, boldface lowercase and uppercase letters denote vectors and matrices, respectively. The conjugate, transpose, conjugate transpose, and trace of matrix $\mathbf{A}$ are denoted as $\mathbf{A}^{\dagger}$, $\mathbf{A}^{T}$, $\mathbf{A}^{H}$, and $\mathrm{Tr}\left(\mathbf{A}\right)$, respectively. $\mathbf{a} = \mathrm{vec}\left(\mathbf{A}\right)$ stacks the columns of matrix $\mathbf{A}$ into a vector $\mathbf{a}$. $\mathbb{H}_{+}^{N}$ denotes the set of all $N \times N$ Hermitian positive semi-definite matrices. $\mathbf{A} \succeq \mathbf{0}$ indicates that $\mathbf{A}$ is a positive semi-definite matrix. $\odot$ denotes the element-wise product. $\arg\{\}$ means the extraction of phase information. $\mathrm{diag}\left(\mathbf{a}\right)$ represents a diagonal matrix with a on the main diagonal. $\mathbf{I}$ is an identity matrix with proper dimension. $\Re\left\{a\right\}$ denotes the real part of a complex variable a. $\mathcal{CN}\left(\mathbf{0}, \mathbf{I}\right)$ denotes a circularly symmetric complex Gaussian random vector with mean $\mathbf{0}$ and covariance $\mathbf{I}$.

II. SYSTEM MODEL AND PROBLEM STATEMENT

A. SYSTEM MODEL

Let us consider a MIMO wiretap system as shown in Fig. 1, which consists of one transmitter (T), one IRS, one information receiver (IR), and one energy receiver (ER), which may be potential eavesdropper (Eve). It is assumed that the T, the IR, and the ER are equipped with N_t, N_i, and N_e antennas, respectively, while the IRS is equipped with $M \geq 1$ reflecting units. We denote $\mathbf{F} \in \mathbb{C}^{M \times N_t}$, $\mathbf{H}_s \in \mathbb{C}^{N_i \times N_t}$, $\mathbf{H}_r \in \mathbb{C}^{N_i \times M}$, $\mathbf{G}_s \in \mathbb{C}^{N_e \times N_t}$, and $\mathbf{G}_r \in \mathbb{C}^{N_e \times M}$ as the channel coefficients from the T to the IRS, the T to the IR, the IRS to the IR, the T to the ER, and the IRS to the ER, respectively. In addition, we denote $\Theta = diag\left(e^{j\phi_1}, \ldots, e^{j\phi_M}\right)$ as the diagonal matrix associated with the effective phase shifts in all IRS elements,

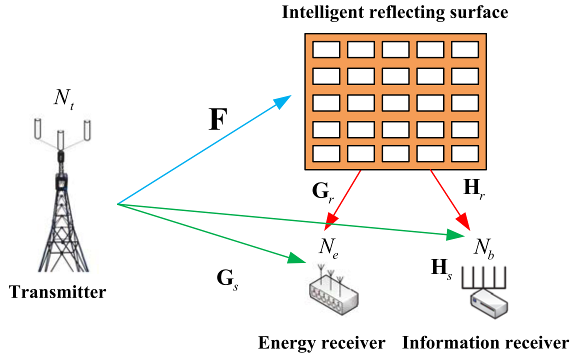

FIGURE 1. An IRS-assisted secure MIMO SWIPT system.

where $\phi_m \in [0, 2\pi], \forall m \in [1, M]$ is the phase shift factor for the m-th IRS element.

At the T, the desired signal vector $\mathbf{s} \in \mathbb{C}^{d\times 1}$ $(d \le N_t)$ is precoded by the precoding matrix $\mathbf{W} \in \mathbb{C}^{N_t\times d}$, and AN is emit to protect the confidential information. Thus, the transmit signal vector $\mathbf{x} \in \mathbb{C}^{N_t\times 1}$ can be expressed as

$$\mathbf{x} = \mathbf{W}\mathbf{s} + \mathbf{z}, \tag{1}$$

where $\mathbf{z} \in \mathbb{C}^{N_t\times 1}$ is the AN vector with $\mathbf{z} \sim \mathcal{CN}(\mathbf{0}, \Sigma)$. In fact, the AN is an energy signal which can enhance the EH for the ER. Without loss of generality (W.l.o.g.), we assume that $\mathbb{E}\left[\mathbf{s}\mathbf{s}^H\right] = \mathbf{I}$.

The IRS phase shifters received all multi-path signals and then reflected this signals by the IRS array. Thus, the received signal at the IR and the ER can be equivalently written, respectively, as

$$y_i = \left(\mathbf{H}_s^H + \mathbf{H}_r^H \Theta \mathbf{F}\right)(\mathbf{W}\mathbf{s} + \mathbf{z}) + \mathbf{n}_i, \tag{2a}$$

$$y_e = \left(\mathbf{G}_s^H + \mathbf{G}_r^H \Theta \mathbf{F}\right)(\mathbf{W}\mathbf{s} + \mathbf{z}) + \mathbf{n}_e, \tag{2b}$$

where $\mathbf{n}_i \in \mathbb{C}^{N_i\times 1}$ and $\mathbf{n}_e \in \mathbb{C}^{N_e\times 1}$ are the noise vectors at the IR and the ER, with $\mathcal{CN}\left(\mathbf{0}, \sigma_i^2\mathbf{I}\right)$ and $\mathcal{CN}\left(\mathbf{0}, \sigma_e^2\mathbf{I}\right)$, respectively. In addition, σ_i^2 and σ_e^2 denote the noise power at the IR and ER, respectively.

Accordingly, the secrecy rate can be expressed as

$$R_s = C_i(\mathbf{W}, \Sigma) - C_e(\mathbf{W}, \Sigma), \tag{3}$$

where C_i and C_e denote the mutual information at the IR and the ER, respectively, and are given by

$$C_i(\mathbf{W}, \Sigma) \triangleq \ln\left|\mathbf{I} + \mathbf{H}\mathbf{W}\mathbf{W}^H\mathbf{H}^H\left(\mathbf{I} + \mathbf{H}\Sigma\mathbf{H}^H\right)^{-1}\right|, \tag{4a}$$

$$C_e(\mathbf{W}, \Sigma) \triangleq \ln\left|\mathbf{I} + \mathbf{G}\mathbf{W}\mathbf{W}^H\mathbf{G}^H\left(\mathbf{I} + \mathbf{G}\Sigma\mathbf{G}^H\right)^{-1}\right|, \tag{4b}$$

where $\mathbf{H} = \left(\mathbf{H}_s^H + \mathbf{H}_r^H\Theta\mathbf{F}\right)/\sigma_i$, $\mathbf{G} = \left(\mathbf{G}_s^H + \mathbf{G}_r^H\Theta\mathbf{F}\right)/\sigma_e$, respectively.

In addition, the harvested energy at the ER is given as

$$E_{EH} = \mathrm{Tr}\left(\mathbf{G}\left(\mathbf{W}\mathbf{W}^H + \Sigma\right)\mathbf{G}^H\right). \tag{5}$$

B. PROBLEM STATEMENT

In this paper, we aim to maximize the secrecy rate, by jointly designing the precoding matrix, the AN covariance and the phase shifter matrix, subject to the transmit power constraint and the unit modulus constraint. Mathematically, the optimization problem is formulated as follows:

$$\max_{\mathbf{W}, \Sigma\succeq\mathbf{0}, \Theta} \; C_i(\mathbf{W}, \Sigma) - C_e(\mathbf{W}, \Sigma) \tag{6a}$$

$$\text{s.t. } \mathrm{Tr}\left(\mathbf{W}\mathbf{W}^H + \Sigma\right) \le P_s, \tag{6b}$$

$$\mathrm{Tr}\left(\mathbf{G}\left(\mathbf{W}\mathbf{W}^H + \Sigma\right)\mathbf{G}^H\right) \ge E_{th}, \tag{6c}$$

$$\left|e^{j\phi_m}\right| = 1, \quad \forall m = 1, \ldots, M, \tag{6d}$$

where P_s is the maximum achievable power for the transmitter and E_{th} denotes the harvested energy threshold for the ER, respectively.

The main difficulties in solving (6) are two folds: Firstly, the OF is non-convex, while the variables $\mathbf{W}$, Σ and Θ are coupled. Secondly, the unit modulus constraint imposed on the phase shift matrix in (6c) aggravates the difficulty. In view of this, we divide (6) into several subproblems to overcome these difficulties.

III. THE IBCD AND PENALTY BASED METHOD

Firstly, we reformulate the objective (6a) into a more handleable expression equivalently. Then, an IBCD method is proposed for optimizing the matrix $\mathbf{W}$, Σ, and Θ in an alternating way.

A. THE OPTIMIZATION OF THE PRECODING AND AN COVARIANCE

Firstly, we aim to obtain the optimal $\{\mathbf{W}, \Sigma\}$ with given Θ.

1) REFORMULATION OF THE OBJECTIVE (6a)

In this subsection, we reformulate (6a) into a linear reformulation. Firstly, we introduce the following Lemma.

Lemma 1 [23]: Define an m by m matrix function,

$$\Xi(\mathbf{U}, \mathbf{V}) \triangleq \mathbf{U}^H\mathbf{N}\mathbf{U} + \left(\mathbf{I} - \mathbf{U}^H\mathbf{M}\mathbf{V}\right)\left(\mathbf{I} - \mathbf{U}^H\mathbf{M}\mathbf{V}\right)^H,$$

where $\mathbf{N}$ is any positive definite matrix. Then, the following three equations hold.

Equation 1: For any positive definite matrix $\mathbf{S} \in \mathbb{C}^{m\times m}$, we have

$$\mathbf{S}^{-1} = \arg\max_{\mathbf{T}\succ\mathbf{0}} \ln|\mathbf{T}| - \mathrm{Tr}(\mathbf{T}\mathbf{S}),$$

and

$$-\ln|\mathbf{S}| = \arg\max_{\mathbf{T}\succ\mathbf{0}} \ln|\mathbf{T}| - \mathrm{Tr}(\mathbf{T}\mathbf{S}) + m.$$

Equation 2: For any positive definite matrix $\mathbf{T}$, we have

$$\tilde{\mathbf{U}} \triangleq \arg\min_{\mathbf{U}} \mathrm{Tr}(\mathbf{T}\Xi(\mathbf{U}, \mathbf{V})) = \left(\mathbf{N} + \mathbf{M}\mathbf{V}\mathbf{V}^H\mathbf{M}^H\right)^{-1}\mathbf{M}\mathbf{V},$$

and

$$\Xi\left(\tilde{\mathbf{U}}, \mathbf{V}\right) = \mathbf{I} - \tilde{\mathbf{U}}^H\mathbf{M}\mathbf{V} = \left(\mathbf{I} + \mathbf{V}^H\mathbf{M}^H\mathbf{N}^{-1}\mathbf{M}\mathbf{V}\right)^{-1}.$$

Equation 3: We have

$$\ln\left|\mathbf{I} + \mathbf{M}\mathbf{V}\mathbf{V}^H\mathbf{M}^H\mathbf{N}^{-1}\right| = \arg\max_{\mathbf{T}\succ\mathbf{0}, \mathbf{U}} \ln|\mathbf{T}| - \mathrm{Tr}(\mathbf{T}\Xi) + m.$$

Equations 1 and 2 can be proven by the first order optimality condition, while Equation 3 directly follows from Equations 1 and 2 and the identity $\ln|\mathbf{I}+\mathbf{AB}| = \ln|\mathbf{I}+\mathbf{BA}|$.

In the following, we will decouple (6) based on these equations.

To utilize the above equations, we denote $\Sigma = \mathbf{QQ}^H$ and rewritten R_s as

$$R_s = \underbrace{\ln\left|\mathbf{I}+\mathbf{HWW}^H\mathbf{H}^H\left(\mathbf{I}+\mathbf{HQQ}^H\mathbf{H}^H\right)^{-1}\right|}_{f_1} + \underbrace{\ln\left|\mathbf{I}+\mathbf{GQQ}^H\mathbf{G}^H\right|}_{f_2} - \underbrace{\ln\left|\mathbf{I}+\mathbf{GWW}^H\mathbf{G}^H+\mathbf{GQQ}^H\mathbf{G}^H\right|}_{f_3}, \quad (7)$$

where

$$f_1 = \max_{\Psi_1\succ\mathbf{0},\mathbf{U}} \ln|\Psi_1| - \mathrm{Tr}\left(\Psi_1\Xi_1\left(\mathbf{U},\mathbf{W},\mathbf{Q}\right)\right)+N_b, \quad (8a)$$

$$f_2 = \max_{\Psi_2\succ\mathbf{0},\mathbf{V}} \ln|\Psi_2| - \mathrm{Tr}\left(\Psi_2\Xi_2\left(\mathbf{V},\mathbf{Q}\right)\right)+N_t, \quad (8b)$$

$$f_3 = \max_{\Psi_3\succ\mathbf{0}} \ln|\Psi_3| + N_e - \mathrm{Tr}\left(\Psi_3\left(\mathbf{I}+\mathbf{GWW}^H\mathbf{G}^H+\mathbf{GQQ}^H\mathbf{G}^H\right)\right). \quad (8c)$$

Furthermore, the matrix functions Ξ_1 and Ξ_2 are defined as follows

$$\Xi_1\left(\mathbf{U},\mathbf{W},\mathbf{Q}\right) \triangleq \mathbf{U}^H\left(\mathbf{I}+\mathbf{HQQ}^H\mathbf{H}^H\right)\mathbf{U} + \left(\mathbf{I}-\mathbf{U}^H\mathbf{HW}\right)\left(\mathbf{I}-\mathbf{U}^H\mathbf{HW}\right)^H, \quad (9a)$$

$$\Xi_2\left(\mathbf{V},\mathbf{Q}\right) \triangleq \mathbf{V}^H\mathbf{V} + \left(\mathbf{I}-\mathbf{V}^H\mathbf{GQ}\right)\left(\mathbf{I}-\mathbf{V}^H\mathbf{GQ}\right)^H. \quad (9b)$$

Combine these relationship, we get the following problem

$$\begin{aligned}\max_{\Omega} &\ln|\Psi_1| - \mathrm{Tr}\left(\Psi_1\mathbf{U}^H\left(\mathbf{I}+\mathbf{HQQ}^H\mathbf{H}^H\right)\mathbf{U}\right) + \mathrm{Tr}\left(\Psi_1\left(\mathbf{I}-\mathbf{U}^H\mathbf{HW}\right)\left(\mathbf{I}-\mathbf{U}^H\mathbf{HW}\right)^H\right)\\ &+\ln|\Psi_2| - \mathrm{Tr}\left(\Psi_2\mathbf{V}^H\mathbf{V}\right) - \mathrm{Tr}\left(\Psi_2\left(\mathbf{I}-\mathbf{V}^H\mathbf{GQ}\right)\left(\mathbf{I}-\mathbf{V}^H\mathbf{GQ}\right)^H\right)+\ln|\Psi_3|\\ &-\mathrm{Tr}\left(\Psi_3\left(\mathbf{I}+\mathbf{H}\left(\mathbf{QQ}^H+\mathbf{WW}^H\right)\mathbf{H}^H\right)\right) \quad (10a)\\ \text{s.t. } &(6b)-(6d), \quad (10b)\end{aligned}$$

where $\Omega = \{\mathbf{W},\mathbf{Q},\Theta,\mathbf{U},\mathbf{V},\Psi_1\succeq\mathbf{0},\Psi_2\succeq\mathbf{0},\Psi_3\succeq\mathbf{0}\}$ denotes the set of the optimization variables.

(10) is still hard to solve due to the non-convex objective and constraints. However, when several variables are fixed, (10) can be turned into convex problem with respect to (w.r.t) the other variables. Specifically, (10) can be divided into the following three subproblems.

2) SUBPROBLEM 1

The first subproblem is optimizing $\{\mathbf{U},\mathbf{V},\Psi_1,\Psi_2,\Psi_3\}$ with given $\{\mathbf{W},\mathbf{Q},\Theta\}$.

In fact, with Lemma 1, the optimal $\{\mathbf{U},\mathbf{V},\Psi_1,\Psi_2,\Psi_3\}$ can be obtained in closed forms, which are, respectively, given as

$$\mathbf{U} = \left(\mathbf{I}+\mathbf{HQQ}^H\mathbf{H}^H+\mathbf{HWW}^H\mathbf{H}^H\right)^{-1}\mathbf{HW}, \quad (11a)$$

$$\mathbf{V} = \left(\mathbf{I}+\mathbf{GQQ}^H\mathbf{G}^H\right)^{-1}\mathbf{GW}, \quad (11b)$$

$$\Psi_1 = \Xi_1(\mathbf{U},\mathbf{W},\mathbf{Q})^{-1} = \mathbf{I}+\mathbf{W}^H\mathbf{H}^H\left(\mathbf{HQQ}^H\mathbf{H}^H\right)^{-1}\mathbf{HW}, \quad (11c)$$

$$\Psi_2 = \Xi_2(\mathbf{V},\mathbf{Q})^{-1} = \mathbf{I}+\mathbf{V}^H\mathbf{G}^H\mathbf{GV}, \quad (11d)$$

$$\Psi_3 = \left(\mathbf{I}+\mathbf{GQQ}^H\mathbf{G}^H+\mathbf{GWW}^H\mathbf{G}^H\right)^{-1}. \quad (11e)$$

The detailed procedures can be found in [23], we omit for brevity.

3) SUBPROBLEM 2

The second subproblem is optimizing $\mathbf{W}$ and $\mathbf{Q}$ with given $\{\Theta,\mathbf{U},\mathbf{V},\Psi_1,\Psi_2,\Psi_3\}$.

Specifically, the subproblem w.r.t to $\mathbf{W}$ and $\mathbf{Q}$ is given as follows

$$\begin{aligned}\min_{\mathbf{W},\mathbf{Q}} &\mathrm{Tr}\left(\Psi_1\mathbf{U}^H\mathbf{HWW}^H\mathbf{H}^H\mathbf{U}\right) + \mathrm{Tr}\left(\Psi_1\mathbf{U}^H\mathbf{HQQ}^H\mathbf{H}^H\mathbf{U}\right)\\ &-\mathrm{Tr}\left(\Psi_1\mathbf{U}^H\mathbf{HW}\right)-\mathrm{Tr}\left(\Psi_1\mathbf{W}^H\mathbf{H}^H\mathbf{U}\right)\\ &+\mathrm{Tr}\left(\Psi_2\mathbf{V}^H\mathbf{GQQ}^H\mathbf{G}^H\mathbf{V}\right)-\mathrm{Tr}\left(\Psi_2\mathbf{V}^H\mathbf{GQ}\right)\\ &-\mathrm{Tr}\left(\Psi_2\mathbf{Q}^H\mathbf{G}^H\mathbf{V}\right)+\mathrm{Tr}\left(\Psi_3\mathbf{GWW}^H\mathbf{G}^H\right)\\ &+\mathrm{Tr}\left(\Psi_3\mathbf{GQQ}^H\mathbf{G}^H\right) \quad (12a)\\ \text{s.t. } &(6b), (6c). \quad (12b)\end{aligned}$$

The main difficult in (12) is the non-convex constraint (6c). Via the first order expansion, (6c) can be approximated as

$$2\Re\left\{\mathbf{G}\left(\mathbf{W}\tilde{\mathbf{W}}^H+\mathbf{Q}\tilde{\mathbf{Q}}^H\right)\mathbf{G}^H\right\} \geq E_{th}+\mathrm{Tr}\left(\mathbf{G}\left(\tilde{\mathbf{W}}\tilde{\mathbf{W}}^H+\tilde{\mathbf{Q}}\tilde{\mathbf{Q}}^H\right)\mathbf{G}^H\right). \quad (13)$$

Thus, around given point $\left\{\tilde{\mathbf{W}},\tilde{\mathbf{Q}}\right\}$, we have the following problem

$$\begin{aligned}\min_{\mathbf{W},\mathbf{Q}} &\mathrm{Tr}\left(\Psi_1\mathbf{U}^H\mathbf{HWW}^H\mathbf{H}^H\mathbf{U}\right)\\ &+\mathrm{Tr}\left(\Psi_1\mathbf{U}^H\mathbf{HQQ}^H\mathbf{H}^H\mathbf{U}\right)-\mathrm{Tr}\left(\Psi_1\mathbf{U}^H\mathbf{HW}\right)\\ &-\mathrm{Tr}\left(\Psi_1\mathbf{W}^H\mathbf{H}^H\mathbf{U}\right)+\mathrm{Tr}\left(\Psi_2\mathbf{V}^H\mathbf{GQQ}^H\mathbf{G}^H\mathbf{V}\right)\\ &-\mathrm{Tr}\left(\Psi_2\mathbf{V}^H\mathbf{GQ}\right)-\mathrm{Tr}\left(\Psi_2\mathbf{Q}^H\mathbf{G}^H\mathbf{V}\right)\\ &+\mathrm{Tr}\left(\Psi_3\mathbf{GWW}^H\mathbf{G}^H\right)+\mathrm{Tr}\left(\Psi_3\mathbf{GQQ}^H\mathbf{G}^H\right) \quad (14a)\\ \text{s.t. } &(6b), (13). \quad (14b)\end{aligned}$$

(14) is convex and the optimal $\{\mathbf{W},\mathbf{Q}\}$ can be effectively obtained by the convex optimization tool CVX [24].

To this end, we have solved the problem w.r.t $\{\mathbf{W}, \mathbf{Q}\}$, nextly we will solve the problem w.r.t Θ.

B. OPTIMIZATION OF THE REFLECT COEFFICIENT (RC)

The third subproblem is optimizing Θ with given $\{\mathbf{W}, \mathbf{Q}, \mathbf{U}, \mathbf{V}, \Psi_1 \succeq \mathbf{0}, \Psi_2 \succeq \mathbf{0}, \Psi_3 \succeq \mathbf{0}\}$.

Specifically, the subproblem w.r.t to Θ is given as follows

$$\begin{aligned}\min_{\Theta}\ & \mathrm{Tr}\left(\Psi_1\mathbf{U}^H\mathbf{HWW}^H\mathbf{H}^H\mathbf{U}\right)\\ &+\mathrm{Tr}\left(\Psi_1\mathbf{U}^H\mathbf{HQQ}^H\mathbf{H}^H\mathbf{U}\right)\\ &-\mathrm{Tr}\left(\Psi_1\mathbf{U}^H\mathbf{HW}\right)-\mathrm{Tr}\left(\Psi_1\mathbf{W}^H\mathbf{H}^H\mathbf{U}\right)\\ &+\mathrm{Tr}\left(\Psi_2\mathbf{V}^H\mathbf{GQQ}^H\mathbf{G}^H\mathbf{V}\right)-\mathrm{Tr}\left(\Psi_2\mathbf{V}^H\mathbf{GQ}\right)\\ &-\mathrm{Tr}\left(\Psi_2\mathbf{Q}^H\mathbf{G}^H\mathbf{V}\right)+\mathrm{Tr}\left(\Psi_3\mathbf{GWW}^H\mathbf{G}\right)\\ &+\mathrm{Tr}\left(\Psi_3\mathbf{GQQ}^H\mathbf{G}\right) \qquad (15a)\\ \text{s.t. }& (6\text{d}). \qquad (15b)\end{aligned}$$

In fact, (15) is the most difficult one among these subproblems. In the following, we will solve (15) using the penalty method [25].

Firstly, we do some reformulation to make (15) more convenient to handle. Denoting $\boldsymbol{W} = \mathbf{WW}^H$, we have

$$\begin{aligned}&\mathrm{Tr}\left(\Psi_1\mathbf{U}^H\mathbf{HWW}^H\mathbf{H}^H\mathbf{U}\right)\\ &\quad+\mathrm{Tr}\left(\Psi_1\mathbf{U}^H\mathbf{HQQ}^H\mathbf{H}^H\mathbf{U}\right)\\ &=\mathrm{Tr}\left(\Theta^H\mathbf{A}_1\Theta\mathbf{F}\left(\boldsymbol{W}+\Sigma\right)\mathbf{F}^H\right)\\ &\quad+2\Re\left\{\mathrm{Tr}\left(\Theta\mathbf{B}_1\right)\right\}+2\Re\left\{\mathrm{Tr}\left(\Theta\mathbf{C}_1\right)\right\}\\ &\quad+\sigma_i^{-2}\mathrm{Tr}\left(\Psi_1\mathbf{U}^H\mathbf{H}_s^H\boldsymbol{W}\mathbf{H}_s\mathbf{U}\right)\\ &\quad+\sigma_i^{-2}\mathrm{Tr}\left(\Psi_1\mathbf{U}^H\mathbf{H}_s^H\Sigma\mathbf{H}_s\mathbf{U}\right), \qquad (16)\end{aligned}$$

where $\mathbf{A}_1 = \sigma_i^{-2}\mathbf{H}_s\mathbf{U}\Psi_1\mathbf{U}^H\mathbf{H}_s^H$, and $\mathbf{B}_1 = \sigma_i^{-2}\mathbf{F}\left(\boldsymbol{W}+\Sigma\right)\mathbf{H}_s\mathbf{U}\Psi_1\mathbf{U}^H\mathbf{H}_r^H$.

Similarly, we have

$$\begin{aligned}&\mathrm{Tr}\left(\Psi_1\mathbf{U}^H\mathbf{HW}\right)+\mathrm{Tr}\left(\Psi_1\mathbf{W}^H\mathbf{H}^H\mathbf{U}\right)\\ &=2\Re\left\{\mathrm{Tr}\left(\Theta\mathbf{A}_2\right)\right\}\\ &\quad+\sigma_i^{-1}\Re\left\{\mathrm{Tr}\left(\Psi_1\mathbf{U}^H\mathbf{H}_s^H\mathbf{W}\right)\right\}, \qquad (17a)\\ &\mathrm{Tr}\left(\Psi_2\mathbf{V}^H\mathbf{GQQ}^H\mathbf{G}^H\mathbf{V}\right)\\ &=\mathrm{Tr}\left(\Theta^H\mathbf{A}_3\Theta\mathbf{F}\Sigma\mathbf{F}^H\right)+2\Re\left\{\mathrm{Tr}\left(\Theta^H\mathbf{B}_2\right)\right\}\\ &\quad+\sigma_e^{-2}\mathrm{Tr}\left(\Psi_2\mathbf{V}^H\mathbf{G}_s^H\Sigma\mathbf{G}_s\mathbf{V}\right), \qquad (17b)\\ &\mathrm{Tr}\left(\Psi_2\mathbf{V}^H\mathbf{GQ}\right)+\mathrm{Tr}\left(\Psi_2\mathbf{Q}^H\mathbf{G}^H\mathbf{V}\right)\\ &=2\Re\left\{\mathrm{Tr}\left(\Theta\mathbf{A}_4\right)\right\}+\sigma_e^{-1}\Re\left\{\mathrm{Tr}\left(\Psi_2\mathbf{V}^H\mathbf{G}_s^H\mathbf{Q}\right)\right\}, \qquad (17c)\\ &\mathrm{Tr}\left(\Psi_3\mathbf{GWW}^H\mathbf{G}\right)+\mathrm{Tr}\left(\Psi_3\mathbf{GQQ}^H\mathbf{G}\right)\\ &=\mathrm{Tr}\left(\Theta\mathbf{A}_5\Theta\mathbf{F}\left(\boldsymbol{W}+\Sigma\right)\mathbf{F}^H\right)\\ &\quad+2\Re\left\{\mathrm{Tr}\left(\Theta^H\mathbf{B}_3\right)\right\}\\ &\quad+\sigma_e^{-2}\mathrm{Tr}\left(\Psi_3\mathbf{G}_s^H\left(\boldsymbol{W}+\Sigma\right)\mathbf{G}_s\right), \qquad (17d)\end{aligned}$$

where $\mathbf{A}_2 = \sigma_i^{-1}\mathbf{FW}\Psi_1\mathbf{U}^H\mathbf{G}_s^H$, $\mathbf{A}_3 = \sigma_e^{-2}\mathbf{G}_r\mathbf{V}\Psi_2\mathbf{V}^H\mathbf{G}_r^H$, $\mathbf{B}_2 = \sigma_e^{-2}\mathbf{G}_r\mathbf{V}\Psi_2\mathbf{V}^H\mathbf{G}_s^H\Sigma\mathbf{F}^H$, $\mathbf{A}_4 = \sigma_e^{-1}\mathbf{FQ}\Psi_2\mathbf{Q}^H\mathbf{G}_r^H$, $\mathbf{A}_5 = \sigma_e^{-2}\mathbf{G}_r\Psi_3\mathbf{G}_r^H$, and $\mathbf{B}_3 = \sigma_e^{-2}\mathbf{G}_r\Psi_3\mathbf{G}_s^H\left(\boldsymbol{W}+\Sigma\right)\mathbf{F}^H$, respectively.

Based on the above relationships, (15) can be changed into the following problem

$$\begin{aligned}\min_{\Theta}\ & \mathrm{Tr}\left(\Theta^H\left(\mathbf{A}_1+\mathbf{A}_5\right)\Theta\mathbf{F}\left(\boldsymbol{W}+\Sigma\right)\mathbf{F}^H\right)\\ &+\mathrm{Tr}\left(\Theta^H\mathbf{A}_3\Theta\mathbf{F}\Sigma\mathbf{F}^H\right)+2\Re\left\{\mathrm{Tr}\left(\Theta\mathbf{Y}\right)\right\} \qquad (18a)\\ \text{s.t. }& (6d), \qquad (18b)\end{aligned}$$

where $\mathbf{Y} = \mathbf{B}_1 - \mathbf{A}_2 + \mathbf{B}_2 + \mathbf{B}_3 - \mathbf{A}_4$.

Nextly, we focus on the EH constraint. Recall that the constraint is

$$\mathrm{Tr}\left(\mathbf{G}\left(\boldsymbol{W}+\Sigma\right)\mathbf{G}^H\right) \geq E_{th}, \qquad (19)$$

by substituting $\mathbf{G} = \left(\mathbf{G}_s^H + \mathbf{G}_r^H\Theta\mathbf{F}\right)/\sigma_e$ into (19), we have

$$\begin{aligned}&\mathrm{Tr}\left(\mathbf{G}_s^H\left(\boldsymbol{W}+\Sigma\right)\mathbf{G}_s\right)\\ &+\mathrm{Tr}\left(\mathbf{G}_s^H\left(\boldsymbol{W}+\Sigma\right)\mathbf{F}^H\Theta^H\mathbf{G}_r\right)\\ &+\mathrm{Tr}\left(\mathbf{G}_r^H\Theta\mathbf{F}\left(\boldsymbol{W}+\Sigma\right)\mathbf{G}_s\right)\\ &+\mathrm{Tr}\left(\mathbf{G}_r^H\Theta\mathbf{F}\left(\boldsymbol{W}+\Sigma\right)\mathbf{F}^H\Theta^H\mathbf{G}_r\right) \geq \sigma_e^2E_{th}. \qquad (20)\end{aligned}$$

Then, the EH constraint can be rewritten as

$$\begin{aligned}&2\Re\left\{\mathrm{Tr}\left(\Theta\mathbf{F}\left(\boldsymbol{W}+\Sigma\right)\mathbf{G}_s\mathbf{G}_r^H\right)\right\}\\ &\quad+\mathrm{Tr}\left(\mathbf{G}_r^H\Theta\mathbf{F}\left(\boldsymbol{W}+\Sigma\right)\mathbf{F}^H\Theta^H\mathbf{G}_r\right)\\ &\geq \sigma_e^2E_{th}-\mathrm{Tr}\left(\mathbf{G}_s^H\left(\boldsymbol{W}+\Sigma\right)\mathbf{G}_s\right). \qquad (21)\end{aligned}$$

In order to solve (18) with the penalty method, we turn (18) into an equivalent problem w.r.t the auxiliary variable $\boldsymbol{\theta} = [\theta_1, \ldots, \theta_M]^T$, where $\theta_m = e^{j\phi_m}$. Moreover, we introduce the following lemma.

Lemma 2 [26]: Let $\mathbf{C}_1 \in \mathbb{C}^{m\times m}$ and $\mathbf{C}_2 \in \mathbb{C}^{m\times m}$ be matrices, $\mathbf{1} = [1, \ldots, 1]^T$ is a $m \times 1$ vector. Assuming that $\mathbf{E} \in \mathbb{C}^{m\times m}$ is a diagonal matrix $\mathbf{E} = \mathrm{diag}\left(e_1, \ldots, e_2\right)$, and $\mathbf{e} = \mathbf{E1}$, then we have:

$$\begin{aligned}\mathrm{Tr}\left(\mathbf{E}^H\mathbf{C}_1\mathbf{EC}_2\right) &= \mathbf{e}^H\left(\mathbf{C}_1\odot\mathbf{C}_2^T\right)\mathbf{e}, \qquad (22a)\\ \mathrm{Tr}\left(\mathbf{EC}_2\right) &= \mathbf{1}^T\left(\mathbf{E}\odot\mathbf{C}_2^T\right)\mathbf{1} = \mathbf{e}^T\mathbf{c}_2, \qquad (22b)\\ \mathrm{Tr}\left(\mathbf{E}^H\mathbf{C}_2^H\right) &= \mathbf{c}_2^H\mathbf{e}^\dagger, \qquad (22c)\end{aligned}$$

where $\mathbf{c}_2 = \left[(\mathbf{C}_2)_{(1,1)}, \ldots, (\mathbf{C}_2)_{(m,m)}\right]^T$.

With Lemma 2, we have the following relationship

$$\mathrm{Tr}\left(\Theta^H\mathbf{G}_r\mathbf{G}_r^H\Theta\mathbf{F}\left(\boldsymbol{W}+\Sigma\right)\mathbf{F}^H\right) = \boldsymbol{\theta}^H\mathbf{T}\boldsymbol{\theta}, \qquad (23)$$

where $\mathbf{T} = \left(\mathbf{G}_r\mathbf{G}_r^H\right)\odot\left(\mathbf{F}\left(\boldsymbol{W}+\Sigma\right)\mathbf{F}^H\right)^T$.

Similarly, we have

$$\begin{aligned}&2\Re\left\{\mathrm{Tr}\left(\Theta\mathbf{F}\left(\boldsymbol{W}+\Sigma\right)\mathbf{G}_s\mathbf{G}_r^H\right)\right\}\\ &\qquad=2\Re\left\{\boldsymbol{\theta}^T\mathbf{z}\right\}=2\Re\left\{\boldsymbol{\theta}^H\mathbf{z}^\dagger\right\}, \qquad (24)\end{aligned}$$

where $\mathbf{Z} = \mathbf{F}\left(\boldsymbol{W} + \Sigma\right)\mathbf{G}_s\mathbf{G}_r^H$, and $\mathbf{z} = \left[\mathbf{Z}_{(1,1)}, \ldots, \mathbf{Z}_{(M,M)}\right]^T$.

Thus, (21) is equivalently to

$$\boldsymbol{\theta}^H\mathbf{T}\boldsymbol{\theta}+2\Re\left\{\boldsymbol{\theta}^H\mathbf{z}^\dagger\right\}\geq\sigma_e^2E_{th}-\mathrm{Tr}\left(\mathbf{G}_s^H\left(\boldsymbol{W}+\Sigma\right)\mathbf{G}_s\right). \quad (25)$$

Then, (18) can be turned into the following problem

$$\min_{\boldsymbol{\theta}} \ f\left(\boldsymbol{\theta}\right) = \boldsymbol{\theta}^H\mathbf{X}\boldsymbol{\theta} + 2\Re\left\{\boldsymbol{\theta}^H\mathbf{y}^\dagger\right\} \quad (26a)$$

$$\text{s.t. } |\theta_m| = 1, m = 1, \ldots, M, (25), \quad (26b)$$

where $\mathbf{X} = \left(\mathbf{A}_1 + \mathbf{A}_5\right)\odot\left(\mathbf{F}\left(\boldsymbol{W} + \Sigma\right)\mathbf{F}^H\right)^T + \left(\mathbf{A}_3 \odot \mathbf{F}\Sigma\mathbf{F}^H\right)^T$, and $\mathbf{y} = \left[\mathbf{Y}_{(1,1)}, \ldots, \mathbf{Y}_{(M,M)}\right]^T$.

The penalty optimization is based on reformulating the EH constraint as an equivalent non-convex constraint and iteratively solving the optimization problem by moving the equivalent constraint into the OF as a penalty function.

Specifically, the EH constraint (25) is first replaced by

$$\boldsymbol{\theta}^H\mathbf{T}\boldsymbol{\theta}+2\Re\left\{\boldsymbol{\theta}^H\mathbf{z}^\dagger\right\}+\mathrm{Tr}\left(\mathbf{G}_s^H\left(\boldsymbol{W}+\Sigma\right)\mathbf{G}_s\right) - \sigma_e^2E_{th}\geq 0. \quad (27)$$

This new constraint can be moved to the OF as a penalty term by including the violation of the constraint, where $\zeta > 0$ is the weight of the violation. Then, we have the following problem

$$\min_{\boldsymbol{\theta}} \ f\left(\boldsymbol{\theta}\right) = \boldsymbol{\theta}^H\mathbf{X}\boldsymbol{\theta} + 2\Re\left\{\boldsymbol{\theta}^H\mathbf{y}^\dagger\right\} - \zeta\left(\boldsymbol{\theta}^H\mathbf{T}\boldsymbol{\theta} + 2\Re\left\{\boldsymbol{\theta}^H\mathbf{z}^\dagger\right\} - c\right) \quad (28a)$$

$$\text{s.t. } |\theta_m| = 1, \quad m = 1, \ldots, M, \quad (28b)$$

where $c = \sigma_e^2E_{th} - \mathrm{Tr}\left(\mathbf{G}_s^H\left(\boldsymbol{W} + \Sigma\right)\mathbf{G}_s\right)$.

For the convenient of the following derivation, we denote $\bar{\mathbf{X}} = \mathbf{X} - \zeta\mathbf{T}$ and $\bar{\mathbf{y}} = \mathbf{y} - \zeta\mathbf{z}$. In addition, to ensure (28a) is a convex quadratic form, ζ should be choose to satisfy $\bar{\mathbf{X}} \succeq \mathbf{0}$.

Nextly, we will discuss the penalty MM and CCM methods in detail.

1) THE PENALTY MM METHOD

Firstly, we adopt the MM algorithm in [27] to solve (28), where the main idea is to solve a difficult problem by constructing a series of more tractable approximated problems. Specifically, we denote the solution of the approximated problem at the t-th iteration by $\bar{\boldsymbol{\theta}}$, and the objective value of (28) at the t-th iteration by $f\left(\bar{\boldsymbol{\theta}}\right)$. Then, at the $(t+1)$-th iteration, we introduce an upper bound of the OF based on the previous solution, which is denoted as $g\left(\boldsymbol{\theta}\left|\bar{\boldsymbol{\theta}}\right.\right)$.

Here, we first introduce the following lemma which proposed in [28].

Lemma 3: For any given solution $\bar{\boldsymbol{\theta}}$ at the t-th iteration and for any feasible $\boldsymbol{\theta}$, we have

$$\begin{aligned}\boldsymbol{\theta}^H\bar{\mathbf{X}}\boldsymbol{\theta} &\leq \boldsymbol{\theta}^H\lambda_{\max}\left(\bar{\mathbf{X}}\right)\mathbf{I}\boldsymbol{\theta} \\ &\quad - 2\Re\left\{\boldsymbol{\theta}^H\left(\lambda_{\max}\left(\bar{\mathbf{X}}\right)\mathbf{I} - \bar{\mathbf{X}}\right)\bar{\boldsymbol{\theta}}\right\} \\ &\quad + \bar{\boldsymbol{\theta}}^H\left(\lambda_{\max}\left(\bar{\mathbf{X}}\right)\mathbf{I} - \bar{\mathbf{X}}\right)\bar{\boldsymbol{\theta}} \\ &= 2M\lambda_{\max}\left(\bar{\mathbf{X}}\right) - 2\Re\left\{\boldsymbol{\theta}^H\left(\lambda_{\max}\left(\bar{\mathbf{X}}\right)\mathbf{I} - \bar{\mathbf{X}}\right)\bar{\boldsymbol{\theta}}\right\} \\ &\quad - \bar{\boldsymbol{\theta}}^H\bar{\mathbf{X}}\bar{\boldsymbol{\theta}} = h\left(\boldsymbol{\theta}\left|\bar{\boldsymbol{\theta}}\right.\right), \end{aligned} \quad (29)$$

where M denotes the number of the elements of the IRS.

Thus, we construct the surrogated OF $g\left(\boldsymbol{\theta}\left|\bar{\boldsymbol{\theta}}\right.\right)$ as follows

$$g\left(\boldsymbol{\theta}\left|\bar{\boldsymbol{\theta}}\right.\right) = h\left(\boldsymbol{\theta}\left|\bar{\boldsymbol{\theta}}\right.\right) + 2\Re\left\{\boldsymbol{\theta}^H\mathbf{y}^\dagger\right\}, \quad (30)$$

where $h\left(\boldsymbol{\theta}\left|\bar{\boldsymbol{\theta}}\right.\right)$ is defined in (29). In fact, the new OF $g\left(\boldsymbol{\theta}\left|\bar{\boldsymbol{\theta}}\right.\right)$ is more tractable than the original OF $f\left(\boldsymbol{\theta}\right)$.

Then, the approximated problem to be solved at the t-th iteration is given by

$$\min_{\boldsymbol{\theta}} \ g\left(\boldsymbol{\theta}\left|\bar{\boldsymbol{\theta}}\right.\right) \quad (31a)$$

$$\text{s.t. } |\theta_m| = 1, \quad m = 1, \ldots, M. \quad (31b)$$

Since $\boldsymbol{\theta}^H\boldsymbol{\theta} = M$, we have $\boldsymbol{\theta}^H\lambda_{\max}\left(\bar{\mathbf{X}}\right)\mathbf{I}\boldsymbol{\theta} = M\lambda_{\max}$, which is a constant. By removing the other constant terms, (31) can be rewritten as follows:

$$\max_{\boldsymbol{\theta}} \ 2\Re\left\{\boldsymbol{\theta}^H\mathbf{u}\right\} \quad (32a)$$

$$\text{s.t. } |\theta_m| = 1, \quad m = 1, \ldots, M, \quad (32b)$$

where $\mathbf{u} = \left(\lambda_{\max}\left(\bar{\mathbf{X}}\right)\mathbf{I} - \bar{\mathbf{X}}\right)\bar{\boldsymbol{\theta}} + \bar{\mathbf{y}}^\dagger$.

It is easily to know that the optimal $\boldsymbol{\theta}^\star$ for (32) should be $\boldsymbol{\theta}^\star = [e^{j\arg(u_1)}, \ldots, e^{j\arg(u_M)}]^T$.

Nextly, we will solve (28) by the penalty CCM method.

2) THE PENALTY CCM METHOD

In this part, we adapt the CCM method proposed in [29] to solve (28) directly. We first transform (28) into the following equivalent problem

$$\min_{\boldsymbol{\theta}} f\left(\boldsymbol{\theta}\right) = \boldsymbol{\theta}^H\left(\mathbf{X} + \alpha\mathbf{I}\right)\boldsymbol{\theta} + 2\Re\left\{\boldsymbol{\theta}^H\mathbf{y}^\dagger\right\} - \zeta\left(\boldsymbol{\theta}^H\mathbf{T}\boldsymbol{\theta} + 2\Re\left\{\boldsymbol{\theta}^H\mathbf{z}^\dagger\right\} - c\right) \quad (33a)$$

$$\text{s.t. } |\theta_m| = 1, \quad m = 1, \ldots, M, \quad (33b)$$

where α is a positive constant parameter which control the convergence of the CCM method. Since $\alpha\boldsymbol{\theta}^H\boldsymbol{\theta} = \alpha M$, (28) is equivalent to (33).

The search space in (33) can be seen as the product of M complex circles, which is a sub-manifold of $\mathbb{C}^M$ given by $\mathcal{S}^M \triangleq \left\{\mathbf{x} \in \mathbb{C}^M : |x_m| = 1, m = 1, \ldots, M\right\}$, where x_m is the m-th element of vector $\mathbf{x}$.

The main idea of the CCM method is to derive a gradient descent algorithm based on the manifold space defined in $\mathcal{S}^M$, which is similar to the concept of the gradient descent technique over the Euclidean space. In each iteration, the main procedure of the CCM algorithm is composed of four steps.

a: GRADIENT IN THE EUCLIDEAN SPACE

Firstly, we need to find the search direction for the minimization problem, e.g., the direction opposite to the gradient in Euclidean space of $f\left(\bar{\boldsymbol{\theta}}\right)$, which is given by

$$\boldsymbol{\eta} = -\nabla_{\boldsymbol{\theta}}f\left(\bar{\boldsymbol{\theta}}\right) = -2\left(\bar{\mathbf{X}} + \alpha\mathbf{I}\right)\bar{\boldsymbol{\theta}} - 2\bar{\mathbf{y}}^\dagger. \quad (34)$$

b: COMPUTER THE RIEMANNIAN GRADIENT

Since we optimize $\boldsymbol{\theta}$ over the manifold space, we have to find the Riemannian gradient. Specifically, the Riemannian gradient of $f\left(\bar{\boldsymbol{\theta}}\right)$ at $\bar{\boldsymbol{\theta}}$ can be obtained by projecting the search

Algorithm 1 The IBCD Algorithm for Problem (6)

1: Initialization: $n = 1$, set P_s, $\mathbf{H}$, $\mathbf{G}$, σ_b, σ_e, and κ.
2: **repeat**
3: Fix $\{\mathbf{W}, \mathbf{Q}, \Theta\}$, obtain $\{\mathbf{U}, \mathbf{V}, \Psi_1, \Psi_2, \Psi_3\}$ by solving (11a)–(11e).
4: Fix $\{\Theta, \mathbf{U}, \mathbf{V}, \Psi_1, \Psi_2, \Psi_3\}$, obtain $\{\mathbf{W}, \mathbf{Q}\}$ by solving (14).
5: Fix $\{\mathbf{W}, \mathbf{Q}, \mathbf{U}, \mathbf{V}, \Psi_1, \Psi_2, \Psi_3\}$, obtain Θ by solving (28) with the penalty MM or CCM methods.
6: Update $\{\mathbf{W}, \mathbf{Q}, \Theta\}$.
7: $n = n + 1$.
8: **until** $R_s^n - R_s^{n-1} < \kappa$ satisfied.
9: Output $(\mathbf{W}^\star, \mathbf{Q}^\star, \Theta^\star)$.

direction $\boldsymbol{\eta}$ onto the tangent space, which is calculated as follows

$$\mathbf{P}(\boldsymbol{\eta}) = \boldsymbol{\eta} - \Re\left\{\boldsymbol{\eta}^\dagger \odot \bar{\boldsymbol{\theta}}\right\} \odot \bar{\boldsymbol{\theta}}. \tag{35}$$

c: UPDATE OVER THE TANGENT SPACE

Update the current point $\bar{\boldsymbol{\theta}}$ on the tangent space as

$$\boldsymbol{\theta} = \bar{\boldsymbol{\theta}} + \beta \mathbf{P}(\boldsymbol{\eta}). \tag{36}$$

where β is a constant parameter.

d: RETRACTION OPERATOR

In general, the $\boldsymbol{\theta}$ obtained in (36) is not in $\mathcal{S}^M$. Hence, it has to be mapped into the manifold $\mathcal{S}^M$ by using the following retraction operator

$$\boldsymbol{\theta} = \boldsymbol{\theta} \odot \frac{1}{|\boldsymbol{\theta}|}. \tag{37}$$

In addition, the range of α and β to guarantee the convergence of the CCM algorithm can be obtained based on the following theorem.

Theorem 1 [29]: The range of α and β should satisfy the following constraint

$$\alpha \geq \frac{M}{8}\lambda_{\max}\left(\bar{\mathbf{X}}\right) + \|\bar{\mathbf{y}}\|, \quad 0 < \beta < \frac{1}{\lambda_{\max}\left(\bar{\mathbf{X}} + \alpha\mathbf{I}\right)}, \tag{38}$$

then the CCM algorithm generates a non-increasing sequence, and finally converges to a finite value.

3) OVERALL ALGORITHM

To this end, we have turned (6) into a solvable problem, in which the three subproblems can be solved with respective methods. The entire procedure is given in Algorithm 1, where κ denotes the stopping criterion.

4) COMPLEXITY ANALYSIS

At the end of this section, we provide the complexity analysis of the proposed MM and CCM methods. Based on [11] and [13], the complexity of the two methods are concluded as follows:

Firstly, the total complexity of the MM algorithm is given by $\mathcal{C}_{MM} = \mathcal{O}\left(M^3 + T_{MM}M^2\right)$, where T_{MM} denotes the total iteration numbers required by the MM algorithm.

On the other hand, the total complexity of the CCM algorithm is given by $\mathcal{C}_{CMM} = \mathcal{O}\left(M^3 + T_{CMM}M^2\right)$, where T_{CMM} denotes the total iteration numbers required by the CCM algorithm. From the equations, we can see that the complexity of the two methods are mainly depend on the iteration times.

Furthermore, for subproblem 1, the complexity to achieve these matrices is $\mathcal{O}\left(N_t^2 N_r\right)$. For subproblem 2, subproblem 2 has one LMI constraint of size dN_i, one LMI constraint of size N_e^2, one LMI constraint of size $N_tN_i + d^2$, one LMI constraint of size $N_tN_i + dN_e$. Based on [30], the computational complexities for subproblem 2 is $\psi\varsigma$, where $\varsigma = nd^3N_i^3 + n^2d^2N_i^2 + nN_e^6 + n^2N_e^4 + n\left(N_tN_i + d^2\right)^3 + n^2\left(N_tN_i + d^2\right)^2 + n(N_tN_i + dN_e)^3 + n^2(N_tN_i + dN_e)^2 + n^3$, $\psi = dN_i + N_e^2 + 2N_tN_i + dN_e + d^2$, and $n = O\left(N_t^2\right)$.

From the above analysis, we can see that the overall complexity of the IBCD algorithm is given by $C_{IBCD} = O\left(\max\left\{M^3 + T_{MM}M^2, \psi\varsigma\right\}\right)$, which is mainly depend on the number of the antennas at the transceiver and the phase shifts at the IRS.

IV. SIMULATION RESULTS

In this section, we provide simulation results to evaluate the performance of the proposed scheme. In fact, the simulation parameters mainly refer the related works such as [11] and [13]. Unless specified, the simulation setting are given as follows: $P_s = 10$dBW, $N_t = 8$, $N_b = N_e = 5$, $\sigma_b^2 = \sigma_e^2 = 10^{-8}$, and $E_{th} = -40$dBm. The number of the elements of the IRS is set as $M = 50$. The large-scale fading is denoted as $L = L_0\left(d/d_0\right)^{-\beta}$, with $L_0 = 10^{-3}$ denotes the channel gain at the reference distance $d_0 = 1$ and β is the path loss exponent. We set the path loss exponent for the direct link and the IRS-related link as $\beta = -2$ and $\beta = -5$, respectively. In addition, for the small-scale fading, we assume that all the links follows the Rayleigh fading. The coordinate of the T, the IRS, the IR and the ER are set as (5,0), (0,100), (3,100), (2,105), respectively.

In addition, to highlight the superiority of the proposed scheme, we compare the design with the following methods:

1) the MM method in [18], which did not consider AN and harvested energy constraint;

2) the IBCD method in [23], which did not consider IRS;

3) the semidefinite programming (SDP) and Gaussian randomization (GR) method in [22] to obtain the phase shifts.

These methods are labelled as "the AO CCM method", "the AO MM method", "the method in [18]", "the method in [23]", and "the SDP–GR method", respectively.

Firstly, we investigated the convergence behaviour of the proposed method. Fig. 2. shows the secrecy rate versus the number of iterations in several channel realization. From this figure, we can see that in different channel scenarios, the proposed methods always converge in limited iterations.

Secondly, in Fig. 3, we show the secrecy rate versus the transmit power budget P_s at the T. From this figure, we can see that all these methods get higher secrecy rates with the increase of P_s, while the proposed methods obtain higher

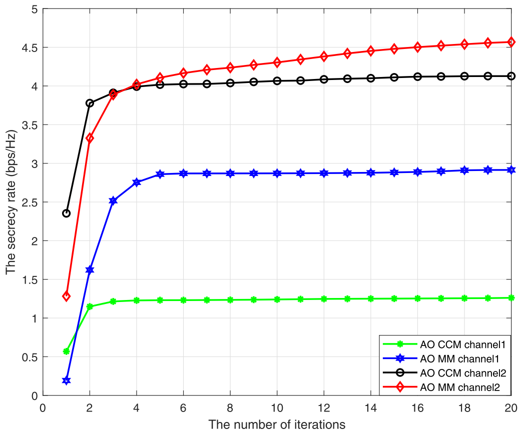

FIGURE 2. The convergence behaviour of the proposed method.

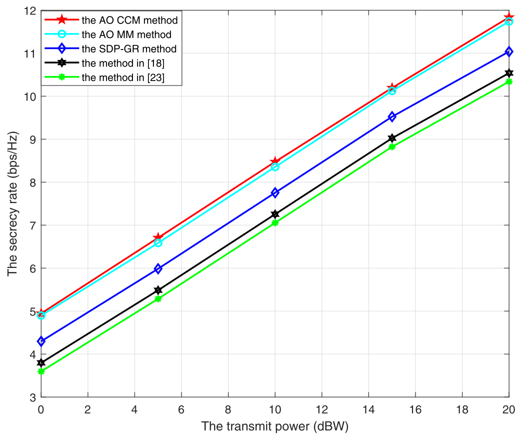

FIGURE 3. The secrecy rate versus the transmit power.

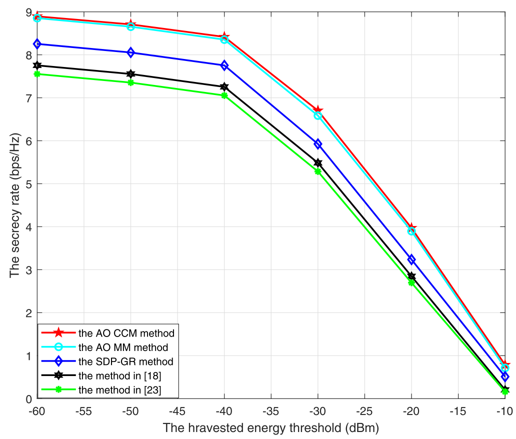

FIGURE 4. The secrecy rate versus the harvested energy threshold.

secrecy rate than the SDP–GR method and the MM method in [18]. In addition, all the methods in the IRS-aided case achieve better performance than the no IRS case, which suggests the effect of IRS in secrecy design.

Nextly, we show the secrecy rate versus the harvested energy threshold E_{th} in Fig. 4. From this figure, we can see that for all these methods, R_s tends to decrease with the increase of E_{th}. Since with the increase of E_{th}, more transmit power used to emit the energy signal in the ER's channel, thus the information rate tends to decrease for the IR and ER, as well as the secrecy rate.

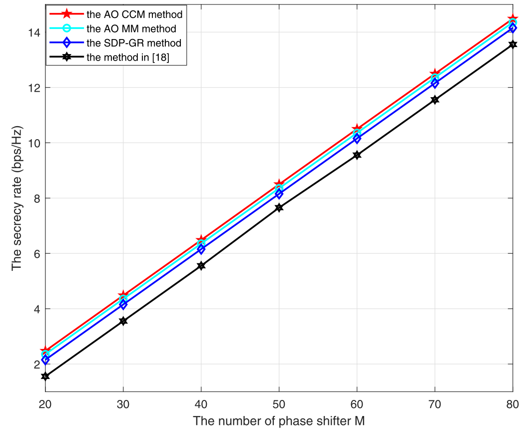

FIGURE 5. The secrecy rate versus the number of phase shifters.

Lastly, in Fig. 5, we show the secrecy rate versus the number of phase shifts M. From this figure, we can see that for all these IRS-aided methods, R_s tends to increase with the increase of M. This is due to more signals can reach the IRS with larger M, and the reflected signal at the IRS increases with M by appropriately designing the phase shifts.

V. CONCLUSION

This paper investigated the IRS aided secrecy design in MIMO SWIPT channel. Specifically, we formulated the SRM problem by jointly optimizing the precoding matrix, the AN covariance and the phase shifters. To solve the formulated non-convex problem, the penalty MM and CCM methods based IBCD algorithm was proposed. Simulation results validated that significant secrecy performance gain can be achieved by IRS with the proposed method.

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