Multiple Intelligent Reflecting Surfaces Assisted Secure Transmissions in MISO Systems

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Abstract—Due to the broadcast nature of wireless communications, physical layer security has always been a fundamental but challenging concern. Fortunately, the recent advance of Intelligent Reflecting Surface (IRS) introduces another dimension for secure wireless communications by reconfiguring the transmission environments. In this paper, we devise secure transmission environments for multi-user MISO systems by collaboratively leveraging multiple IRSs. Specifically, achievable secrecy rate represents the amount of information per unit time that can be securely sent through a communication link, which is an important criterion for measuring secure communication. To guarantee the worst-case achievable secrecy rate among multiple legitimate users, we formulate a max-min problem and adopt an alternative optimization method to decouple multiple variables. Based on semidefinite relaxation and successive convex approximation, each sub-problem can be further converted into convex problem and easily solved. Extensive experimental results demonstrate that the proposed scheme can adapt to complex scenarios and achieve the significant gain in terms of achievable secrecy rate. To show the gap between the proposed problem and the traditional sum-rate problem, we also evaluate the performance sum-rate problem and make the comparison. The results show that performance of max-min problem converges to the performance of sum-rate problem in terms of the sum of secrecy rate with the increase of elements on IRSs.

Index Terms—Physical layer security, intelligent reflecting surface, achievable secrecy rate.

I. INTRODUCTION

Due to the broadcast nature of wireless signals, it is vulnerable for user’s confidential messages in wireless communications. To safeguard communication security, physical layer security, which can be traced back to 1970’s Wyner’s seminal work [1, 2, 3], has been regarded as a fundamental issue and a key complement to higher-layer encryption techniques [4, 5]. In traditional communication systems, beamforming and Artificial Noise (AN) are considered as two effective approaches to degrade wiretap channel and achieve secure communication. By exploiting multiple antennas and shaped beams, beamforming technology can be implemented to direct the signal towards the legitimate user and thus reduce the signal leakage. In addition to beamforming, AN technology can create significant interference and lower the SINR at eavesdroppers by properly designing AN signals. Thus, the achievable secrecy rate, which is a widely used criterion to represent the difference between mutual information of “Alice-Bob” channel and “Alice-Eve” channel and measure the security level, can be effectively improved especially when the channel state of transmitter-user and transmitter-eavesdropper are highly correlated during the transmission. Nevertheless, due to the complex environment of wireless communication, the proposed approaches do not always work as expected.

As a promising technology for achieving smart radio environment/intelligent radio environment in the next generation cellular system [6, 7], Intelligent Reflecting Surfaces (IRSs) can provide reconfigurable signal propagation environments to support cost-effective and power-efficient wireless communication services. In specific, IRS is a metasurface composed of a large number of passive reflecting elements, it consumes much lower energy compared with traditional active relays/transceivers [8, 9]. By adaptively adjusting the reflection amplitude and/or phase shift of each element, the strength and direction of the incident electromagnetic wave becomes highly controllable. Thus, IRS is regarded as a novel solution to achieve configurable wireless environment/intelligent radio environment/wireless 2.0 with low hardware/energy cost, and has been applied in various wireless applications such as coverage extension, interference cancellation and energy efficiency enhancement [6, 8, 10]. Due to the aforementioned advantages, the IRS-assisted communication system has great potential to benefit physical layer security. By jointly optimizing operations on transmitter and passive reflecting elements of IRS, the transmitter-user channel state can be reconfigured and avoid the signal leakage to eavesdropper. Intuitively, users geographically close to the IRS are more likely beneficial from IRS by receiving the tuned signal, whose achievable secrecy rate can be significantly improved.

Recently, some efforts have been done to study IRS-assisted system for physical layer security. Cui et al. [11] investigated an IRS-aided secure wireless communication system where a simple scenario with one eavesdropper is conducted to show the effectiveness of IRS. To explore the effectiveness of traditional approach in IRS-assisted scenarios, Guan et al. [5] further considered AN in an IRS-assisted system, whose performance was verified with the significant gain of secrecy rate. To improve the algorithm efficiency, Yu et al. [12] proposed an efficient algorithm adopted Block Coordinate Descent (BCD) and minorization maximization method for faster convergence especially for large-scale IRS. Dong et al. [13] also adopted a similar efficient design for Mutiple-Input Mutiple-Output (MIMO) systems. Lyu et al. [14] considered a potential IRS threat called IRS jamming attack, which can leverage signals from a transmitter by controlling reflected signals to diminish the signal-to-interference-plus-noise ratio at the user. Since the IRS jammer operates in passive way, it can be even harder to defend. Xu et al. [15] studied resource allocation design in multi-user scenario and also considered AN at transmitter. However, the aforementioned efforts only
focus on the proof of work by implementing a single IRS. Thus, the security gain of collaboratively leveraging multiple IRSs has not been explored yet, it is critical to jointly optimize wireless environments and allocate resources for legitimate users in multiple IRSs-assisted systems.

To guarantee the security of confidential messages from users, in this paper, we study the secure transmission mechanism for multi-user Multiple-Input Single-Output (MISO) systems assisted by multiple IRSs. The main contributions of this paper are summarized as follows:

- To deal with the threat of potential eavesdroppers, we propose a secure communication scheme in multiple IRSs-assisted system. Considering the security requirement for each legitimate user in the system, we formulate a max-min problem to maximize the lower bound of the security performance to guarantee the worst performance of multiple users in case the eavesdropper “steal” too much useful information from a certain user.

- To solve the formulated max-min problem, an alternating algorithm is adopted to decouple different variables. In each iteration, only one type of variable is considered and the other variables are fixed, then we apply SemiDefinite Relaxation (SDR) and Successive Convex Approximation (SCA) method to obtain a convex optimization problem, which makes the original problem can be easily solved.

- To verify the effectiveness of the proposed scheme, extensive numerical evaluations are conducted. Compared with the traditional IRS scheme with beamforming, the results show that the proposed scheme can achieve significant improvement, and the additional AN can improve achievable secrecy rate in some degree especially in multi-user scenarios. Meanwhile, we also make the comparison with the traditional sum-rate problem to show the gap of security performance. With the increase of elements on IRSs, it shows that the performance of max-min problem converges to the performance of sum-rate problem in terms of sum of secrecy rate.

**Symbol Notation:** Boldface lowercase and uppercase letters denote vectors and matrices, respectively. For a vector \( a \), \(|a|\) denotes the Euclidean norm. For matrix \( A \), the conjugate transpose, rank and trace of \( A \) are denoted as \( A^H \), \( \text{Rank}(A) \) and \( \text{Tr}(A) \), respectively. For a complex number \( c \), \(|c|\) denotes the modulus. \( \text{angle}(c) \) denotes the phase of the complex value \( c \). The set of \( n \)-by-\( m \) real matrices, complex matrices and complex Hermitian matrices are denoted as by \( \mathbb{R}^{n \times m} \), \( \mathbb{C}^{n \times m} \) and \( \mathbb{H}^{n \times m} \), respectively. \( A \succeq 0 \) means \( A \) is a positive semidefinite matrix, and \( N(\mu, \Sigma) \) denotes Gaussian distribution with mean \( \mu \) and covariance matrix \( \Sigma \).

**II. SYSTEM MODEL**

We consider a wireless communication system as shown in Fig. 1, a base station equipped with \( M \) antennas intends to transmit confidential messages to \( I \) legitimate users equipped with single antenna. Meanwhile, \( K \) IRSs have been deployed in advance to assist wireless communication, and each IRS has \( N \) reflecting elements.

**Adversary Model:** Concerning to the valuable information containing in the confidential messages, one eavesdropper (Eve) wants to wiretap users’ signals, and further crack the confidential messages to steal users’ private information or hack users’ equipments. To eliminate the potential threat from eavesdropper and guarantee the security of legitimate users, the base station and IRSs need to cooperatively transmit signals to increase received signal power at legitimate users and also degrade the signal leakage at the eavesdropper. In this paper, we try to adjust the transmission strategy at base station and also on IRSs to improve the security level of the system.

**Channel Model:** There are two parts of channel experienced from base station to users/Eve, i.e., direct (transmitter-users/Eve) channel and reflecting (transmitter-IRS-users/Eve) channel. The composite reflecting channel is modeled as a combination of three components, i.e., the base station to IRS link, IRS’s reflection with phase shift and IRS to users/Eve link. The baseband equivalent channels from the base station to \( k \)-th IRS, \( i \)-th user and Eve are denoted by \( G_k^H \in \mathbb{C}^{N \times M} \), \( h_i^H \in \mathbb{C}^{1 \times M} \), \( h_e^H \in \mathbb{C}^{1 \times M} \), respectively. The baseband equivalent channels from \( k \)-th IRS to \( i \)-th user and Eve are denoted by \( g_{ik}^H \in \mathbb{C}^{1 \times N} \), \( g_{ei}^H \in \mathbb{C}^{1 \times N} \), respectively. Since the IRS is a passive reflecting device, we consider a Time Division Duplexing (TDD) protocol for uplink and downlink transmissions and quasi-static flat-fading model (constant within the transmission frame) is adopted for all channels. As discussed in [5], by applying various channel acquisition methods, we also assume that the Channel State Information (CSI) of all channels are perfectly known. Linear transmit precoding is considered at the base station similar to [9], each user served by the base station is assigned with one dedicated beamforming vector. To further enhance the physical layer security, additional AN is also adopted. Thus, the signal transmitted from the base station to the \( i \)-th user can be described as:

\[
x_i = \omega_i s_i + z_i, i = 1, \ldots, U,
\]

where \( \omega_i \in \mathbb{C}^{M \times 1} \) is the beamforming vector for \( i \)-th user, \( s_i \) is the corresponding transmitted data and \( z_i \in \mathbb{C}^{M \times 1} \) is AN vector.

Since multiple IRSs have been deployed in the system, each legitimate user can be served by a selected IRS to receive tuned signal, which is effective especially when there exists obstacle and no Light-of-Sight (LoS) channel between base station and user. Let \( \alpha_{i,k} \in \{0,1\} \) denote the IRS selection for \( i \)-th user, i.e., \( i \)-th user can receive reflecting signal through \( k \)-th IRS if \( \alpha_{i,k} = 1 \). Meanwhile, let \( \Theta_k = \text{diag}(A_{k,1}e^{j\theta_{k,1}}, \ldots, A_{k,N}e^{j\theta_{k,N}}) \in \mathbb{C}^{N \times N} \) denote the diagonal phase-shifting matrix of \( k \)-th IRS, while \( A_{k,n} \in [0,1] \) and \( \theta_{k,n} \in [0,2\pi) \) denote amplitude reflection coefficient and the phase shift of \( n \)-th element on \( k \)-th IRS. In practice, each element of the IRS is usually designed to maximize the signal reflection [9]. Thus, we set \( A_{k,n} = 1 \) in this paper. In this case, for \( i \)-th user, the received signal from base station and IRS can be represented by:

\[
y_i = (\sum_{k=1}^{K} \alpha_{i,k} g_{ik}^H \Theta_k G_k^H + h_i^H)(\omega_i s_i + z_i) +
\]
where $n_0 \in \mathcal{CN}(0, \sigma^2)$ is the complex Additive White Gaussian Noise (AWGN). For eavesdropper, the received signal can be represented by:

$$y_i^e = \sum_{j \neq i} \alpha_{i,j}g^H_{e,k}\Theta_k G^H_k + h^H_i(\omega_js_i + z_i) + n_0.$$  

(2)

For notation simplicity, let $\hat{D}_{ij} = \sum_{k=1}^{K} \alpha_{i,k}g^H_{e,k}\Theta_k G^H_k + h^H_i \in \mathbb{C}^{1 \times M}$, $D_{e,i} = \sum_{k=1}^{K} \alpha_{i,k}g^H_{e,k}\Theta_k G^H_k + h^H_i \in \mathbb{C}^{1 \times M}$. Accordingly, the Signal-to-Noise Ratio (SINR) of received signal at $i$-th user can be calculated by:

$$SINR_i = \frac{\| \sum_{k=1}^{K} \alpha_{i,k}g^H_{e,k}\Theta_k G^H_k + h^H_i \omega_i \|^2}{\sum_{j \neq i} \| \hat{D}_{ij}\omega_j \|^2 + \sum_{j \in U} \| \hat{D}_{ij}z_j \|^2 + N_0}. $$  

(3)

where $N_0$ is the power of AWGN. Similarly, the SINR of $i$-th user’s signal at the eavesdropper can be calculated by:

$$SINR_i^e = \frac{\| \sum_{k=1}^{K} \alpha_{i,k}g^H_{e,k}\Theta_k G^H_k + h^H_i \omega_i \|^2}{\sum_{j \neq i} \| D_{e,j}\omega_j \|^2 + \sum_{j \in U} \| D_{e,j}z_j \|^2 + N_0}. $$  

(4)

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$$SINR_i^e = \frac{\| \sum_{k=1}^{K} \alpha_{i,k}g^H_{e,k}\Theta_k G^H_k + h^H_i \omega_i \|^2}{\sum_{j \neq i} \| D_{e,j}\omega_j \|^2 + \sum_{j \in U} \| D_{e,j}z_j \|^2 + N_0}. $$  

(5)

### III. Problem Formulation and Solution

Considering the security requirement for each legitimate user in the system, we want to guarantee the worst performance of all legitimate users in case eavesdropper might wiretap too much useful information from a certain user. Thus, in this paper, we aim to maximize the minimum achievable secrecy rate of legitimate users in the system. By jointly configuring the beamforming matrix $\hat{\omega} = [\omega_1, \omega_2, ..., \omega_I]$ and AN matrix $\bar{\alpha} = [\bar{\alpha}_1, \bar{\alpha}_2, ..., \bar{\alpha}_K]$ at the base station, phase shift matrix $\hat{\Theta} = [\Theta_1, \Theta_2, ..., \Theta_K]$ at IRSs and surface selection matrix $\alpha = [\alpha_{1,1}, ..., \alpha_{1,K}]$ between users and IRSs, the optimization problem can be formulated as:

**Problem 1:**

$$\max_{\hat{\omega}, \hat{\Theta}, \bar{\alpha}} \min_i [R_i^e - R_i^s]^+ \quad (6)$$

s.t. $$\| \omega_i \|^2 + || z_i ||^2 \leq P_{\text{max}}, \forall i \in \mathcal{U},$$  

(1)

$$|\omega_j(jn)| = 1, k \in [1, K], \forall n \in [1, N],$$  

(2)

$$\sum_k \alpha_{i,k} = 1, \alpha_{i,k} \in \{0, 1\}, \forall i \in \mathcal{U},$$  

(3)

where (1) represents the transmission power constraint, (2) limits the unit modulus for each element and (3) indicates that each user should be served by one IRS in the system. Considering the SINR expression in (4), (5) and Shannon equation, the achievable secrecy rate (bits/s/Hz) in (6) can be calculated by:

$$R_i^e - R_i^s = log_2(1 + \frac{\| \sum_{k=1}^{K} \alpha_{i,k}g^H_{e,k}\Theta_k G^H_k + h^H_i \omega_i \|^2}{\sum_{j \neq i} \| \hat{D}_{ij}\omega_j \|^2 + \sum_{j \in U} \| \hat{D}_{ij}z_j \|^2 + N_0})$$

$$- log_2(1 + \frac{\| \sum_{k=1}^{K} \alpha_{i,k}g^H_{e,k}\Theta_k G^H_k + h^H_i \omega_i \|^2}{\sum_{j \neq i} \| D_{e,j}\omega_j \|^2 + \sum_{j \in U} \| D_{e,j}z_j \|^2 + N_0}).$$

(7)

It is intuitive to know that variables $\hat{\omega}$, $\bar{\alpha}$, $\hat{\Theta}$ and $\alpha$ in **Problem 1** are coupled, which makes **Problem 1** difficult to solve. However, if only one variable is considered, the original problem becomes solvable when the other variables are fixed. Inspired by the alternating optimization approaches in [4, 5, 12, 13, 14, 15], we adopt BCD technique to decouple variables and get the sub-optimal solution efficiently. To optimize a multi-variable objective in BCD method, we optimize the objective in terms of one of the coordinate blocks while the other blocks are fixed at each iteration. In the next, **Problem 1** is divided into three sub-problems and each sub-problem is solved iteratively as described in **Algorithm 1**. For each sub-problem, we utilize SDR and SCA to convert the original problem into a convex problem. The detailed solving process of each sub-problem is described in the following sections.
\[ \nabla_{W_i} F_i^3(W_i, Z_i) = \frac{1}{\ln^2} \text{Tr}(W_i D_{e,i}^H D_{e,i}) + \sum_{j \in U} \text{Tr}(W_j D_{e,j}^H D_{e,j}) + \sum_{j \in U} \text{Tr}(Z_j D_{e,j}^H D_{e,j}) + N_0, \]

\[ \nabla_{Z_i} F_i^4(W_i, Z_i) = \frac{1}{\ln^2} \text{Tr}(W_i D_{e,i}^H D_{e,i}) + \sum_{j \in U} \text{Tr}(W_j D_{e,j}^H D_{e,j}) + \sum_{j \in U} \text{Tr}(Z_j D_{e,j}^H D_{e,j}) + N_0. \]

**Algorithm 1: BCD-based Algorithm**

**Input:** Number of elements \( N \), number of antennas \( M \), number of surfaces \( K \);

**Output:** Beamforming vector \( \hat{\omega} \), AN vector \( \hat{z} \), phase-shift matrix \( \hat{\Theta} \) and IRS selection vector \( \hat{a} \);

1. **Initialize:**
   - Initialize \( \hat{\omega}(0), \hat{z}(0), \hat{\Theta}(0) \) and \( \hat{a}(0) \);
   - \( t = 0, \Delta(t) = \text{Int}_{\text{max}} \);
2. **while** \( \Delta(t) < \delta \) do
3. **solve** each sub-problem to find solution for \( \hat{\omega}(t+1), \hat{z}(t+1), \hat{\Theta}(t+1) \) and \( \hat{a}(t+1) \) for given \( \hat{\omega}(t), \hat{z}(t), \hat{\Theta}(t) \) and \( \hat{a}(t) \), respectively;
4. Calculate \( \rho(t+1) = \min \left[ R_i^u - R_i^c \right] \);
5. Update \( t = t + 1 \) and \( \Delta(t) = \rho(t+1) - \rho(t) \);
6. **end**

**A. Sub-Problem for Beamforming and AN**

At first, beamforming and AN matrices are considered to be solved. For given phase shift operation \( \hat{\Theta} \) and surface matching \( \hat{a} \), we can rewrite **Problem 1** as:

**Problem 2a:** \[
\text{max } \min_{\omega, \hat{z}} \quad [R_i^u - R_i^c]^+ \quad \text{s.t.} \quad ||\omega||^2 + ||\hat{z}||^2 \leq P_{\text{max}}, \quad \forall i \in \mathcal{U}. \quad (11)
\]

To solve this sub-problem for beamforming and AN, we reformulate the objective with some mathematical transformations at first. Let \( \omega_i = \omega_i \omega^H \in \mathbb{C}^{M \times M}, \quad \hat{z}_i = z_i \hat{z}_i^H \in \mathbb{C}^{M \times M}, \quad D_i = k = 1, k \in \mathbb{C}^{I \times M}, \quad D_{e,i} = k \in \mathbb{C}^{I \times M}, \quad D_{e,i} = k \in \mathbb{C}^{I \times M} \), \( \hat{D}_{ij} = k \in \mathbb{C}^{I \times M}, \quad \hat{D}_{ij} = k \in \mathbb{C}^{I \times M} \). Then, the achievable secrecy rate can be reformulated as:

\[ R_i^u - R_i^c = \log_2(1 + \frac{\text{Tr}(W_i D_{e,i}^H D_{e,i})}{\sum_{j \in U} \text{Tr}(W_j D_{e,j}^H D_{e,j}) + \sum_{j \in U} \text{Tr}(Z_j D_{e,j}^H D_{e,j}) + N_0}), \]

\[ = \log_2(1 + \frac{\text{Tr}(W_i D_{e,i}^H D_{e,i})}{\sum_{j \in U} \text{Tr}(W_j D_{e,j}^H D_{e,j}) + \sum_{j \in U} \text{Tr}(Z_j D_{e,j}^H D_{e,j}) + N_0}), \]

\[ \text{Tr}(W_i D_{e,i}^H D_{e,i}) + \sum_{j \in U} \text{Tr}(W_j D_{e,j}^H D_{e,j}) + \sum_{j \in U} \text{Tr}(Z_j D_{e,j}^H D_{e,j}) + N_0), \]

\[ = \log_2(1 + \frac{\text{Tr}(W_i D_{e,i}^H D_{e,i})}{\sum_{j \in U} \text{Tr}(W_j D_{e,j}^H D_{e,j}) + \sum_{j \in U} \text{Tr}(Z_j D_{e,j}^H D_{e,j}) + N_0}), \]

\[ \text{Tr}(W_i D_{e,i}^H D_{e,i}) + \sum_{j \in U} \text{Tr}(W_j D_{e,j}^H D_{e,j}) + \sum_{j \in U} \text{Tr}(Z_j D_{e,j}^H D_{e,j}) + N_0), \]

\[ = \log_2(1 + \frac{\text{Tr}(W_i D_{e,i}^H D_{e,i})}{\sum_{j \in U} \text{Tr}(W_j D_{e,j}^H D_{e,j}) + \sum_{j \in U} \text{Tr}(Z_j D_{e,j}^H D_{e,j}) + N_0}), \]

\[ \text{Tr}(W_i D_{e,i}^H D_{e,i}) + \sum_{j \in U} \text{Tr}(W_j D_{e,j}^H D_{e,j}) + \sum_{j \in U} \text{Tr}(Z_j D_{e,j}^H D_{e,j}) + N_0), \]

\[ = - (F_i^1 + F_i^3 + F_i^4) \]

where \( F_i^1, F_i^3 \) and \( F_i^4 \) are represented by:

\[ F_i^1 = -\log_2(\text{Tr}(W_i D_{e,i}^H D_{e,i})), \]

\[ F_i^2 = -\log_2(\text{Tr}(W_i \hat{D}_{e,i}^H \hat{D}_{e,i} + \text{Tr}(Z_i \hat{D}_{e,i}^H \hat{D}_{e,i}) + N_0)), \]

\[ F_i^3 = \log_2(\text{Tr}(W_i \hat{D}_{e,i}^H \hat{D}_{e,i} + \text{Tr}(Z_i \hat{D}_{e,i}^H \hat{D}_{e,i}) + N_0)), \]

\[ F_i^4 = \log_2(\text{Tr}(W_i D_{e,i}^H D_{e,i})), \]

\[ \text{Tr}(W_i D_{e,i}^H D_{e,i}) + \sum_{j \in U} \text{Tr}(W_j D_{e,j}^H D_{e,j}) + \sum_{j \in U} \text{Tr}(Z_j D_{e,j}^H D_{e,j}) + N_0). \]

However, the secrecy rate \( R_i^u - R_i^c \) in [12] is still in the form of Difference of Convex (DC) functions. To solve the DC problem in [12], we adopt SCA method [15, 17, 18, 19] to obtain a convex upper bound for the DC objective in an iterative manner. At first, we construct global overestimators of \( F_i^3 \) and \( F_i^4 \), respectively. For any feasible solution \( (W_i, Z_i) \), the differentiable convex functions \( F_i^3(W_i, Z_i) \) and \( F_i^4(W_i, Z_i) \) satisfy the following inequality:

\[ F_i^3(W_i, Z_i) \leq F_i^3(W_i^{(t)}, Z_i^{(t)}), \]

\[ + \text{Tr}(\nabla_{W_i} F_i^3(W_i^{(t)}, Z_i^{(t)})^H (W_i - W_i^{(t)})) \]

\[ + \text{Tr}(\nabla_{Z_i} F_i^3(W_i^{(t)}, Z_i^{(t)})^H (Z_i - Z_i^{(t)})) \]

\[ = \bar{F}_i^3(W_i, Z_i, W_i^{(t)}, Z_i^{(t)}), \]

\[ F_i^4(W_i, Z_i) \leq F_i^4(W_i^{(t)}, Z_i^{(t)}), \]

\[ + \text{Tr}(\nabla_{W_i} F_i^4(W_i^{(t)}, Z_i^{(t)})^H (W_i - W_i^{(t)})) \]

\[ + \text{Tr}(\nabla_{Z_i} F_i^4(W_i^{(t)}, Z_i^{(t)})^H (Z_i - Z_i^{(t)})) \]

\[ = \bar{F}_i^4(W_i, Z_i, W_i^{(t)}, Z_i^{(t)}), \]

where the right hand side terms in [17] and [18] are global overestimations of \( F_i^3 \) and \( F_i^4 \) by using first-order Taylor approximation, respectively. The gradients of functions \( F_i^3 \) and \( F_i^4 \) with respect to \( W_i \) and \( Z_i \) are given as [8, 10]. Hence, a convex upper bound of objective function in [12] can be obtained as \( R_i^u - R_i^c = -(F_i^1 + F_i^3 + F_i^4) \).

After deploying SCA, the objective function becomes convex. In order to further solve the max-min problem, we also introduce an auxiliary variable \( x \) into the formulation. By doing so, the original **Problem 2a** can be transformed as:

**Problem 2b:** \[
\text{min } x, W, Z \quad x \quad (19)
\]

\[ F_i^3(W_i, Z_i) \leq F_i^3(W_i^{(t)}, Z_i^{(t)}), \]
Since constraint (C5) is non-convex, we drop this rank-1 constraint by applying SDR. If the obtained solution \( (W_i^{(t)}, Z_i^{(t)}) \) are of rank-1, they can be written as \( W_i^{(t)} = \omega_i \omega_i^H \) and \( Z_i^{(t)} = z_i z_i^H \). Then, the optimal beamforming vector \( \omega_i \) and AN \( z_i \) can be obtained by applying eigenvalue decomposition. Otherwise, we can adopt Gaussian Randomization to recover \( \omega_i \) and \( z_i \) approximately from higher rank solution \( (W_i^{(t)}, Z_i^{(t)}) \) [21][22][23]. In this case, Problem 2b becomes a convex optimization problem. In Algorithm 2, Problem 2b can be efficiently solved at each iteration by using convex optimization solvers, e.g., Sedumi and CVX. In the following, we prove that SCA-based approach in Algorithm 2 can reach the optimal solution at each iteration.

**Proposition 1.** Algorithm 2 generates a sequence of non-decreasing feasible solutions that converge to a point \((W^*, Z^*)\) satisfying the KKT conditions of the original problems.

**Proof.** For notation convenience, let \( f_i(W_i, Z_i) = F_i^1 + F_i^2 + F_i^3 + F_i^4 \) and \( g_i(W_i, Z_i) = F_i^1 + F_i^2 + F_i^3 + F_i^4 \). The constraint (C4) can be rewritten as \( x \geq \max_i \{g_i(W_i, Z_i)\} \).

According to (17) and (18), we can have \( f_i(W_i, Z_i) \leq g_i(W_i, Z_i), \forall i \in \mathcal{U} \). This means that the optimal solution \((W^{(t)}, Z^{(t)})\) of the approximated problem [19] at \( t \)-th iteration always belongs to the feasible set of the original problem [11] since constraints (C1), (C4) and (C6) are always satisfied. Meanwhile, we can have \( \max_i \{f_i(W_i^{(t)}, Z_i^{(t)})\} \leq \max_i \{g_i(W_i^{(t)}, Z_i^{(t)})\}, \forall W, Z \in \mathbb{C}^{M \times 1} \). At each iteration, it follows that [24][25]:

\[
\max_i \{f_i(W_i^{(t)}, Z_i^{(t)})\} \leq \max_i \{g_i(W_i^{(t)}, Z_i^{(t)})\} = \min_{W, Z} \max_i \{g_i(W_i, Z_i)\} \\
\leq \max_i \{g_i(W_i^{(t-1)}, Z_i^{(t-1)})\} = \max_i \{g_i(W_i^{(t-1)}, Z_i^{(t-1)})\} + \mu_i(T_i - r_i) \]

where the second inequality is because for [19], \((W_i^{(t)}, Z_i^{(t)})\) is globally optimum at \( t \)-th iteration, and the last equality holds because \( g_i(W_i^{(t-1)}, Z_i^{(t-1)}) = f_i(W_i^{(t-1)}, Z_i^{(t-1)}) \). This means that \( \max_i \{f_i(W_i^{(t)}, Z_i^{(t)})\}\) is a monotonically decreasing sequence. As the actual objective value of [19] is nonincreasing after every iteration, Algorithm 2 will eventually converge to a point \((W^*, Z^*)\) as \( t \) increases.

Next, we prove that \((W^*, Z^*)\) satisfies the KKT conditions of the original problem. For [19], the optimal solution can be found when \( x = \max_i \{g_i(W_i, Z_i)\} \), thus, Problem 2b can be rewritten as:

\[
\min_{x, W, Z} \max_i \{g_i(W_i, Z_i)\} \tag{20}
\]

s.t. (C1),(C6).

Then, the Lagrangian of (20) is:

\[
L(W, Z, \mu) = \max_i \{g_i(W_i, Z_i)\} + \sum_{i \in \mathcal{U}} \mu_i (T_i - r_i).
\]

For a feasible point \((W^{(t-1)}, Z^{(t-1)})\) obtained by Algorithm 2 at \( t - 1 \)-th iteration, it is the global optimum for (20), the KKT conditions of (20) must be satisfied, i.e., \((W^{(t-1)}, Z^{(t-1)})\) is feasible for (20) and there exist nonnegative real values \( u_i, i \in \mathcal{U} \) satisfying:

\[
\nabla L(W^{(t-1)}, Z^{(t-1)}, \mu)_{W, Z} = 0, \quad \mu_i(T_i - r_i) = 0, \quad \forall i \in \mathcal{U}.
\]

Since the gradient of the first-order Taylor approximations \( F_i^3(W_i, Z_i) \) and \( F_i^4(W_i, Z_i) \) are the same as \( F_i^3(W_i, Z_i) \) and \( F_i^4(W_i, Z_i) \), we can also verify that:

\[
\nabla L'(W, Z, \mu)_{W=\omega^{(t-1)}, Z=\omega^{(t-1)}} = \nabla L(W, Z, \mu)_{W=\omega^{(t-1)}, Z=\omega^{(t-1)}}, \quad \nabla L'(W, Z, \mu)_{Z=\omega^{(t-1)}} = \nabla L(W, Z, \mu)_{Z=\omega^{(t-1)}}.
\]

which means that \((W^{(t-1)}, Z^{(t-1)})\) satisfies the KKT conditions for (11). The results imply that the KKT conditions of the original problem will be satisfied after the series of approximations converges to the point \((W^*, Z^*)\). This completes the proof.

### B. Subproblem for Phase Shift

For given beamforming matrix \( \bar{\omega} \), AN matrix \( \bar{\zeta} \) and surface selection matrix \( \bar{\sigma} \), we can rewrite Problem 1 as:

**Problem 3a:**

\[
\min_{\bar{\theta}} \max_i \left[ R_i^0 - R_i^1 \right] ^+
\]

s.t. \( |e^{j\theta_{k,n}}| = 1, k \in [1, K], \forall n \in [1, N] \). \tag{C2}

Next, similar to the procedures in the previous section III-A, we also transform the objective function to a solvable convex function by applying SDR and SCA. Let \( \bar{G}_{i,k} = \)
The achievable secrecy rate in (7) can be reformulated as:

\[ R_i^3 = \log_2\left(1 + \frac{||\alpha_i,k g_{i,k}^H\Theta_k^i G_k^H\omega_i + h_i^H\omega_i|^2|}{\sum_{j \notin k} \alpha_i,k g_{i,k}^H\Theta_k^i G_k^H\omega_j + \sum_{j \in k} \alpha_j,k g_{i,k}^H\Theta_k^i G_k^H\omega_j + |h_i^H\omega_i|^2}ight). \]

Accordingly, the power of received signal of i-th user at eavesdropper in (5) becomes:

\[ R_i^4 = \log_2\left(1 + \frac{||\alpha_i,k g_{i,k}^H\Theta_k^i G_k^H\omega_i + h_i^H\omega_i|^2|}{\sum_{j \notin k} \alpha_i,k g_{i,k}^H\Theta_k^i G_k^H\omega_j + \sum_{j \in k} \alpha_j,k g_{i,k}^H\Theta_k^i G_k^H\omega_j + |h_i^H\omega_i|^2}ight). \]

Furthermore, let \( v = [v_1, v_2, ..., v_k] \in \mathbb{C}^{1 \times NK} \), and \( a_i = [k_i,1; k_i,2; ..., k_i,k] \in \mathbb{C}^{NK \times 1} \). Thus, we have \( K \sum_{k=1}^{K} \alpha_i,k g_{i,k}^H \Theta_k^i G_k^H = \alpha_i v_i \). Let \( b_i = h_i^H \omega_i \), \( \hat{b}_{i,j} = h_i^H \omega_j \). The optimization problem (23) can be further reformulated as:

\[ R_i^5 - R_i^4 = \log_2(1 + \frac{||v_i - b_i|^2|}{\sum_{j \notin k} |v_j + b_j|^2 + \sum_{j \in k} |v_j + b_j|^2}) - \log_2(1 + \frac{|v_i - b_i|^2}{\sum_{j \notin k} |v_j + b_j|^2 + \sum_{j \in k} |v_j + b_j|^2}). \]

Note that \( |v_i - b_i|^2 = \overline{\tau^H R_i^3 \tau} \), and \( \overline{\tau^H R_i^3 \tau} = \text{trace}(R_i^3 \overline{\tau^H \tau}) \). Define \( V = \overline{\tau^H R_i^3 \tau} \), which needs to satisfy \( V \geq 0 \) and Rank(\( V \)) = 1. Note that \( R_i = [a_i, a_i^H, a_i^H; b_i, b_i^H, 0] \in \mathbb{C}^{NK \times 1 \times NK \times 1} \), \( \hat{R}_{i,j} = [a_j, a_j^H, a_j^H; b_j, b_j^H, 0] \in \mathbb{C}^{NK \times 1 \times NK \times 1} \), \( R_{i,j} = [a_i, a_i^H, a_i^H; b_i, b_i^H, 0] \in \mathbb{C}^{NK \times 1 \times NK \times 1} \), \( v = [v_i, v_i^H, v_i^H; v_i, v_i^H, v_i^H] \in \mathbb{C}^{1 \times \min\{N, K\}} \). Then (22) can be further reformulated as:

\[ R_i^5 - R_i^4 = \frac{F_i^1 + F_i^2 + F_i^3 + F_i^4}{2}, \]

where \( F_i^1, F_i^2, F_i^3 \) and \( F_i^4 \) are:

\[ F_i^1 = -\log_2(\sum_{j \notin k} |(\hat{R}_{i,j} - \hat{R}_{i,j}) V| + |\hat{b}_{i,j}|^2) + \sum_{j \notin k} |(\hat{R}_{i,j} - \hat{R}_{i,j}) V| + |\hat{b}_{i,j}|^2 + \sum_{j \notin k} |(\hat{R}_{i,j} - \hat{R}_{i,j}) V| + |\hat{b}_{i,j}|^2 + |\hat{b}_{i,j}|^2 + |\hat{b}_{i,j}|^2), \]

\[ F_i^2 = \log_2(\sum_{j \notin k} |\hat{R}_{i,j} V| + |\hat{b}_{i,j}|^2) + \sum_{j \notin k} |\hat{R}_{i,j} V| + |\hat{b}_{i,j}|^2 + \sum_{j \notin k} |\hat{R}_{i,j} V| + |\hat{b}_{i,j}|^2 + |\hat{b}_{i,j}|^2 + |\hat{b}_{i,j}|^2), \]

\[ F_i^3 = \log_2(\sum_{j \notin k} |\hat{R}_{i,j} V| + |\hat{b}_{i,j}|^2) + \sum_{j \notin k} |\hat{R}_{i,j} V| + |\hat{b}_{i,j}|^2 + \sum_{j \notin k} |\hat{R}_{i,j} V| + |\hat{b}_{i,j}|^2 + |\hat{b}_{i,j}|^2 + |\hat{b}_{i,j}|^2), \]

\[ F_i^4 = \log_2(\sum_{j \notin k} |\hat{R}_{i,j} V| + |\hat{b}_{i,j}|^2) + \sum_{j \notin k} |\hat{R}_{i,j} V| + |\hat{b}_{i,j}|^2 + \sum_{j \notin k} |\hat{R}_{i,j} V| + |\hat{b}_{i,j}|^2 + |\hat{b}_{i,j}|^2 + |\hat{b}_{i,j}|^2). \]

Similarly, we apply SDR method to remove rank-one constraint Rank(\( V \)) = 1 and SCA method to construct global overestimators of \( F_i^3 \) and \( F_i^4 \) and make (23) become convex function:

\[ F_i^5(V) \leq F_i^3(V) + \text{trace}(V V^H) \]

\[ F_i^4(V) \leq F_i^3(V) + \text{trace}(V V^H). \]

Thus, Problem 3a is transformed into a convex problem by introducing auxiliary variable \( x \):

\[ \text{Problem 3b: } \min_{x} x \]

\[ s.t. \quad |e^{j\theta_n}| = 1, \quad n \in [1, N], \quad x \geq F_i^1 + F_i^2 + F_i^3 + F_i^4, \quad x \in \mathbb{U}, \quad V \geq 0. \]

To restore desired solution \( \Theta = diag(v) \) from convex SemiDefinite Program (SDP) solution \( V \), eigenvalue decomposition with Gaussian randomization can be used to obtain a feasible solution based on the higher-rank solution obtained by solving Problem 3b. Since unit modulus constraint (23) for each element on IRS should be satisfied, the reflection coefficients can be obtained by [5][9]:

\[ \mu_{k,n} = e^{j \angle(e^{j\theta_n \tan(x_{k,n})} - 1)/N}, \quad n = 1, 2, ..., NK \]

where \( \angle(x) \) denotes the phase of \( x \) and obtained solution can satisfy \( |\mu_{k,n}| = 1 \).

C. Subproblem for Surface Selection

For given beamforming vector \( \tilde{w} \), AN vector \( \tilde{z} \), and phase shift of IRS \( \Theta \), the original problem becomes a 0-1 integer programming problem, we can rewrite Problem 1 as:

\[ \text{Problem 4a: } \max_{\alpha} \min_{\alpha} \left[ R_i^5 - R_i^4 \right] \]

\[ s.t. \quad \sum_{k} \alpha_{i,k} = 1, \quad \alpha_{i,k} \in [0, 1], \quad \forall \ i \in \mathbb{U}. \]

At first, according to the constraint described in (33), each user is served by one specific IRS, thus, we can have \( \alpha_{i,k,k'} = 0 \) when \( k \neq k' \) and \( \sum_{k=1}^{K} \alpha_{i,k} = 1 \). Then, we can simplify the expression in (22) and the power of received signal at i-th user becomes:

\[ \sum_{k=1}^{K} (\sum_{l \notin k} a_{i,k} g_{i,k}^H \Theta_k^i G_k^H + a_{i,k}^H h_i^H \omega_i)^2 \]

\[ = \sum_{k=1}^{K} a_{i,k} g_{i,k}^H (T_{i,k} \omega_i)^H T_{i,k} \omega_i + (h_i^H \omega_i) h_i^H \omega_i. \]
where $T_{i,k} = g^H_k \Theta_k G_k^H$, $T_{e,k} = g^H_k \Theta_k G_k^H$, $T_{i,k}^1 = (T_{i,k} \omega_j)^H T_{i,k} \omega_j$, $T_{i,k}^2 = (T_{i,k} \omega_j)^H (h_i^H \omega_j + T_{i,k} \omega_j)(h_i^H \omega_j)^H$.

Similarly, the power of received signal of $i$-th user at eavesdropper in (5) can be expressed as:

$$
|\sum_{k=1}^K \alpha_{i,k} T_{i,k}^1 + \hat{F}_{i,k}^1 + \hat{F}_{i,k}^2 + |b_i|^2].
$$

(34)

Furthermore, let $T_{N_{i,k}}^1 = (T_{i,k} \omega_j)^H T_{i,k} \omega_j$, $T_{N_{i,k}}^2 = (T_{i,k} \omega_j)^H (h_i^H \omega_j + T_{i,k} \omega_j)(h_i^H \omega_j)^H$. In this case, the achievable secrecy rate in (7) can be reformulated as:

$$
R_i^s - R_i^c = F_i^1 + F_i^2 - F_i^3 - F_i^4,
$$

where $F_i^1$, $F_i^2$, $F_i^3$ and $F_i^4$ are represented by:

$$
F_i^1 = \log_2 \left[ \sum_{k=1}^K \alpha_{i,k} (T_{i,k}^1 + \hat{T}_{i,k}^1) + |b_i|^2 + \sum_{j \neq i} \sum_{k=1}^K \alpha_{j,k} (T_{j,k}^1 + \hat{T}_{j,k}^1) \right].
$$

(35)

$$
F_i^2 = \log_2 \left[ \sum_{j \neq i} \sum_{k=1}^K \alpha_{j,k} (T_{j,k}^1 + \hat{T}_{j,k}^1) + |b_{i,j}|^2 + \sum_{k=1}^K \alpha_{i,k} (T_{N_{i,k}}^1 + T_{N_{i,k}}^2) + |c_{i,j}|^2 + N_0 \right].
$$

(36)

$$
F_i^3 = \log_2 \left[ \sum_{j \neq i} \sum_{k=1}^K \alpha_{j,k} (T_{j,k}^1 + \hat{T}_{j,k}^1) + |b_{i,j}|^2 + \sum_{k=1}^K \alpha_{i,k} (T_{N_{i,k}}^1 + T_{N_{i,k}}^2) + |c_{i,j}|^2 + N_0 \right].
$$

(37)

$$
F_i^4 = \log_2 \left[ \sum_{j \neq i} \sum_{k=1}^K \alpha_{j,k} (T_{j,k}^1 + \hat{T}_{j,k}^1) + |b_{i,j}|^2 + \sum_{k=1}^K \alpha_{i,k} (T_{N_{i,k}}^1 + T_{N_{i,k}}^2) + |c_{i,j}|^2 + N_0 \right].
$$

(38)

In order to solve the subproblem, we first relax integer variable $\alpha$, then we solve the problem by using convex optimization. Similarly, we adopt SCA method to construct global overestimators of $F_i^3$ and $F_i^4$:

$$
F_i^3(\tilde{\alpha}_i) \leq F_i^3(\tilde{\alpha}_i) + \text{Tr}(\nabla_\tilde{\alpha}_i F_i^3(\tilde{\alpha}_i)^T (\tilde{\alpha}_i - \tilde{\alpha}_i)) = F_i^3(\tilde{\alpha}_i, \tilde{\alpha}_i),
$$

(39)

$$
F_i^4(\tilde{\alpha}_i) \leq F_i^4(\tilde{\alpha}_i) + \text{Tr}(\nabla_\tilde{\alpha}_i F_i^4(\tilde{\alpha}_i)^T (\tilde{\alpha}_i - \tilde{\alpha}_i)) = F_i^4(\tilde{\alpha}_i, \tilde{\alpha}_i).
$$

(40)

Fig. 2. Overall setups for numerical evaluation.

where $\tilde{\alpha}_i = [\alpha_{i,1}, ..., \alpha_{i,K}]$. Thus, can be transformed into a convex problem by introducing auxiliary variable $x$:

$$
\text{Problem 4b: } \min_{x, \alpha} x \quad (41)
$$

s.t. $x \geq F_i^1 + F_i^2 + \tilde{F}_i^1 + \tilde{F}_i^2$, $\forall i \in \mathcal{U}$, (C9)

$$
\sum_{k} \alpha_{i,k} = 1, \quad \alpha_{i,k} \in [0, 1], \quad \forall i \in \mathcal{U}. \quad (C10)
$$

In this case, Problem 4b becomes a general convex problem. By solving the convex problem and round the relaxed solution, we can get integer feasible solution.

IV. NUMERICAL EVALUATION

To evaluate the performance of the proposed scheme, a series of numerical evaluations are conducted in this section. The overall setups are shown in Fig. 2, we consider the base station is located at $(10, 0, 10)$, IRSs and legitimate users are uniformly distributed around base station for a constant angle $\theta^*$. The first user and IRS is located at $(5, 67, 5)$ and $(8, 67, 2)$, respectively. The Eve is located at $(10, 60, 5)$ where in the middle of base station and the first user. We also consider that the direct channel between base station and users are blocked by obstacles, which means the channel state of base station to user is much worse than the channel state of IRS to user. Specifically, the channel from base station to IRS/users/Eve is assumed as the distance-dependent path loss model, which can be generated by $h = \sqrt{L_0 d^{-\delta} h^*}$, where $d_{ab}$ denotes the distance from location $a$ to location $b$, and $h^*$ is the small-scale fading component assumed to be Rician fading [26, 27].

$$
h^* = \sqrt{\frac{K}{K + 1}} h_{LoS}^* + \sqrt{\frac{1}{K + 1}} h_{NLoS}^*.
$$

(42)

where $h_{LoS}^*$ and $h_{NLoS}^*$ represent the deterministic Line-of-Sight (LoS) and Rayleigh fading/Non-LoS (NLoS) components, respectively. The LoS components are expressed by the responses of the N-elements uniform linear array $h_{LoS}^* = a_m(\theta) \Delta \omega$, where $m = 1, ..., M$.

$$
a_m = \exp(j \frac{2\pi}{\Delta \omega} d_t (m - 1) \sin \theta_{LoS}), m = 1, \ldots, M.
$$
where $d_i$ and $d_r$ are the inter-antenna separation distance at the transmitter and receiver, $\phi_{LoSi}$ and $\phi_{LoSi}$ are LoS azimuth at base station and IRS, $\theta_{LoSi}$ and $\theta_{LoSi}$ are the angle of departure at base station and angle of arrival at IRS, respectively. The rest of parameter settings are listed in Table I and two baselines are considered:

- **Baseline 1**: Only beamforming is considered at base station, and IRS is not deployed in the system.
- **Baseline 2**: Beamforming is considered at base station, and only one IRS is deployed in the system.

To learn the influence of different number of reflecting elements $N$ on each IRS, the performance comparison is shown in Fig. 3. Due to the existence of obstacles, the LoS component is relatively bad for wireless transmission between base station and user. When only one user is considered, the proposed scheme with AN has almost the same performance as the one without AN, the same conclusion is also verified by [9]. When there are 2 or more users, additional AN can help to improve secrecy rate about 4-6% especially with the increase of $N$. Without the assistance of IRS and AN, baseline 1 has the worst performance compared with other schemes since the direct channel between base station and user is blocked. For fair comparison, we change $\beta_{BU} = \beta_{BE} = 2$ for the beamforming scheme and the result also shows that the performance of beamforming scheme is relatively bad when there are multiple users. For baseline 2, since users are distributed apart from each other, only one IRS cannot satisfy the requirement of secure communication.

The achievable secrecy rate versus number of users is shown in Fig. 4. As we can see, the performance of all schemes in terms of achievable secrecy rate are degrading rapidly with the increase of users. When there are more than 2 users, the proposed scheme perform better than AN-disabled scheme with 5% to 18.9% advantages. Here, for a fair comparison, we also set $\beta_{BU} = \beta_{BE} = 2$ in baseline 1. The result also shows that beamforming scheme in baseline 1 can not deal with multiple users scenario. Meanwhile, since the distance between IRS and users will significantly influence the performance of IRS-assisted scheme, we also set up a friendly scenario to baseline 2, i.e., all users are uniformly located in the line from (8, 67, 2) to (8, 75, 2). When only single IRS is deployed, the performance becomes even worse than baseline 1. The reason is that the spatial diversity provided by the IRS is limited. If the overall performance is considered, e.g., the sum of secrecy rate, the system still can sacrifice a part of users’ performance to have a better overall performance. If the worst performance in the system is considered as the objective, it becomes hard to optimize since each user matters. In this case, the algorithm tends to sacrifice the user who has the highest secrecy rate and make up for the user who has the worst secrecy rate, but the compensation is not valued due to the lack of spatial diversity. In this case, a bad performance is obtained.

The performance of achievable secrecy rate versus transmission power is shown in Fig. 5. The maximum transmission power ranges from 7W (38.45dBm) to 10W (40dBm). With the increase of transmission power, the performance of all schemes increase linearly. Similar to the results in Fig. 4,

---

**TABLE I**

**SIMULATION PARAMETERS**

| Parameter                      | Value                                                                 |
|-------------------------------|----------------------------------------------------------------------|
| Carrier frequency             | 2GHz                                                                |
| IRS configuration             | Uniform rectangular array with 5 elements in a row and N/5 columns, 3λ/8 spacing |
| Path loss exponent           | $\beta_{BU} = \beta_{BE} = 5$, $\beta_{BI} = \beta_{IU} = \beta_{IE} = 2$, respectively |
| Rician channel factor        | $K_{BU} = K_{BE} = 0$, $K_{BI} = K_{IU} = K_{IE} = \infty$, respectively |
| Path loss at 1 meter         | $L_0 = -30dB$                                                        |
| Other parameters             | $N_0 = -174dBm$, $Tx = 4$, $\delta = 0.001$, $\theta^* = 20^\circ$ |

---

![Figure 3](image-url)  
Fig. 3. Achievable secrecy rate vs number of elements ($P_{max} = 40dBm$).

![Figure 4](image-url)  
Fig. 4. Achievable secrecy rate vs number of users ($P_{max} = 40dBm$ and $N = 20$).
the proposed scheme can have better performance than AN-disabled scheme when there are more than 2 users in the system. To have a fair comparison, we also consider LoS channel is not blocked by obstacle and set $\beta_{BU} = \beta_{BE} = 2$ for baseline 1 with 2 users. However, the result shows that the performance of baseline 1 is much lower than IRSs-assisted schemes. For baseline 2, since the performance is mainly limited by spatial diversity, it remains relatively steady and increases linearly from 0.9bps/Hz to 0.96bps/Hz with the increase of transmission power.

In general, fairness problem and overall system performance are two common objectives considered in wireless communication. To compare the performance of max-min problem proposed in this paper with sum-rate problem, we also plot Fig. 6 to show the difference in terms of the sum of secrecy rate and the minimum secrecy rate, and the problem in (43) with constraints (C1)-(C3) is adopted as another optimization problem:

$$\max_{\alpha, \xi, \theta, \sigma} \sum_i [R_i^a - R_i^e]^+ \quad (43)$$

$$s.t. \quad (C1) - (C3).$$

As shown in Fig. 6 for the performance in terms of the minimum secrecy rate, the gap between two objectives can vary rapidly with different number of elements, especially for more users scenario, which means sum-rate objective can hardly guarantee the worst secrecy rate of different users. For the performance in terms of the sum of secrecy rate, with the increase of elements, overall sum secrecy rate of these two objective tends to converge and have similar performance. This phenomenon indicates that a max-min problem can achieve better minimum secrecy rate and also reach similar performance of overall secrecy rate for a large-scale IRS-assisted system. Meanwhile, in Fig. 7 the sum of secrecy rate increases with the number of users. Even though it can sacrifice a part of users’ performance to improve overall performance, the curve shows that the gain becomes lose and the sum secrecy rate can reach a threshold with the increase of users, which indicates the maximum secrecy capacity in the system. For the gap between two different objectives, it also becomes larger with the increase of users, which is reasonable since the solution space becomes larger with more users in the system, and different solutions obtained from the aforementioned objectives can also influence more users.

V. CONCLUSION

In this paper, we studied physical layer security in multiple IRSs-assisted systems. In order to guarantee the worst secrecy performance of multiple users in case eavesdropper might eavesdrop useful information from a certain user, beamforming and AN vector at the base station, phase shift matrix at IRSs and surface selection matrix were jointly considered and a max-min objective was formulated. Considering the coupled variables in the objective, an alternative optimization was adopted and the sub-problems could be solved based on SDP and SCA. To verify the performance of the proposed scheme, a series of numerical evaluations were conducted. The results...
show that the proposed scheme can effectively adapt to the sophisticated application scenario and the performance can be significantly improved compared with the traditional schemes.

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