Robust Security Energy Efficiency Optimization for RIS-Aided Cell-Free Networks With Multiple Eavesdroppers

Wanming Hao, Senior Member, IEEE, Junjie Li, Ming Zeng, Member, IEEE, Gangcan Sun, Member, IEEE, Chongwen Huang, Member, IEEE, Octavia A. Dobre, Fellow, IEEE, and Chau Yuen, Fellow, IEEE

Abstract—In this paper, we investigate the energy efficiency (EE) problem under reconfigurable intelligent surface (RIS)-aided secure cell-free networks, where multiple legitimate users and eavesdroppers (Eves) exist. We formulate a max-min security EE optimization problem by jointly designing the distributed active beamforming and artificial noise at base stations as well as the passive beamforming at RISs under practical constraints. To deal with it, we first divide the original optimization problem into two sub-ones, and then propose an iterative optimization algorithm to solve each sub-problem based on the fractional programming, constrained concave-convex procedure (CCCP) and semi-definite programming (SDP) techniques. After that, these two sub-problems are alternatively solved until convergence, and the final solutions are obtained. Next, we extend to the imperfect channel state information of the Eves’ links, and investigate the robust security EE beamforming optimization problem by bringing the outage probability constraints. Based on this, we first transform the uncertain outage probability constraints into the certain ones by the Bernstein-type inequality and sphere boundary techniques, and then propose an alternatively iterative algorithm to obtain the solutions of the original problem based on the S-procedure, successive convex approximation, CCCP, and SDP techniques. Finally, the simulation results are conducted to show the effectiveness of the proposed schemes.

Index Terms—Cell-free networks, reconfigurable intelligent surface (RIS), security energy efficiency.

I. INTRODUCTION

WITH the rapid development of global mobile communications, the demand for high-speed traffic is increasing [2], [3], [4]. To satisfy such huge requirement of wireless data, more base stations (BSs) should be deployed. However, this will lead to more serious interference among BSs [5]. To address this, a multi-point cooperative transmission-based cell-free (CF) network structure can be developed, where users are served by multiple BSs simultaneously, effectively mitigating the interference [6]. Additionally, more BSs will also result in a large power consumption, which is undesirable for energy source [7]. Fortunately, the low-power and low-cost reconfigurable intelligent surface (RIS) technique can be deployed nowadays, and it can smartly change the wireless circumstance so as to improve the signal’s strength or wireless coverage via adjusting the reflecting coefficients (RCs) of RIS elements [8], [9], [10]. Deploying more RISs instead of BSs will improve the spectral efficiency (SE) and energy efficiency (EE) of the system in future.

Undoubtedly, due to the open nature of wireless communications, the CF works can enhance the desired signals by the cooperation among BSs and RISs, while the information are also susceptible to be eavesdropped by Eves due to more paths [11]. Recently, the physical layer security (PLS) is regarded as a promising technique to improve the wireless data security via designing beamforming and artificial noise (AN) at the BS [12]. The decoding probability can be
improved by reasonably aligning the beamforming and AN at the legitimate receiver. Consequently, the confidentiality and integrity of the communication can be guaranteed even if the Eve owns high computational power [13]. Compared with traditional secure encryption mechanisms, PLS requires only simple computational operations to design the precoding without incurring additional complexity and communication overhead [14]. Therefore, it is more suitable for securing complex cell-free networks. Moreover, RIS can adjust the phase shift of the incident signal via a microcontroller to enhance the desired signal while weakening Eve’s signal reception [9], which effectively improve the PLS.

It is worth noting that the recent application of the PLS technique to the CF networks and RIS-aided secure networks has aroused great interest among researchers [11].

A. State-of-the-Art

Recently, it has been verified that the CF networks can enhance information security via cooperative beamforming optimization [15], [16], [17], [18], [19], [20]. For example, to maximize the security SE (SSE) of the full duplex CF networks, an effective double-loop algorithm was proposed [15]. Reference [16] investigated the impact of hardware impairments on security performance in a CF network, and proposed a successive convex approximation (SCA) and path-following algorithm to maximize the SE of the system. Reference [17] investigated the simultaneous wireless information and power transfer (SWIPT) in the secure CF networks, and derived the lower bound of ergodic SSE and average capture energy. Reference [18] analyzed the security in a multiple-input multiple-output (MIMO) system based on the digital-to-analog converter (DAC) architecture, and derived the additive quantization noise model-based precise closed-form expression of the SE. After that, it proposed a path tracking-based power optimization algorithm to maximize the achievable SE. In [19], PLS in scalable CF massive MIMO is studied, and the system security performance is characterized based on the outage SSE and ergodic SSE. In [20], the authors assume that multiple Eves collude with each other to wiretap signals in a CF massive MIMO network, and investigate the SSE maximization problem.

Additionally, RIS is beneficial for information security owing to its ability to enhance the signal strength of the legitimate users and weaken that of the eavesdroppers (Eves) by adjusting the RC of each RIS element [21], [22], [23], [24], [25]. For example, [21] studied the secure transmission problem in the multi-layer RIS-aided integrated terrestrial-aerial networks, and proposed a block coordinate reduction-based optimization framework. Dong et al. [22] proposed for the first time to apply active RIS to PLS, and designed an alternative optimization (AO) algorithm, which effectively overcome the dual fading impact of the reflective link channel. Using the stochastic geometry tool, [23] derived the exact closed-form expressions of probability density function and cumulative distribution function (CDF) of the received signals with/without RIS. By jointly optimizing the trajectory and passive beamforming, the SSE of the system is effectively improved. In [24], a location model based on Eve with/without RIS orientation is considered, respectively. The probability distribution function of Eve’s location/link is studied, and the cumulative density function of the signal-to-noise ratio (SNR) is derived. In [25], a collaborative internet of things (IoT) security network with refracting/reflecting RIS is investigated. A scheme of linearized objective function is proposed for the formulated maximum weighted sum secrecy rate, and a joint optimization algorithm based on Lagrangian dual method and penalty dual decomposition is proposed.

Notably, introducing RISs to CF networks has the following benefits compared with the conventional CF networks: 1) Enhance signal strength and coverage: RISs can act as an array of antennas away from the BS, enabling users to obtain better signal quality over a wider area [26]; 2) Improve network throughput and latency: RISs can be used to optimize network topology and transmission routing, making data transmission more efficient, thereby increasing network throughput and reducing latency [26]; 3) Dynamically adjust the network: RISs can dynamically adjust the network topology and transmission routing according to practical circumstance, and thus optimizing the system performance and improving the quality of service [27]; 4) Reduce cost and power consumption: The MIMO systems require complex digital-to-analog converters, energy-consuming radio frequency chains, higher hardware costs, introduce additional noise, and the large number of MIMO BSs will lead to the huge cost. Replacing several MIMO BSs with several low-cost and low-power RISs can effectively reduce the power consumption and hardware complexity compared to the conventional CF networks [5]. 5) Enhance the network security: RISs can precisely adjust the amplitude and phase of incoming electromagnetic waves, and provide a high degree of control over wave direction and intensity, thereby enhancing the desired destination signal reception and suppressing interference to unintended users [28]. These motivate this paper to investigate the PLS technique for RIS-aided CF networks.

B. Main Contributions

Based on the above analysis, the recent works mainly focus on the SE of CF networks or RIS-aided networks. In addition, several works considering the RIS-aided CF networks, only the SSE is investigated [11], [12]. The security EE (SEE), as another important indicator [29], has not been investigated. Additionally, the above works all assume perfect channel state information (CSI). Although the legitimate users’ CSI can be obtained by advanced channel estimation techniques, the Eves’ CSI is difficult to obtain for the BSs. Therefore, a more practical system model for the RIS-aided secure CF networks should be conducted when beamforming resources are studied.

To fill in the above gap, in this paper we investigate robust max-min SEE optimization problem in the RIS-aided secure CF networks based on perfect and imperfect CSI.\(^1\) While, it also brings more challenges. Summarily, the main contributions of this works as follows:

\(^1\)Robust means that our proposed algorithms can be applied to different scenarios including the perfect CSI and imperfect CSI, as our research in this work.
We consider a RIS-aided secure CF network, where multiple low-cost efficient RISs are deployed in the CF network to enhance signal strength and coverage, and AN is added at the BS to interfere Eves. Meanwhile, we assume that there exist multiple Eves and legitimate users based on the practical scenario. To investigate the SEE, we formulate a max-min SEE optimization problem by jointly designing the cooperative active beamforming and AN at BSs as well as the passive beamforming at RISs under the constraints of each BS transmit power and the unit modulus of each RIS element. This aims to improve the minimum user’s SEE.

We first study the above problem based on perfect CSI to obtain a upper bound of the performance. In fact, it is extremely difficult to directly solve the formulated problem because the objective function is a non-smooth fractional form of convex difference, and it is characterized by multiple disturbances and strong coupling. Thus, we divide it into two subproblems by fixing variables, namely, the cooperative active beamforming and AN optimization subproblem as well as the cooperative passive beamforming optimization subproblem. For the former, several auxiliary variables are introduced to remove the non-smoothness of the max-min objective function, and the corresponding constraints are transformed into a subtractive form using the first-order Taylor expansion and fractional programming (FP) techniques, and then the constraints are decoupled based on SCA, constrained concave-convex procedure (CCCP), and SDP techniques. For the latter, a similar scheme is used to optimize the cooperative passive beamforming of RISs. Finally, we propose an iterative algorithm that alternately updates these two sub-ones until convergence, and the final solution are obtained.

Next, considering the difficulty to obtain the perfect CSI for eavesdropping links, we re-investigate the max-min robust SEE problem based on imperfect CSI in term of Eves’ links, and introduce the outage probability constraint for the eavesdropping rate. Due to the semi-infinite constraint and outage probability constraint, the overall solution is extremely complex. To deal with it, we first apply the Bernstein-type inequality (BTI) and sphere boundary theories to transform the uncertain outage probability constraints into the certain ones. Next, we divide the transformed optimization problem into two sub-ones, and solve the semi-infinite constraints and decoupling variables based on the S-procedure, SCA, CCCP and SDP techniques, and linearly optimize the phase shift by singular value decomposition (SVD) technique. Next, we obtain the solutions of the original problem by alternatively solving these two subproblems until convergence. Finally, we prove the convergence and analyze the computational complexity for the proposed algorithms.

The rest of this paper is organized as follows. In Section II, the system model of the downlink RIS-aided secure CF networks is introduced, and the max-min SEE optimization problem is formulated. Section III presents the proposed joint optimization framework based on the perfect CSI, and Section IV supplements the solutions based on imperfect CSI for the Eves’ links. Section V analyzes the proposed algorithms. The simulation results are shown in Section VI. Finally, conclusions are given in Section VII.

Notation: Boldface letters denote vectors or matrices. \( \mathbb{R}^{K \times J} \) and \( \mathbb{C}^{K \times J} \) denote real-valued and complex-valued matrices of size \( K \times J \), respectively. \( \mathbf{1}^T \), \( \mathbf{1} H \), \( \text{Tr}(\cdot) \), \( \text{Rank}(\cdot) \), respectively, denote the transpose, conjugate transpose, trace and rank. For a complex value \( x \), \( |x| \) represents its modulus. For a vector \( \mathbf{a} \), \( \text{diag}(\mathbf{a}) \) represents the diagonal operation, \( \| \mathbf{a} \| \) represents the Euclidean norm. For a matrix \( \mathbf{A} \), \( [\mathbf{A}]_{i,j} \) is the element at position \((i, j)\), \( \mathbf{A} \geq 0 \) represents the semi-definite matrix, \( \text{vec}(\mathbf{A}) \) represents the matrix vec operator of \( \mathbf{A} \). \( \mathbf{I}_M \) is an identity matrix of size \( M \times M \). \( [\cdot]^+ \) denotes the max \( \{0, \cdot\} \), and \( \text{Pr}\{\cdot\} \) denotes the probability.

II. SYSTEM MODEL AND PROBLEM FORMULATION

In this section, we first introduce the system model for the considered RIS-aided secure CF networks, and then formulate the max-min SEE optimization problem under practical constraints.

A. System Model

We consider a RIS-aided downlink secure CF network, as shown in Fig. 1, which includes \( B \) BSs and \( R \) RISs.\(^2\) We assume that all BSs are connected to a central processing unit (CPU) via high-speed backhaul links and RISs are connected to the CPU or BSs via wired or wireless [5], and the CPU owns extremely high computational power, thus the overall decision-making and regulation latency can be guaranteed [30]. BSs and RISs are controlled and planned through the CPU to serve all users collaboratively, and the algorithm running at the CPU ensures synchronization between BSs and RISs. Additionally, BSs within a certain range cooperate in a distributed manner, signaling messages can be exchanged between nearby BSs in a timely manner [31], and then conveyed by BSs closer to the CPU thereby reducing signaling overhead and latency.\(^3\)

Meanwhile, there are \( M \) antennas for each BS and \( N \) reflecting elements for each RIS for convenience. Additionally, we assume that there are \( K \) single-antenna legitimate users and \( J \) single-antenna Eves, and the Eves are independent each other. Since all BSs collaboratively serve users in the CF networks, it is only required that the total number of antennas of all BSs is larger than the number of users. Let \( \forall b \in B = \{1, \ldots, B\}, \forall r \in \mathcal{R} = \{1, \ldots, B\}, \forall n \in \mathcal{N} = \{1, \ldots, N\}, \forall k \in \mathcal{K} = \{1, \ldots, K\} \) and \( \forall j \in \mathcal{J} = \{1, \ldots, J\} \) denote the sets of BSs, RISs, RIS elements, users and Eves, respectively. The main symbols of the paper are listed in TABLE I.

Each BS allocates a dedicated beamforming vector for each user, and thus the transmission signal of the \( b \)-th BS can be guaranteed. In this paper, the scenario of one CPU is considered.

\(^2\)Multiple RISs in communication limited vision areas can enable users to obtain better serve quality over a wider range [30].

\(^3\)Furthermore, nearby BSs and RISs form a CF network sharing one CPU, and other neighboring BSs and RISs form another CF network using another CPU. Then, the coverage of each CPU is relatively small and the signal delay can be guaranteed. In this paper, the scenario of one CPU is considered.
Thus, the signals received by the $k$-th BS, $k \in \{1, \ldots, K\}$, are expressed as

$$y_{k,j} = \sum_{b \in \mathcal{B}} \left( h_{b,k,j}^H + \sum_{r \in \mathcal{R}} f_{r,k,j}^H \Theta_r^H G_{b,r} \right) x_b + n_{e,j}, \quad (1b)$$

where $h_{b,k} \in \mathbb{C}^{M \times 1}$ and $h_{b, e,j}^r \in \mathbb{C}^{M \times 1}$ denote the direct link channels from the $b$-th BS to the $k$-th user and the $j$-th Eve, respectively. $G_{b,r} \in \mathbb{C}^{N \times M}$, $f_{r,k} \in \mathbb{C}^{N \times 1}$ and $f_{r,e,j} \in \mathbb{C}^{N \times 1}$ denote the reflective link channels from the $b$-th BS to the $r$-th RIS, the $r$-th RIS to the $k$-th user, and the $r$-th RIS to the $j$-th Eve, respectively. $n_k \in \mathcal{CN}(0, \sigma_k^2)$ and $n_{e,j} \in \mathcal{CN}(0, \sigma_{e,j}^2)$ denote the complex additive white Gaussian noise (AWGN) of the $k$-th user and the $j$-th Eve, respectively, and own zero mean and variances $\sigma_k^2$ and $\sigma_{e,j}^2$, respectively. $\Theta_r$ represents the phase shift matrix of the $r$-th RIS and can be written as $\Theta_r = \text{diag}(\theta_{r,1}, \ldots, \theta_{r,N})$, where $\theta_{r,n}$ is the $n$-th reflecting element of the $r$-th RIS denoted as $\mathcal{F} = \{ \theta_{r,n} | r \in \mathcal{R}, \theta_{r,n} \in [0, 2\pi], \eta_{r,n} \in [0, 1] \}$, and $\eta_{r,n}$ represents the reflection efficiency of the $n$-th reflecting element of the $r$-th RIS. Without loss of generality, we set $\eta_{r,n} = 1$ to maximize the reflection signal. Additional, since the signals reflected via multiple times by RISs are very weak, we omit them here [32]. Besides, the RIS works in a full-duplex model [26], and thus it only needs one time slot for the RIS-aided networks, similar to the existing works [5], [12].

We assume that the system operates in time-division duplex mode, and in the uplink the users first transmit orthogonal pilots to BSs via direct and RISs cascade channels, and through the high-speed forward link to the CPU, which performs a typical channel estimation technique to obtain the CSI [33], [34]. Next, the downlink CSI is obtained based on channel reciprocity, according to which the CPU designs precoding orders to be transmitted to the corresponding BSs and RISs for dynamic regulation, and then the BS transmits signals to users with the help of RISs. In particular, for the case where Eves are active, the BS can easily obtain their CSI [35]. For the case of passive Eves, their specific locations can be detected by positioning techniques, and the approximation CSI can be obtained by the line-of-sight (LoS) path component [36], or by detecting the Eves’ CSI from the local oscillator power leaked by the radio frequency front-end [37]. In addition, Eves’ CSI can also be obtained by channel information prediction techniques, such as deep learning-based CSI prediction [38].

The desired signals for the $k$-th user and the $j$-th Eve who steals the information of the $k$-th user can be expressed as

$$y_k^D = \sum_{b \in \mathcal{B}} \left( h_{k,b,k}^H + \sum_{r \in \mathcal{R}} f_{r,k}^H \Theta_r^H G_{b,r} \right) x_b + s_k \quad (2a)$$

$$y_{k,j}^D = \sum_{b \in \mathcal{B}} \left( h_{k,b,j}^H + \sum_{r \in \mathcal{R}} f_{r,k,j}^H \Theta_r^H G_{b,r} \right) x_b + s_k \quad (3a)$$

where (3a) defines $h_{d,k} = [h_{d,k}^T, \ldots, h_{d,b,k}^r]$, $\Theta = [\Theta_1^T, \ldots, \Theta_R^T]$, $\Theta_r = \text{diag}(\Theta_r)$, $H_k^R = \text{diag}(f_k^H)$. 

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**TABLE I**

| Notation | Description |
|----------|-------------|
| $\mathcal{B}/\mathcal{R}/\mathcal{C}$ | The number of BSs, RISs, users, and Eves |
| $\mathcal{M}/\mathcal{N}$ | The number of antennas each BS and RIS |
| $s_k$ | Transmission symbol of the $k$-th user |
| $\mathbf{x}_k$ | Transmission signal of the $b$-th BS |
| $\mathbf{w}_{b,k}$ | Beamforming and AN vectors of the $k$-th user at the $b$-th BS |
| $\mathbf{w}_{b,k}/\mathcal{V}_k$ | Equivalent beamforming and AN matrix of the $k$-th user |
| $\mathbf{h}_{b,k}$ | Direct channels from the $b$-th BS to the $k$-th user and the $j$-th Eve |
| $G_{b,r}$ | Reflected channel from the $b$-th BS to the $r$-th RIS |
| $f_{r,k}/\mathcal{F}_{r,e,j}$ | Reflected channel from the $r$-th RIS to the $k$-th user and the $j$-th Eve |
| $n_k$ | Complex AWGN of the $k$-th user and the $j$-th Eve |
| $\sigma_k^2/\sigma_{e,j}^2$ | Variances of $n_k$ and $n_{e,j}$ |
| $\Theta_r$ | Phase shift matrix of the $r$-th RIS |
| $\mathbf{\Theta}_r$ | The $n$-th reflecting element of the $r$-th RIS |
| $\mathbf{\Theta}_r$ | Equivalent RIS phase shift vector and matrix |
| $\eta_{r,n}$ | Reflection efficiency of $\theta_{r,n}$ |
| $R_k$ | Achievable secrecy rate of the $k$-th user |
| $\mathbf{P}_b/\mathbf{P}_{c}/\mathbf{P}_R$ | Hardwire-powered power at the BS, user, and RIS element |
| $P_c$ | Circuit power consumption |
| $P_{c_{\text{max}}}$ | Total power consumption of the $k$-th user |
| $P_{e,b}$ | Maximum transmit power of the $b$-th BS |
| $\xi$ | Power amplifier efficiency |
| $\eta_{\text{BB}}$ | SIR of the $k$-th user |
| $\mathbf{h}_{d,e,j}/\mathcal{F}_{e,j}$ | Actual estimation vectors of $h_{d,e,j}$ and $f_{e,j}$ |
| $\Delta h_{d,e,j}/\Delta f_{e,j}$ | Estimation errors of $h_{d,e,j}$ and $f_{e,j}$ |
| $\mathcal{E}_{d,e,j}/\mathcal{E}_{e,j}$ | Variances of $\Delta h_{d,e,j}$ and $\Delta f_{e,j}$ |
| $s_{j}/\Delta s_{j}$ | The $j$-th Eve’s equivalent channel and error vectors |
| $R_{e,j}$ | The redundancy of the $j$-th Eve |
| $\varphi_k$ | Maximum outage probability of the $k$-th user |

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The signals received by the $k$-th user and the $j$-th Eve wiretapping the $k$-th user’s information are expressed as

$$y_k = \sum_{b \in \mathcal{B}} \left( h_{b,k}^H + \sum_{r \in \mathcal{R}} f_{r,k}^H \Theta_r^H G_{b,r} \right) x_b + n_k, \quad (1a)$$

be expressed as $\mathbf{x}_k = \sum_{k=1}^K (w_{b,k} s_k + v_{b,k})$ where $w_{b,k} \in \mathbb{C}^{M \times 1}$ represents the beamforming vector of the $k$-th user at the $b$-th BS, $s_k$ represents the transmission symbol of the $k$-th user with $\{ |s_k|^2 \} = 1$, and $v_{b,k} \in \mathbb{C}^{M \times 1}$ represents the AN vector of the $b$-th BS for the $k$-th user. Thus, the signals received by the $k$-th user and the $j$-th Eve wiretapping the $k$-th user’s information are expressed as
\[f_k = [f_{1,k}^T, \ldots, f_{R,k}^T]^T, \quad G = [G_1, \ldots, G_B], \quad G_b = [G_{b,1}^T, \ldots, G_{b,R}^T]^T, \quad \text{and} \quad w_k = [w_{1,k}^T, \ldots, w_{B,k}^T]^T,\]
deefines \( \theta = [\theta^T, 1]^T \) and \( H_k = [(H_k)^H, h_{d,k}]^H, \)
(3e) defines \( h_{d,c,j} = [h_{d,1,c}^T, \ldots, h_{d,R,c}^T]^T, \)
and \( f_{d,c,j} = [f_{d,1,c}^T, \ldots, f_{d,R,c}^T]^T, \)
(3e) defines \( H_{c,j} = [(H_{c}^R)^H, h_{d,c}]^H. \) For convenience, we define
\[w = [w_1^T, \ldots, w_T^T], \quad v = [v_1^T, \ldots, v_T^T], \quad \text{and} \quad v_k = [v_{1,k}^T, \ldots, v_{B,k}^T].\]
On this basis, the achievable secrecy rate of the \( k \)-th user can be expressed as
\[R_k = \left[ \log_2 \left( 1 + \gamma_k \right) - \max_{j \in J} \left[ \log_2 \left( 1 + \gamma_{k,j} \right) \right] \right]^+ , \quad (4)\]
where \( \gamma_k \) and \( \gamma_{k,j} \) denote the signal-to-interference-plus-noise ratio (SINR) of the \( k \)-th user and the \( j \)-th Eve, respectively, which are given by
\[\gamma_k = \frac{\left| \theta^H H_k w_k \right|^2}{\sum_{i=1, i \neq k}^{K} \left| \theta^H H_i w_i \right|^2 + \sum_{i=1}^{K} \left| \theta^H H_i v_i \right|^2 + \sigma_k^2}, \quad (5a)\]
and
\[\gamma_{k,j} = \frac{\left| \theta^H H_{c,j} w_{k} \right|^2}{\sum_{i=1, i \neq k}^{K} \left| \theta^H H_{c,j} w_i \right|^2 + \sum_{i=1}^{K} \left| \theta^H H_{c,j} v_i \right|^2 + \sigma_{c,j}^2}. \quad (5b)\]
The total power consumption for the \( k \)-th user consists of transmit power and circuit power consumption, which can be calculated as
\[P_{k}^{\text{total}} = \frac{1}{\zeta} \left( \text{Tr} \left( w_k w_k^H \right) + \text{Tr} \left( v_k v_k^H \right) \right) + P_c, \quad (6)\]
where \( \zeta \) denotes the power amplifiers efficiency, and \( P_c \) denotes the circuit power consumption denoted as \( P_c = B P_B + P_U + R N P_R, \) where \( P_B, P_U \) and \( P_R \) are denoted as the hardware-dissipated power at the BS, user and RIS element, respectively. Finally, the SEE of the \( k \)-th user is defined as the ratio of the security rate of the \( k \)-th user to its power consumption, which can be expressed as
\[\eta_k^{\text{EE}} = \frac{R_k}{P_k^{\text{total}}}, \quad (7)\]

\section*{III. PROPOSED JOINT OPTIMIZATION SCHEME}

To deal with \( \mathcal{P}_0 \), we propose an alternatively iterative scheme, namely solving \( \theta \) and \( (W, V) \) alternatively until convergence. We will give the detailed procedure next.

\subsection*{A. Fix \( \theta \) and Solve \( (W, V) \)}

We first introduce two auxiliary variables \( \alpha \in \mathbb{R}^{K \times 1} \) with \( \alpha = [\alpha_1, \ldots, \alpha_K] \) and \( \beta \in \mathbb{R}^{K \times J} \) with \( \beta = [\beta_1, \ldots, \beta_K] \), where \( \beta_k = [\beta_{k,1}, \ldots, \beta_{k,J}] \). Consequently, for given \( \theta^H \), \( \mathcal{P}_0 \) can be converted to the following one
\[\mathcal{P}_1: \min_{w, v, \alpha, \beta, k \in K} \max_{j \in J} \min_{\theta_k \in \mathcal{J}} \log_2 \left( 1 + \alpha_k \right) - \max_{j \in J} \left[ \log_2 \left( 1 + \beta_{k,j} \right) \right]\]
\[\frac{1}{\zeta} \left( \text{Tr} (W_k W_k^H) + \text{Tr} (V_k V_k^H) + P_c \right) \quad (10a)\]
s.t. \( C3: \alpha_k \leq \frac{\theta^H \theta^H}{\beta^H H_k L_k H_k^H \beta} + \sigma_k^2, \quad \forall k \in K, \quad (10b)\]
\[C4: \beta_{k,j}^2 \geq \frac{\theta^H \theta^H}{H_{c,j}^H H_{c,j} + \sigma_{c,j}^2}, \quad \forall k \in K, \forall j \in J, \quad (10c)\]
\[C5: \text{Rank} (W_k) = 1, \quad \forall k \in K, \quad (10d)\]
\[C6: \text{Rank} (V_k) = 1, \quad \forall k \in K, \quad (10e)\]
where \( \mathcal{J} = \{ 1, \ldots, R \} \). Since the objective function of \( \mathcal{P}_1 \) is not smooth enough, we introduce an auxiliary variable \( z \) to reformulate \( \mathcal{P}_1 \) as
\[\mathcal{P}_2: \max_{w, v, \alpha, \beta, z} \quad z \quad (11a)\]
s.t. \( C7: \log_2 \left( 1 + \alpha_k \right) - \log_2 \left( 1 + \beta_{k,j}^2 \right) \geq z, \forall k, \forall j, \quad (11b)\]
\[C1, C3, C4, C5, C6. \quad (11c)\]

The molecule of \( C7 \) is a convex difference function, and the first-order Taylor approximation can be used to transform it into the following convex one
\[\log_2 (1 + \alpha_k) - \log_2 (1 + \beta_{k,j}^2) \approx \log_2 (1 + \alpha_k) - \log_2 (1 + \beta_{k,j}^2) \frac{\beta_{k,j}^2 - \beta_{k,j}^2 \beta_{k,j}^2}{1 + \beta_{k,j}^2}. \]
\[ f \left( \alpha_k, \beta_k, \beta_k^* \right). \] 

where \([t]\) represents the \(t\)-th iteration. Thus, \(C7\) can be rewritten as \(\check{C}7\), namely

\[ \check{C}7 : \frac{1}{\zeta} \left( \text{Tr}(W_k) + \text{Tr}(V_k) \right) + P_e \geq z, \forall k \in K, \forall j \in J. \] (13)

Due to the non-convex constraints of the coupling of \(W\) and \(V\) in \(C3, C4\), and the fractional constraint of \(C7\), it is still difficult to solve \(P_2\). Next, we use the FP method to convert the fractional constraint \(\check{C}7\) into a reformulated form equivalently [39]. It is obvious \(f \left( \alpha_k, \beta_k^*, \beta_k^* \right) > 0 \) and \(\frac{1}{\zeta} \left( \text{Tr}(W_k) + \text{Tr}(V_k) \right) + P_e > 0\), then we introduce an auxiliary variable \(\rho \in \mathbb{R}^{K \times J}\) with \(\rho = [\rho_1, \ldots, \rho_K]\) and \(\rho_k = [\rho_k^1, \ldots, \rho_k^J]\). \(\check{C}7\) can be rewritten as

\[ \check{C}7 : f \left( \alpha_k, \beta_k^*, \beta_k^* \right) = 2 \rho_k^j \left( f \left( \alpha_k^j, \beta_k^*, \beta_k^* \right) \right) - \rho_k^j \left( \frac{1}{\zeta} \text{Tr}(W_k + V_k) + P_e \right) \geq z, \forall k \in K, \forall j \in J. \] (14)

Then, \(P_2\) can be rewritten as

\[ P_3 : \max_{w, v, \alpha, \nu, \rho, \phi} z \] (15a)

s.t.

\[ C1, \quad C3, \quad C4, \quad C5, \quad C6, \quad \check{C}7. \] (15b)

On this basis, we divide two steps to solve \(P_3\).

1) **Solve \( \rho \) and \( \gamma \) (\(W, V\)):** We first fix \(W, V\), and solve \(\rho\). Let

\[ \partial f \left( \alpha_k^j, \beta_k^*, \beta_k^* \right) / \partial \rho_k^j = 0, \] (16)

the optimal \(\rho_k^j^\text{opt}\) can be obtained as

\[ \rho_k^j^\text{opt} = \frac{1}{\frac{1}{\zeta} \text{Tr}(W_k + V_k) + P_e} \left( f \left( \alpha_k^j, \beta_k^*, \beta_k^* \right) \right) \in \mathbb{R}_+^{K \times J}, \forall k \in K, \forall j \in J. \] (17)

2) **Solve (\(W, V\)) and fix \(\rho\):** After obtaining \(\rho\), \(P_3\) is still intractable due to the non-convex constraints of \(C3\) and \(C4\). Here, we introduce auxiliary variable \(\delta \in \mathbb{R}^K\) with \(\delta = [\delta_1, \ldots, \delta_K]\), and \(C3\) can be transformed as

\[ C8 : \alpha_k \delta_k \leq \tilde{H}_k^H W_k \tilde{H}_k, k \in K, \] (18a)

\[ C9 : \delta_k \geq \tilde{H}_k^H L_k \tilde{H}_k + \sigma_k^2, k \in K, \] (18b)

where \(\tilde{H}_k = H_k^H \theta^j^\text{opt}\). For \(\alpha_k \delta_k\), we can write its upper bound as [40]

\[ \alpha_k \delta_k \leq \frac{\alpha_k^j}{2} \delta_k^2 + \frac{\delta_k^j}{2} \alpha_k^2, k \in K. \] (19)

As a result, \(C8\) can be transformed into the following convex constraint

\[ C8 : \frac{\alpha_k^j}{2} \delta_k^2 + \frac{\delta_k^j}{2} \alpha_k^2 \leq \tilde{H}_k^H W_k \tilde{H}_k, k \in K. \] (20)

To deal with \(C4\), we introduce two auxiliary variables \(\varsigma \in \mathbb{R}^{K \times J}\) with \(\varsigma = [\varsigma_1, \ldots, \varsigma_K]\), \(\varsigma_k = [\varsigma_k^1, \ldots, \varsigma_k^J]\) and \(\chi \in \mathbb{R}^{K \times J}\) with \(\chi = [\chi_1, \ldots, \chi_K]\), \(\chi_k = [\chi_k^1, \ldots, \chi_k^J]\), which can be reformulated as

\[ C10 : \beta_k^j \tilde{H}_k^H L_k \tilde{H}_k \geq \varsigma_k^j, \forall k \in K, \forall j \in J, \] (21a)

\[ C11 : \varsigma_k^j \geq \chi_k^j, \forall k \in K, \forall j \in J, \] (21b)

\[ C12 : \chi_k^j \geq \tilde{H}_k^H W_k \tilde{H}_k - \beta_k^j \sigma_c^2, \forall k \in K, \forall j \in J, \] (21c)

where \(\tilde{H}_k = H_k^H \theta^j\). Meanwhile, the non-convex constraint \(C10\) can be written as a convex linear matrix inequality as

\[ \check{C}10 : \begin{bmatrix} \beta_k^j \tilde{H}_k^H L_k \tilde{H}_k & \varsigma_k^j \\ \varsigma_k^j & \chi_k^j \end{bmatrix} \geq 0, \forall k \in K, \forall j \in J. \] (22)

As for \(C11\), we apply the first-order Taylor expansion to \(\varsigma_k^j\) for a given point \(\varsigma_k^j\), and it can be approximately translated into \(\varsigma_k^j \approx \varsigma_k^j \varsigma_k^j - \left( \varsigma_k^j \right)^2 \). Next, \(C11\) can be converted as

\[ \check{C}11 : 2 \varsigma_k^j \varsigma_k^j - \left( \varsigma_k^j \right)^2 \geq \chi_k^j, \forall k \in K, \forall j \in J. \] (23)

Finally, \(P_3\) can be formulated as following one

\[ P_4 : \max_{w, v, \alpha, \nu, \beta, \varsigma, \chi} z \] (24a)

s.t.

\[ C1, \quad C5, \quad C6, \quad \check{C}7, \quad \check{C}8, \quad C9, \quad \check{C}10, \quad \check{C}11, \quad \check{C}12. \] (24b)

\(P_4\) is still intractable due to the existence of the rank-one constraints \(C5\) and \(C6\). Therefore, we choose to drop it and solve its relaxed optimization problem by SDP technique. However, after solving the problem, we need to consider how to convert the obtained \(W^{\text{opt}}\) and \(V^{\text{opt}}\) into feasible \(w^*\) and \(v^*\). Specifically, if the optimal solutions \(W^{\text{opt}}\) and \(V^{\text{opt}}\) of \(P_4\) satisfy the rank-one condition, we can directly use eigenvalue decomposition to obtain feasible \(w^*\) and \(v^*\). Otherwise, we can obtain an approximate solution by Gaussian randomization technique [41].

**B. Fix (W, V) and Solve \(\theta\)**

We define \(Q = \theta \theta^H\) and \(\check{Q} = \tilde{\theta} \tilde{\theta}^H\), and then introduce two auxiliary variables \(\varsigma \in \mathbb{R}^{K \times J}\) with \(\varsigma = [\varsigma_1, \ldots, \varsigma_K]\) and \(\beta \in \mathbb{R}^{K \times J}\) with \(\beta = [\beta_1, \ldots, \beta_K]\), \(\beta_k = [\beta_k^1, \ldots, \beta_k^J]\). Similarly, for given \(W[\gamma]\) and \(V[\gamma]\), \(P_0\) can be reformulated as

\[ P_5 : \max_{Q, \alpha, \beta, \varsigma, \check{Q}} z \] (25a)

s.t.

\[ C3 : \alpha_k \leq \text{Tr} \left( \tilde{H}_k^H Q \tilde{H}_k \right) + \sigma_k^2, \forall k \in K, \] (25b)

\[ C4 : \beta_k^j \geq \left( \text{Tr} \left( \tilde{H}_k^H Q \tilde{H}_k \right) + \sigma_c^2 \right), \forall k \in K, \forall j \in J, \] (25c)

\[ C13 : \text{Tr} \left( E_m \check{Q} \right) = 1, \check{Q} \geq 0, m = 1, \ldots, RN + 1, \] (25d)
Algorithm 1 Proposed Algorithm Based on Perfect CSI

Input: $h_{b,k}, h_{b,e,j}, f_{b,k}, f_{b,e,j}, G_{b,r},$ and $\sigma_{b,e}.$
Output: Beamforming matrix $W$, AN matrix $V$, phase shift matrix $Q$, and SEE $z.$

1: Initialize $W^{[t]}, V^{[t]}, \tilde{Q}^{[t]}, \alpha^{[t]}, \beta^{[t]}, \beta^{[t-1]}, \delta^{[t]}, \varsigma^{[t]}, z^{[t]}$, $t = 0$, and threshold $\tau$;
2: while $z^{[t]} - z^{[t-1]} > \tau$ do
3: \hspace{1em} $t = t + 1$;
4: \hspace{1em} Update $\rho^{[t]}$ by (17);
5: \hspace{1em} Update $W^{[t]}, V^{[t]},$ by solving $P_4$;
6: \hspace{1em} Update $z^{[t]}, \tilde{Q}^{[t]},$ by solving $P_6$;
7: end while
8: return $W^{[t]}, V^{[t]}, \tilde{Q}^{[t]},$ and $z^{[t]}.$

\[ C14: \text{rank} (\tilde{Q}) = 1, \quad \tilde{C}_7, \quad (25e) \]

where $E_{in} \in \mathbb{R}^{(RN+1)\times(RN+1)}$ satisfies that the element at position $(m, n)$ is 1, otherwise it is 0, $\tilde{H}_k = H_k W^L H_k^H$, $\tilde{H}_k = H_k L_k^H H_k^H$, $\tilde{H}_k = H_\epsilon j W_k^H H_\epsilon j^H$, and $\tilde{H}_k = H_\epsilon j L_k^H H_\epsilon j^H$. We can clearly observe that $P_6$ is intractable due to the existence of constraints $C3$ and $C4$. Similar to deal with $C3$ and $C4$ in Section III-B, we can obtain

\[ P_6 : \max_{\sigma, \alpha, \beta, \varsigma, \epsilon, \chi} z \quad (26a) \]

s.t. $C8 : \frac{\delta_k}{2 \kappa_k} \delta_k^2 + \frac{\delta_k}{2 \kappa_k} \epsilon^2 \leq \text{Tr} (\tilde{H}_k W \tilde{Q}), \quad k \in K, \quad (26b)$

$C9 : \delta_k \geq \text{Tr} (\tilde{H}_k W \tilde{Q}) + \sigma^2, \quad k \in K, \quad (26c)$

$C10 : \left[ \frac{\beta_k}{\delta_k} \frac{\varsigma_j}{\kappa_j} \text{Tr} (\tilde{H}_k L_k \tilde{Q}) \right] \geq 0, \quad \forall k \in K, \forall j \in J, \quad (26d)$

$C12 : \chi_k \geq \text{Tr} (\tilde{H}_k W \tilde{Q}) - \beta_k \sigma^2, \quad \forall k \in K, \forall j \in J, \quad (26e)$

$\tilde{C}_7, \tilde{C}_{11}, \tilde{C}_{13}, \tilde{C}_{14}.$

$P_6$ is still difficult to solve due to the rank-one constraint. Similar to the solutions of $W$ and $V$ for the rank-one constraints in Section III-A, we use the SDP technique to solve the above optimization problem. Meanwhile, we can use the Gaussian random method to obtain the approximate solution of $\theta^*$ when it does not satisfy the rank-one constraint.

Summarily, to solve $P_6$, we first initialize the feasible points $W^{[t]}, V^{[t]}, \tilde{Q}^{[t]}, \alpha^{[t]}, \beta^{[t]}, \beta^{[t-1]}, \delta^{[t]}$ and $\varsigma^{[t]}$, and then solve $\rho$ by (17), and solve $P_6$ to obtain $W^{[t+1]}, V^{[t+1]}$, and solve $P_6$ to obtain $z^{[t+1]}, \tilde{Q}^{[t+1]}$, and then repeat (17), $P_4$ and $P_6$ until the result $z$ converges to a stable value, which is summarized as Algorithm 1.

IV. EXTEND TO IMPERFECT CSI FOR THE EVES’ LINKS

In practical communication environment, the BS may rely estimated CSI of legitimate users’ links with negligible estimation error. However, the passive nature of Eves makes the BS difficult to accurately estimate the CSI for the Eves’ links. In this section, we consider imperfect CSI for the Eves’ links, which are expressed as follows:

\[ h_{d,e,j} = \tilde{h}_{d,e,j} + \Delta h_{d,e,j}, \quad \forall k \in K, \forall j \in J, \quad (27) \]

\[ f_{e,j} = \tilde{f}_{e,j} + \Delta f_{e,j}, \quad \forall k \in K, \forall j \in J, \quad (27) \]

where $\tilde{h}_{d,e,j}$ and $\tilde{f}_{e,j}$ represent the corresponding actual estimation values, $\Delta h_{d,e,j}$ and $\Delta f_{e,j}$ represent the corresponding estimation errors and satisfy $\Delta h_{d,e,j} \sim D_h = CN(0, \sigma_{d,e,j})$ with $E_{d,j} = \sigma_{d,e,j}^2 I_M$, and $\Delta f_{e,j} \sim D_f = CN(0, \sigma_{f,j})$ with $E_{f,j} = \sigma_{f,j}^2 I_N$. We define $R_k$ as the achievable rate of the $j$-th Eve eavesdropping on the $k$-th user. When $R_k$ exceeds the redundancy $R_k^*$, a secrecy outage event of the $k$-th user will occur at the BS. Based on this, $P_6$ can be converted to the following one

\[ P_0 : \max_{\mathbf{w}, \mathbf{v}, \alpha} \min_{k \in K} \eta_k \quad (28a) \]

s.t. $C15 : \Pr \{ \log_2 (1 + \gamma_{k,j}) \leq R_k^* \} \geq 1 - \varphi_k, \quad \forall k \in K, \forall j \in J, \quad (28b)$

$C16 : \Delta h_{d,e,j} \in D_h, \quad \Delta f_{e,j} \in D_f, \quad \forall k \in K, \forall j \in J, \quad (28c)$

$C1, C2, \quad (28d)$

where $\varphi_k \in (0, 1)$ denotes the maximum outage probability. As stated before, solving the optimization problem is extremely challenging due to the non-convexity of the objective function and the new constraints $C15$ and $C16$.

We first deal with $C15$, which can be simplified to (29), as shown at the bottom of the next page, where

\[ D_k = \sum_{k = 1}^{K} \sum_{j = 1}^{J} (2 \Delta r_{k,j} - 1) W_i - W_k, \quad \tilde{h}_j = h_{d,e,j} + G^H \Phi \tilde{f}_{e,j}, \quad \Delta h_j = h_{d,e,j} + G^H \Phi \Delta f_{e,j}, \quad (29) \]

\[ \Delta f_{e,j} = (2 \Delta r_{k,j} - 1) \sigma_{f,j}^2. \quad (29) \]

However, the above transformation is still difficult to address. Fortunately, the outage constraint can be handled with the BTL of Lemma 1 [42], i.e.

\[ \text{Lemma 1 (BTL): Assume a probability constraint} \]

\[ f(x) = \Pr \{ x^H Ax + 2Re \{ u^H x \} + c \geq 0 \} \geq 1 - \varphi, \quad (30) \]

where $A \in \mathbb{R}^{p \times p}$, $u \in \mathbb{C}^{p \times 1}$, $x \in \mathbb{C}^{p \times 1}$, $\varphi \in (0, 1)$. By introducing two slack variables $\lambda$ and $\epsilon$, the following relationship always holds

\[ \begin{align*}
\left\{ \begin{array}{l}
\text{Tr} (A) - \sqrt{2} \ln (\varphi) \lambda + \ln (\varphi) \epsilon + c \geq 0, \\
\left\| \text{vec} (A) \right\| \leq \lambda, \\
\epsilon + A \geq 0, \epsilon \geq 0.
\end{array} \right.
\end{align*} \quad (31) \]

We define $\Delta h_{d,e,j} = \sigma_{d,j} \Delta e_{d,j}$ and $\Delta f_{e,j} = \sigma_{f,j} \Delta e_{f,j}$, where $\Delta e_{d,j} \sim CN(0, 1)$ and $\Delta e_{f,j} \sim CN(0, 1)$. By citing Lemma 1, (30) becomes

\[ \Pr \{ \Delta e_{f,j} A_k \Delta e_{j} + 2 \text{Re} \{ u_{k,j}^H \Delta e_{j} \} + c_{k,j} \geq 0 \} \geq 1 - \varphi_k, \quad (32) \]

where $\Delta e_{j} = [\Delta e_{d,j}; \Delta e_{f,j}]$, $c_{k,j} = \tilde{h}_j^H D_k \tilde{h}_j + \sigma_{f,j}^2$,

\[ A_k = \begin{bmatrix}
\sigma_{d,j}^2 D_k^H \sigma_{d,j} \sigma_{f,j} \Theta^H G_k \sigma_{f,j} \Theta G_k D_k^H \Theta \\
\sigma_{d,j} \sigma_{f,j} \Theta^H G_k \sigma_{f,j} \Theta G_k D_k^H \Theta
\end{bmatrix}, \quad (32) \]

\[ u_{k,j} = \begin{bmatrix}
\sigma_{d,j}^2 D_k^H \tilde{h}_j^H \sigma_{f,j} \Theta^H G_k \tilde{h}_j^H \\
\sigma_{d,j} \sigma_{f,j} \Theta^H G_k \tilde{h}_j^H \sigma_{f,j} \Theta G_k \tilde{h}_j^H \Theta
\end{bmatrix}^H. \quad (33) \]

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We introduce two auxiliary variables $\lambda \in \mathbb{R}^{K \times J}$ with $\lambda = [\lambda_1, \ldots, \lambda_K]$, $\lambda_k = [\lambda_{k1}, \ldots, \lambda_{kJ}]$ and $\varepsilon \in \mathbb{R}^{K \times J}$ with $\varepsilon = [\varepsilon_1, \ldots, \varepsilon_K]$, $\varepsilon_k = [\varepsilon_{k1}, \ldots, \varepsilon_{kJ}]$, then (31) can be converted as

$$
\tilde{C}_{15} : \begin{cases}
\left( \text{Tr} (A_k) - \sqrt{-2 \ln (\varphi_k)} \lambda_k^{2} + \ln (\varphi_k) \varepsilon_k^{2} + c_{k,j} \right) \geq 0, \\
\varepsilon_k^2 I + A_k \geq 0, \forall k, \varepsilon_k \geq 0,
\end{cases}
$$

(34)

where $\forall k \in K$ and $\forall j \in J$. $C_{2}^*$, $C_{3}$, $C_{4}$, $C_{7}$, and $\tilde{C}_{15}$ are still non-convex and intractable due to the coupling of $W$, $V$ and $\theta$ as well as the constraint of the unit modulo. Next, we propose an alternative scheme to deal with it.

A. Fix $\theta$ and Solve ($W, V$)

Similar to the above scheme, when $\theta$ is fixed, $\tilde{P}_0$ can be transformed into

$$
\hat{P}_3 : \max_{W, V, \alpha, \beta, p, \lambda, \varepsilon, z} \frac{z}{2}
$$

s.t. $\tilde{C}_{4} : \beta_k \geq \left( \hat{h}_j + \Delta h_j \right)^H W_k \left( \hat{h}_j + \Delta h_j \right) + \sigma_{e,j}^2, \forall k \in K, \forall j \in J, (35b)$

$$
C_{1}, C_{3}, C_{5}, C_{6}, \tilde{C}_{7}, \tilde{C}_{15}, C_{16}. \quad (35c)
$$

The optimal $\rho^{opt}$ can be obtained by using (18), and $C_{3}$ can be transformed into $\tilde{C}_{8}$ and $C_{9}$. Next, we introduce three auxiliary variables $\varsigma \in \mathbb{R}^{K \times J}$ with $\varsigma = [\varsigma_1, \ldots, \varsigma_K]$, $\varsigma_k = [\varsigma_{k1}, \ldots, \varsigma_{kJ}]$, $\chi \in \mathbb{R}^{K \times J}$ with $\chi = [\chi_1, \ldots, \chi_K]$, $\chi_k = [\chi_{k1}, \ldots, \chi_{kJ}]$, and $\varpi \in \mathbb{R}^{K \times J}$ with $\varpi = [\varpi_1, \ldots, \varpi_K]$.

Consequently, we can transform (36b) and (36c) into convex constraints as follows:

$$
C_{17} : \varpi_k^j \leq 2 \psi_k^j \left( \bar{w}^j_k \right)^2, \forall k \in K, \forall j \in J, \quad (37a)
$$

$$
C_{18} : \left[ \beta_k \right] \left[ \varsigma_k^j \right] \geq 0, \forall k \in K, \forall j \in J. \quad (37b)
$$

Next, we observe that (36a) and (36d) are non-probabilistic constraints that cannot be handled with BTI. For convenience, we define the Eves’ equivalent estimation channel and estimation error vectors as

$$
\tilde{x}_j = \left[ \tilde{h}_{d,e,j}^H, \tilde{f}_{e,j}^H \right]^H, \quad (38)
$$

$$
\Delta x_j = \left[ \Delta h_{d,e,j}^H, \Delta f_{e,j}^H \right]^H.
$$

To remove the estimation error, we adopt the Sphere Boundary method [43] and $C_{15}$ can be rewritten as

$$
e_j^H A_k \Delta e_j + 2 \Re \{ u_{k,j}^H \Delta e_j \} + c_{k,j} \geq 0, \forall \Delta e_j^H \Delta e_j \leq \psi_k^j, \forall k \in K, \forall j \in J, \quad (39)
$$

$$
C_{19} : \left[ \begin{array}{c}
\kappa_{k_j}^{j} I_{(M+R)} - C_{W,k} \bar{w}_{k_j}^j - \sigma_{k_j}^2 \psi_{k_j}^2 (\text{Tr} (E_{d,j}) + \text{Tr} (E_{f,j})) - \varpi_{k_j}^j C_{W,k} \varpi_{k_j}^j \\
- \bar{w}_{k_j}^j C_{W,k} \bar{w}_{k_j}^j - \kappa_{k_j}^{j} \psi_{k_j}^2 \bar{w}_{k_j}^j C_{W,k} \bar{w}_{k_j}^j + \varpi_{k_j}^j C_{W,k} \varpi_{k_j}^j \end{array} \right] \geq 0, \forall k \in K, j \in J, \quad (47)
$$

$$
C_{20} : \left[ \begin{array}{c}
\omega_{k_j}^{j} I_{(M+R)} + C_{L,k} \bar{w}_{k_j}^j - \sigma_{k_j}^2 \psi_{k_j}^2 (\text{Tr} (E_{d,j}) + \text{Tr} (E_{f,j})) + \varpi_{k_j}^j C_{L,k} \varpi_{k_j}^j \\
\bar{w}_{k_j}^j C_{L,k} \bar{w}_{k_j}^j - \omega_{k_j}^{j} \psi_{k_j}^2 \bar{w}_{k_j}^j C_{L,k} \bar{w}_{k_j}^j + \varpi_{k_j}^j C_{L,k} \varpi_{k_j}^j \end{array} \right] \geq 0, \forall k \in K, j \in J, \quad (50)
$$

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where the Gaussian random vector $e_j$ satisfying
\[
S = \{ \Delta e_j | \text{Pr} \{ \Delta e_j^H \Delta e_j \leq \psi_k \} = 1 - \varphi_k \},
\]
and the region radius $\psi_k$ satisfying
\[
\psi_k = \sqrt{\frac{1}{2} F_{(MB+RN)}^{-1}(1 - \varphi_k)}, \forall k \in K,
\]
where $F_{(MB+RN)}^{-1}(1 - \varphi_k)$ represents the inverse CDF of a Chi-square random variable $1 - \varphi_k$ with $2(MB + RN)$ degrees of freedom. Thus, we complete the transformation of the uncertain region of closed-form. Furthermore, the channel estimation error can be expressed as
\[
\tilde{C}16: \Delta x_j^H \Delta x_j \leq \psi_k^2 \left( \text{Tr} (E_{d,j}) + \text{Tr} (E_{f,j}) \right),
\]
where $\forall k \in K, \forall j \in J$. Since (36a), (36d) and $\tilde{C}16$ belong to semi-infinite constraints, to obtain the exact equivalent constraints, we first introduce the following lemma [44]:

**Lemma 2 (S-Procedure):** Assume a function
\[
g_j(x) = x^H C_i x + 2 \text{Re} \{ b_i^H x \} + d_i, i = 1, 2,
\]
where $C_i \in \mathbb{C}^{P \times P}$, $b_i \in \mathbb{C}^{P \times 1}$, $x \in \mathbb{C}^{P \times 1}$, and $d_i \in \mathbb{R}$. Then, the function $g_j(x) \geq 0 \Rightarrow g_2(x) \leq 0$ holds if and only if there exists $\kappa \geq 0$ such that
\[
\kappa \left[ C_i b_i \right] \leq \left[ b_i d_i \right] \geq 0.
\]
For convenience, (36a) can be rewritten as
\[
\Delta x_j^H C_{W,k} \Delta x_j + \Delta x_j^H C_{W,k} \tilde{x}_j + \tilde{x}_j^H C_{W,k} \Delta x_j + \tilde{x}_j^H C_{W,k} \tilde{x}_j - \varpi_k \leq 0, \forall k \in K, \forall j \in J,
\]
where
\[
C_{W,k} = \begin{bmatrix} W_k & \overline{W}_k G^H \Theta \end{bmatrix} \overline{W}_k G^H \Theta.
\]
By Lemma 2, combining (42) and (45), we can obtain an LMI as (47), shown at the bottom of the previous page, $\nu = \frac{1}{MB+RN}$. Meanwhile, (36d) can be rewritten as
\[
-\Delta x_j^H C_{L,k} \Delta x_j - \Delta x_j^H C_{L,k} \tilde{x}_j - \tilde{x}_j^H C_{L,k} \Delta x_j - \tilde{x}_j^H C_{L,k} \tilde{x}_j + \chi^H \sigma_{x_j^H} \leq 0, \forall k \in K, \forall j \in J,
\]
where
\[
C_{L,k} = \begin{bmatrix} L_k & \overline{L}_k G^H \Theta \end{bmatrix} \overline{L}_k G^H \Theta.
\]
Similar to (47), we can convert (48) to an LMI as (50), shown at the bottom of the previous page. Finally, we can transform the optimization problem $\tilde{P}_3$ into $\tilde{P}_1$ as follows
\[
\tilde{P}_1: \max_{W, V, a, \beta, \lambda, \varepsilon, \delta, x, \varpi, k, \omega, z} z
\]
subject to $C1, C5, C6, C7, C8, C9, C15, C17 - C20$.

It can be observed that except for the rank-one constraints of $C5$ and $C6$, the other parts are solvable convex constraints. To this end, we can solve $\tilde{P}_3$ using SDP technique by removing the rank-one constraint, and Gaussian randomization method can used to obtain the rank-one solution.

**B. Fix ($W, V$) and Solve $\Theta$**

Based on obtaining $W$ and $V$ at the first section, we rewrite the optimization problem as follows
\[
\tilde{P}_6: \max_{Q, \tilde{a}, \tilde{b}, \lambda, \varepsilon, \delta, x, \varpi, k, \omega, z} z
\]
s.t. $C7, C8, C9, C13, C14, C15 \{ \hat{A}_k, \tilde{u}_k \}$,
\[
C17, C18, C19 \{ \tilde{C}_{W,k} \}, C20 \{ \tilde{C}_{L,k} \}.
\]

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Algorithm 2 Proposed Algorithm Based on Imperfect CSI

Input: $h_{b,k}, \tilde{h}_{b,e,j}, f_{e,k}, \tilde{f}_{e,j}, G_{b,r}, \text{ and } \sigma_k, \sigma_c$.
Output: Beamforming matrix $\bfW$, AN matrix $\bfV$, phase shift matrix $\tilde{\bfW}$, and SEE $z$.
Initialize $W^{[t]}, V^{[t]}, \tilde{Q}^{[t]}, \alpha^{[t]}, \beta^{[t-1]}, \delta^{[t]}, \zeta^{[t]}$, $z^{[t]}$, $t = 0$ and threshold $\tau$;
2: while $z^{[t]} - z^{[t-1]} > \tau$ do
3: $t = t + 1$;
4: Update $\rho^{[t]}$ by (17);
5: Update $W^{[t]}, V^{[t]}$ by solving $\hat{P}_1$;
6: Update $z^{[t]}, \tilde{Q}^{[t]}$, by solving $\hat{P}_6$;
end while
8: return $W^{[t]}, \tilde{Q}^{[t]}$, and $z^{[t]}$.

By using SDP technique to remove the rank-one constraint of $C13$, $P_0$ becomes a convex problem that is easy to solve. Similarly, a feasible solution $\theta^*$ can be obtained from $\tilde{Q}^{opt}$ by using the Gaussian randomization method when it does not satisfy the rank-one constraint. Moreover, we summarize the above procedure as Algorithm 2.

V. SUPPLEMENTARY FRAMEWORK

In this section, we analyze the convergence, optimality and computational complexity of the proposed algorithms.

A. Convergence and Optimality

For Algorithm 1, we need to alternatively solve $P_4$ and $P_6$ until convergence. Since the rank-one constraints are all dropped, $P_4$ and $P_6$ are both convex optimization problems, and thus the KKT solutions can be guaranteed. Similarly, $P_4$ and $P_6$ are solved alternatively for Algorithm 2, and they are also both convex optimization problems after removing the rank-one constraints, and thus the KKT solutions are also guaranteed. However, due to the utmost coupling of the variables in $P_0$ and $P_6$, finding the optimal performance in $P_0$ and $P_6$ is still a rather challenging task. Additionally, since $W$ and $V$ are bounded because of the limited transmit power and phase shift $\theta$ is bounded due to the unit modulo, $P_0$ and $P_6$ both have an upper bound. Based on this, SEE under Algorithm 1 and Algorithm 2 should be monotonically non-decreasing and converge to a local optimal solution at least, which can be verified in the following simulation results.

B. Computational Complexity Analysis

In this subsection, we analyze the computational complexity of the proposed algorithms. First, we give an iteration precision $\omega$, and the number of iterations of $P_4$ can be expressed as $\sqrt{\ln(1/\omega)}$ [45]. There are equivalent $(B+3K+4KJ)$ LMI constraints and $K$ second-order cone constraints. Therefore, the barrier parameter $\Delta$ can be expressed as $\Delta = B + 2MBK + 3K + 5KJ$. The computational complexity of solving $P_4$ is calculated as

$$O\left( \sqrt{\ln(1/\omega)} \left( n_0n_1 + n_0^2n_2 + n_0^3 \right) \right), \quad (59)$$

where $n_0 = O\left( 2KM^2B^2 \right)$ and $2KM^2B^2$ represents the number of main optimization variables, $n_1 = 6K + 2B^3M^3K + 11JK$, $n_2 = 2K + 2M^2B^2K + 7JK$. For $P_6$, there are equivalent $2 + K + 4KJ + RN$ LMI constraints and $K$ second-order cone constraints. Given an iteration accuracy $\omega$, the computational complexity of solving $P_6$ is calculated as

$$O\left( \sqrt{\ln(1/\omega)} \left( n_0n_1 + n_0^2n_2 + n_0^3 \right) \right), \quad (60)$$

where the barrier parameter $\Delta = 2 + 2RN + 3 + 5KJ$, $n_0 = O\left((RN + 1)^2\right)$, $n_1 = 5K + 11KJ + (RN + 1) + (RN + 1)^3$, and $n_2 = K + 7KJ + (RN + 1) + (RN + 1)^2$. Therefore, the total computational complexity of Algorithm 1 is $O\left( m\left(n_0n_1 + n_0^2n_2 + n_0^3\right) + \bar{m}\left(n_0n_1 + n_0^2n_2 + n_0^3\right)\right)$, where $m = \sqrt{\ln(1/\omega)}$ and $\bar{m} = \sqrt{\Delta\ln(1/\omega)}$.

Similarly, for $P_4$, there are equivalent $B + 3K + 8KJ$ LMI constraints and $K + KJ$ second-order cone constraints. Given an iteration accuracy $\omega$, the computational complexity of solving $P_4$ is calculated as

$$O\left( \sqrt{\Delta\ln(1/\omega)} \left( n_0n_1 + n_0^2n_2 + n_0^3 \right) \right), \quad (61)$$

where $\Delta = B + 3K + 2MBK + (10 + 3MB + 3RN)KJ$, $n_0 = O\left( 2KM^2B^2 \right)$, $n_1 = 6K + 2M^2B^2K + 12KJ + (MB + RN)^3KJ + 2(MB + RN + 1)^3KJ + ((MB + RN)^2 + (MB + RN))^2 KJ$, $n_2 = 2K + 8KJ + 2KM^2B^2 + (MB + RN)^2KJ + 2(MB + RN + 1)^2 KJ$. For $P_6$, there are equivalent $2 + RN + K + 8KJ$ LMI constraints and $K + KJ$ second-order cone constraints. Given an iteration accuracy $\omega$, the computational complexity of solving $P_6$ is calculated as

$$O\left( \sqrt{\Delta\ln(1/\omega)} \left( n_0n_1 + n_0^2n_2 + n_0^3 \right) \right), \quad (62)$$
where $\Delta = 2 + 2RN + 3K + (10 + 3MB + 3RN) KJ$, $\tilde{n}_0 = O((RN + 1)^2)$, $\tilde{n}_1 = (RN + 1) + (RN + 1)^3 + 5K + 12KJ + (MB + RN)^3 KJ + 2(MB + RN + 1)^3 KJ + ((MB + RN)^3 + (MB + RN)^2) KJ$, $\tilde{n}_2 = RN + 1 + (RN + 1)^3 + K + 8KJ + 2(MB + RN + 1)^2 KJ + (MB + RN)^2 KJ$. Therefore, the total computational complexity of Algorithm 2 is $O(\tilde{n}_0 \tilde{n}_1 + \tilde{n}_0^2 \tilde{n}_2 + \tilde{n}_0^3)$, where $\tilde{m} = \sqrt{\Delta} \ln (1/\hat{\omega})$ and $\tilde{m} = \sqrt{\Delta} \ln (1/\hat{\omega})$.

VI. Simulation Results

In this section, we provide the simulation results to evaluate the performance of the proposed algorithms. We set $B = 2$, $R = 2$, $K = 2$, and $J = 2$. The heights of the BS, RIS, user, and Eve are 12 m, 8 m, 1.5 m, and 1.5 m, respectively. And their plane coordinates are (0 m, 40(b-1)+30 m), (65 m, 40(r-1)+30 m), (60 m, $y_k$ m), and (55 m, $y_j$ m), respectively. The numbers of each BS antenna and each RIS elements are $M = 2$ and $N = 4$, respectively. We set the maximum transmit power and power amplifier efficiency of each BS to $P_0 = 15$ dBm and $\zeta = 1/3$, respectively. The channel model includes large-scale and small-scale fading [5]. Large scale fading is given by $L(d) = \frac{L_0}{d^\nu}$, $d \in \{v_{BU}, v_{BE}, v_{BR}, v_{BE}\}$, where $d$, $L_0$ and $\nu$, respectively, represent the distance between the receiver and the transmitter, the path loss of reference distance $d_0 = 1$ m, and the path loss exponent. Small scale fading model is considered as $\bfH^* = \sqrt{\frac{K + 1}{K - 1}} \bfH_{\text{LoS}} + \sqrt{\frac{1}{K - 1}} \bfH_{\text{NLoS}}$, $\bfH_{\text{LoS}}, \bfH_{\text{NLoS}}$ represent the LoS path, the non-LoS path (Rayleigh fading component) and Rayleigh factor respectively. $\bfH_{\text{LoS}}$ is expressed as $\bfH_{\text{LoS}} = \mathbf{a}(\vartheta_{\text{AOD}}) \mathbf{a}(\vartheta_{\text{AOD}})^H$, where $\mathbf{a}(\vartheta_{\text{AOD}}) = \exp\left(\frac{j\pi d_r}{\lambda_d}(0, \ldots, (A_r - 1) \sin \vartheta_{\text{AOD}})^T\right)$ and $\mathbf{a}(\vartheta_{\text{AoA}}) = \exp\left(\frac{j\pi d_t}{\lambda_d}(0, \ldots, (A_r - 1) \sin \vartheta_{\text{AoA}})^T\right)$. Here $A_r, d_r$ and $\vartheta_{\text{AOD}}$, respectively, denote the number of antennas of the receiver, the inter-antenna separation distance and the angle of arrival (AoA), and $A_s, d_t$ and $\vartheta_{\text{AoA}}$, respectively, denote the number of antennas of the transmitter, the inter-antenna separation distance and the angle of departure (AoD). The maximum outage probability of $k$-th user security rate is $\varphi_k = 0.1$. We define the maximum normalized error as $\bar{\sigma} = \frac{||\bfH_{k,s}||^2}{||\Delta \bfH_{k,s}||^2} = \frac{||\bfL_k||^2}{||\Delta \bfL_k||^2}$. Other parameters setting can be found in TABLE II. Unless otherwise stated, the following experimental parameters remain unchanged.

For comparison, we first define the following legend:

- **Perfect CSI without RISs**: Maximizing the minimum user’s SEE under perfect CSI without RISs (Algorithm 1).
- **Imperfect CSI without RISs**: Maximizing the minimum user’s SEE under imperfect CSI without RISs (Algorithm 2).

- **Perfect CSI with multiple RISs**: Maximizing the minimum user’s SEE under perfect CSI with multiple RISs (Algorithm 1).
- **Imperfect CSI with multiple RISs**: Maximizing the minimum user’s SEE under imperfect CSI with multiple RISs (Algorithm 2).

- **Perfect CSI with single RIS**: Deploy a single RIS with a total number of elements equal to the multi-RIS scheme.
- **Max-min SEE**: maximize the minimum user’s SEE scheme and use the minimum user’s SEE as the indicator under perfect CSI with multiple RISs.
- **Perfect CSI with single RIS**: Deploy a single RIS with a total number of elements equal to the multi-RIS scheme.
- **Max-min user SE**: Maximizing the minimum user’s SEE under perfect CSI with multiple RISs.
- **Max-min Eve SE**: Minimizing the maximum Eve’s SEE under perfect CSI with multiple RISs.

| Parameters | Values |
|------------|--------|
| Path loss exponent | $\nu_{BU} = \nu_{BE} = 3.6, \nu_{BR} = \nu_{BE} = 2.2, \nu_{BR} = 2.0$ |
| Rican channel factor | $K'_{BU} = K'_{BE} = K'_{BR} = K'_{BE} = 0, K'_{BR} = \infty$ |
| The inter-antenna separation distance | $d_s = \lambda_d/2$, where $\lambda_d$ denotes wavelength |
| Path loss at 1 meter | $L_0 = -30$ dB |
| Hardware-dissipated power | $P_B = 100$ mW, $P_E = 20$ mW, $P_R = 1$ mW |
| The noise power | $\sigma^2 = \sigma_{\text{N}}^2 = -80$ dBm |
| The maximum normalized error level | $\bar{\sigma} = 0.01$ |
| The redundancy of the k-th user | $R_k = 0.5$ bits/Hz |

![Fig. 2. SEE versus the number of iterations.](image-url)
1) Relationship between SEE and the number of iterations: Fig. 2 shows the convergence of different schemes. We can observe that the SEE first increases and then trends to stable after 6 iterations under all schemes. Meanwhile, one can observe that the proposed “Perfect CSI with multiple RISs” and “Imperfect CSI with multiple RISs” schemes own higher SEE than the corresponding “Perfect CSI without RIS”, “Imperfect CSI without RIS” and “Perfect CSI with single RISs” schemes. The performance of the “Random RC” scheme is even slightly lower than that of the “Perfect CSI without RIS” scheme. The reason is that the reflected signals with random RC cannot precisely toward users, and may toward Eves. Additionally, it is easy to find that the SEE of the “Imperfect CSI” scheme is slightly lower than that of the corresponding “Perfect CSI” scheme. Besides, the SEE of “2-bit RC” schemes is close to that of the “Perfect CSI with multiple RISs” scheme.

2) Relationship between SEE and BS transmit power: We plot Fig. 3 to show the relation between SEE and BS transmit power under different schemes. One can observe that the SEE first increases and then keeps stable as the transmit power increases under “Perfect CSI with multiple RISs”, “Imperfect CSI with multiple RISs”, “Perfect CSI without RIS”, “Imperfect CSI without RIS”, “2-bit RC” and “SSEEM” schemes. The performance of the “Random RC” scheme is even slightly lower than that of the “Perfect CSI without RIS” scheme. The reason is that the reflected signals with random RC cannot precisely toward users, and may toward Eves. Additionally, it is easy to find that the SEE of the “Imperfect CSI” scheme is slightly lower than that of the corresponding “Perfect CSI” scheme. Besides, the SEE of “2-bit RC” schemes is close to that of the “Perfect CSI with multiple RISs” scheme.

3) Relationship between SEE and RIS elements \( N \): Fig. 4 shows the SEE versus the number of RIS elements under different schemes. One can observe that the SEE increases as the number of RIS elements increases under “Perfect CSI with multiple RISs”, “Imperfect CSI with multiple RISs” schemes. However, with the increase of RIS elements, since the scheme aims to maximize SE only ensuring the increase of SE, its SEE is unknown. Fortunately, the SEE of the “Max-min SSE” scheme in Fig. 4 can still be improved with the increase of the number of RIS elements. Meanwhile, with the increase of the number of RIS elements, the scheme aims to maximize the sum SEE only ensuring the increase of the sum SEE, and the minimum user’s SEE is unknown. For example, the SEE under the “SSEEM” scheme in the Fig. 4 increases firstly and then decreases slightly with the increase of the number of RIS elements. Additionally, the SEE keeps constant for any number of RIS elements under “Perfect CSI without RIS” and “Imperfect CSI without RIS” schemes, and this is easy to understand.

4) Relationship between SEE and the number of BSs \( B \): Here, we plot Fig. 6 to show the SEE versus the number of BSs under the proposed schemes based on the different number of users, as shown in Fig. 5. We can observe that the SEE decreases as the number of Eves increases under all schemes. This can be explained, as more Eves lead to a higher eavesdropping rate, and thus the SEE decreases accordingly. Meanwhile, it can be found that the SEE decreases with the number of users. This is because more users lead to more serious interference among users, which may change the channel gain of the worst user and decreases the SEE. In addition, the proposed “Perfect CSI with multiple RISs” scheme achieves better SEE compared to the “Max-min SS” and “SSEEM” schemes, which proves the effectiveness of the proposed scheme.

5) Relationship between SEE and the number of Eves \( J \): We set \( P_b = 20 \) dBm, and illustrate the SEE versus the number of Eves under the proposed schemes based on the different number of users, as shown in Fig. 5. We can observe that the SEE decreases as the number of Eves increases under all schemes. This can be explained, as more Eves lead to a higher eavesdropping rate, and thus the SEE decreases accordingly. Meanwhile, it can be found that the SEE decreases with the number of users. This is because more users lead to more serious interference among users, which may change the channel gain of the worst user and decreases the SEE. In addition, the proposed “Perfect CSI with multiple RISs” scheme achieves better SEE compared to the “Max-min SS” and “SSEEM” schemes, which proves the effectiveness of the proposed scheme.
BSs $B$. It is obvious that the SEE first increases and then decreases with the number of BSs. This contributes to the fact that when the number of BSs exceeds a threshold, the growth rate of SE is smaller than that of BS transmit power and circuit dissipation. This implies that in cell-free networks, we can dynamically adjust the service pattern of BSs, and instead of transmitting signals for distant users, only closer users can be selected for service. This is due to the fact that serving distant users has little impact on the performance benefit and is quite costly. With this dynamic design, the signaling overhead, transmission delay and synchronization computational resources can be greatly reduced.

6) Relationship between SEE and the error level $\sigma$: Fig. 7 shows the SEE versus the error level under different schemes. Here, we add the “Imperfect CSI without outage”, “Max-min SSE imperfect CSI” and “SSEEM with imperfect CSI” schemes for comparison. One can observe that the SEE of “Imperfect CSI with multiple RISs”, “Imperfect CSI without RIS” and “Imperfect CSI without outage” schemes decreases with the increase of the error level, which is easy to understand. Since “Max-min SSE imperfect CSI” and “SSEEM with imperfect CSI” schemes do not aim to guarantee the minimum user's SEE, it is possible that their SEE varies irregularly with the error level. Meanwhile, it is inevitable that the “Perfect CSI with multiple RISs” scheme remains unchanged with the increase of $\sigma$. Besides, we can observe that the expected performance of the “Imperfect CSI with multiple RISs” scheme is lower than that of the “Imperfect CSI without outage” scheme.

7) Comparison of SEE fairness: In Fig. 8, we plot the sum SEE and minimum user’s SEE under different schemes. Here, we increase the number of users to three, and set $P_b = 18$ dBm. It can be observed that the sum SEE of “SSEEM” scheme is relatively high while the minimum user’s SEE is very low. Meanwhile, the sum SEE of our proposed schemes is slightly lower than that of “SSEEM” scheme, but the minimum user’s SEE is relatively high. This can be explained, as the SEEM scheme aims to maximize the sum SEE, but it sacrifices the minimum user’s SEE for improving the sum SEE. However, our proposed schemes aim to maximize the minimum user’s SEE, and ensure the user’s fairness. In addition, the sum SEE and the minimum user’s SEE of the “Perfect CSI with multiple RISs” approximate the “Max-min SSE”.

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In this paper, we investigated the SEE in the RIS-aided secure CF networks. We designed a joint active and passive beamforming optimization at BSs and RISs to maximize the minimum user’s SEE, and solved it based on the perfect and imperfect CSI. The simulation results showed that the proposed schemes outperform the existing schemes in term of SEE. Meanwhile, the obtained results also revealed the relations between SEE and the number of BSs, RISs, users, Eves, error level as well as transmit power. It could provide a useful guidance for the application of RIS-aided secure CF networks in future. Meanwhile, the case where multiple Eves collaborate to enhance their decoding rate is an interesting topic, which will be our future work.

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Wanning Hao (Senior Member, IEEE) received the Ph.D. degree from the School of Electrical and Electronic Engineering, Kyushu University, Japan, in 2018. He was a Research Fellow with the 5G Innovation Center, Institute of Communication Systems, University of Surrey, U.K. He is currently an Associate Professor with the School of Electrical and Information Engineering, Zhengzhou University, China. His research interests include millimeter wave and RIS. He is an Editor of IEEE OPEN JOURNAL OF THE COMPUTER SOCIETY.

Junjie Li received the B.S. degree from Yangtze University, China, in 2020. He received the M.S. degree in information and communication engineering from Zhengzhou University, Zhengzhou, China. His research interests include cell-free networks, reconfigurable intelligent surfaces (RISs), and physical layer security.

Gangwen Huang (Member, IEEE) received the B.Sc. degree from Nankai University in 2010, the M.Sc. degree from the University of Electronic Science and Technology of China in 2013, and the Ph.D. degree from Singapore University of Technology and Design (SUTD) in 2019. From October 2019 to September 2020, he was a Post-Doctoral with SUTD. Since September 2020, he has been a tenure-track Young Professor with Zhejiang University. His research interests include holographic MIMO surface/reconfigurable intelligent surface, BS/5G wireless communications, mmWave/THz communications, and deep learning technologies for wireless communications. He was a recipient of the 2021 IEEE Marconi Prize Paper Award, the 2023 IEEE Fred W. Ellersick Prize Paper Award, and the 2021 IEEE ComSoc Asia-Pacific Outstanding Young Researcher Award. He has served as an Editor for IEEE COMMUNICATIONS LETTER, Signal Processing (Elsevier), EURASIP Journal on Wireless Communications and Networking, and Physical Communication since 2021.
Ming Zeng (Member, IEEE) received the B.E. and master’s degrees from Beijing University of Post and Telecommunications, Beijing, China, in 2013 and 2016, respectively, and the Ph.D. degree in telecommunications engineering from Memorial University, St. John’s, NL, Canada, in 2020. He is currently an Assistant Professor with the Department of Electrical and Computer Engineering, Université Laval, Quebec City, QC, Canada. He has authored or coauthored more than 90 journal articles and conference papers. He has been cited over 4000 times. His research interests include resource allocation for beyond 5G systems and machine learning-empowered optical communications. He is the Canada Research Chair of the Radio Access Networks. He is an Editor of IEEE OPEN JOURNAL OF THE COMPUTER SOCIETY.

Octavia A. Dobre (Fellow, IEEE) was a Visiting Professor with Massachusetts Institute of Technology, USA, and Université de Bretagne Occidentale, France. She is currently a Professor and the Canada Research Chair Tier 1 with Memorial University, Canada. Her research interests include wireless communication and networking technologies and optical and underwater communications. She has (co)authored over 500 refereed articles in these areas. She is an Elected Member of European Academy of Sciences and Arts and a fellow of the Engineering Institute of Canada and Canadian Academy of Engineering. She serves as the VP of Publications of the IEEE Communications Society. She was a Fulbright Scholar, a Royal Society Scholar, and a Distinguished Lecturer with the IEEE Communications Society. She received the Best Paper Awards at various conferences, including IEEE ICC, IEEE Globecom, IEEE WCNC, and IEEE PIMRC. She was the Inaugural Editor-in-Chief (EiC) of IEEE OPEN JOURNAL OF THE COMMUNICATIONS SOCIETY and the EiC of IEEE COMMUNICATIONS LETTERS.

Chau Yuen (Fellow, IEEE) received the B.Eng. and Ph.D. degrees from Nanyang Technological University, Singapore, in 2000 and 2004, respectively. He was a Post-Doctoral Fellow with Lucent Technologies Bell Labs, Murray Hill, in 2005. From 2006 to 2010, he was with the Institute for Infocomm Research, Singapore. From 2010 to 2023, he was with the Engineering Product Development Pillar, Singapore University of Technology and Design. Since 2023, he has been with the School of Electrical and Electronic Engineering, Nanyang Technological University, where he is currently the Provost’s Chair of Wireless Communications and the Assistant Dean of the Graduate College. He has four U.S. patents and published over 400 research articles in international journals. Dr. Yuen received the IEEE Communications Society Leonard G. Abraham Prize in 2024, the IEEE Communications Society Best Tutorial Paper Award in 2024, the IEEE Communications Society Fred W. Ellersick Prize in 2023, the IEEE Marconi Prize Paper Award in Wireless Communications in 2021, the IEEE APB Outstanding Paper Award in 2023, and the EURASIP Best Paper Award for Journal on Wireless Communications and Networking in 2021. He serves as the Editor-in-Chief for Computer Science (Springer Nature) and an Editor for IEEE TRANSACTIONS ON VEHICULAR TECHNOLOGY, IEEE SYSTEM JOURNAL, and IEEE TRANSACTIONS ON NETWORK SCIENCE AND ENGINEERING, where he was awarded as IEEE TRANSACTIONS ON NETWORK SCIENCE AND ENGINEERING Excellent Editor Award and the Top Associate Editor for IEEE TRANSACTIONS ON VEHICULAR TECHNOLOGY from 2009 to 2015. He also served as the Guest Editor for several special issues, including IEEE JOURNAL ON SELECTED AREAS IN COMMUNICATIONS, IEEE Wireless Communications Magazine, IEEE Communications Magazine, IEEE Vehicular Technology Magazine, IEEE TRANSACTIONS ON COGNITIVE COMMUNICATIONS AND NETWORKING, and Applied Energy (Elsevier). He is a Distinguished Lecturer of the IEEE Vehicular Technology Society, the Top 2% Scientists by Stanford University, and a Highly Cited Researcher by Clarivate Web of Science.