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Simultaneous Wireless Information Power Transfer for MISO Secrecy Channel

Zheng Chu, Zhengyu Zhu, *Student Member, IEEE*, Martin Johnston, *Member, IEEE* and Stéphane Le Goff

Abstract—This paper investigates simultaneous wireless information and power transfer (SWIPT) for a multiple-input-single-output (MISO) secrecy channel. First, transmit beamforming without artificial noise (AN) is designed to achieve the secrecy rate maximization problem subject to the transmit power and the energy harvesting constraints. This problem is not convex, but can be solved by applying a bisection search to a sequence of the associated power minimization problems, each of which can be solved by using a novel relaxation approach. Moreover, we extend our proposed algorithms to the robust case by incorporating channel uncertainties. Then, transmit beamforming with AN is investigated for the secrecy rate maximization problem, where two relaxation approaches are presented, a two-level optimization algorithm and a successive convex approximation (SCA) to solve the secrecy rate maximization problem. In addition, tightness analyses of rank relaxation are provided to show that the optimal transmit covariance matrix exactly returns rank-one. Simulation results are provided to validate the performance of the proposed algorithms.

Index Terms—MISO system, SWIPT, physical-layer secrecy, bisection method, successive convex approximation (SCA).

I. INTRODUCTION

Energy harvesting is employed in fifth-generation (5G) wireless communication networks to circumvent the issue of energy limitations in mobile devices and improve the energy efficiency of these networks by extracting energy from the external natural environment (e.g., solar power, wind energy, etc.) [1], [2].

Traditionally, energy is directly harvested from external sources without exploiting the resources of the communication network itself. However, when the natural environment is not able to provide stable energy, wireless mobile receivers have to find an alternative energy source in the communication network. This source can be the information-carrying radio-frequency (RF) signal radiated by the fixed transmitters (base stations, hot spots, etc.) [3]–[5]. In this case, the role of the transmitter is not only to send the signal to the mobile receivers, but also transfer power that can be used to charge these receivers' batteries. Simultaneous wireless information and power transfer (SWIPT) is a promising paradigm to provide power for communication devices to mitigate the energy scarcity and extend the lifetime of wireless networks [3], [4].

Over the past few years, the issue of secrecy performance has become increasingly crucial in wireless communication networks. In particular, there has been a growing interest in physical-layer security. Unlike traditional cryptographic methods that are employed to improve secrecy performance in the network layer, physical-layer security relies upon the principles of information theory to improve the security of wireless communications [6]–[8].

Among all configurations that have been considered in the study of physical-layer security algorithms, the multiple antenna wiretap channel model has recently received a great deal of attention due to the advent of multiple-input multiple-output (MIMO) communication systems [9], [10]. Several algorithms have thus been introduced to improve the physical-layer security performance of multiple-antenna transceivers. Some of these techniques, i.e., cooperative beamforming (CB), cooperative jamming (CJ), artificial noise (AN) and device-to-device transmission (D2D) achieve their goal by attempting to increase the amount of interference received by eavesdroppers [11]–[18].

Recently, secure communication in SWIPT has been investigated in [19]–[26]. In [19], the authors have considered a MISO system. Two optimization problems: 1) secrecy rate maximization of IR subject to individual harvested energy constraints of ERs, 2) energy harvesting maximization subject to a secrecy rate constraint for the IR, have been developed to guarantee a reliable information transmission to the IR and the target harvested energy simultaneously transferred to the ERs are satisfied by optimally designing the beamforming vectors and their power allocation at the transmitter. In [21], the authors first addressed the secure communication system with SWIPT when two types of eavesdroppers (i.e., passive eavesdroppers and potential eavesdroppers) coexist. A total transmit power minimization problem was formulated to jointly optimize the transmit beamforming, AN and energy beamforming, achieving secure communications with a target amount of harvested power by incorporating channel uncertainties of the idle receivers (potential eavesdroppers). While [22] considered a multiuser MISO SWIPT system with multi-antenna energy harvesting receivers (potential eavesdroppers) only, where an energy harvesting maximization problem is proposed to guarantee secure communications. In addition, the authors have shown that there always exists a rank-one optimal transmit covariance solution and proposed one efficient algorithm to construct an equivalent rank-one optimal solution [19], [22]. However, in [19], [22], the CSI is assumed to be available, or only the CSI of the potential eavesdropper is unavailable at the transmitter [20], [21], for which there are practical difficulties to obtain the CSI of the link between the transmitter and the users due to the channel estimation and the quantization

Zheng Chu, Martin Johnston, and Stéphane Le Goff are with the School of Electrical and Electronic Engineering, Newcastle University, Newcastle upon Tyne, NE1 7RU, U.K. (Emails: z.chu@ncl.ac.uk; martin.johnston@ncl.ac.uk; stephane.le-goff@ncl.ac.uk)

Zhengyu Zhu is with School of Information Engineering, Zhengzhou University, Zhengzhou, China, also with School of Electrical Engineering, Korea University, Seoul, Korea. (Email: zhuzhengyu6@gmail.com)

errors. Furthermore, robust secure transmission for a MISO SWIPT system have been proposed without AN [24], with AN [25], and with CJ [26], respectively, by incorporating the channel uncertainties of all channels. In [24], [25], semidefinite relaxation (SDR) has been studied to solve the secrecy rate maximization problem, however, the suboptimal solution has been proposed to guarantee the solution of the relaxed problem is rank-one [24], whereas in [25], [26], the authors have shown the optimal solution of the relaxed problem is rank-two, which are not exact.

Motivated by the existing work, in this paper, we consider the SWIPT scheme for a MISO secrecy system with multiple eavesdroppers and multiple EH receivers, where secure transmit beamforming without AN and with AN are designed. The contribution of this paper is that we address the following problems:

- 1) *Secrecy rate optimization without AN*: We formulate the secrecy rate maximization problem to design the transmit beamforming without AN, which is not convex and cannot be solved directly. Unlike the conventional SDR [24], we propose a novel reformulation for the secrecy rate maximization problem based on the bisection search to solve a sequence of the associated power minimization problems, each of which can be solved by employing a novel relaxation. In addition, these associated robust schemes are investigated by incorporating channel uncertainties.
- 2) *Secrecy rate optimization with AN*: The secrecy rate maximization problem is formulated to jointly optimize transmit beamforming and AN. In this paper, we first propose the two-level problem, the inner level problem can be relaxed by semidefinite relaxation (SDR), the outer level problem is a single-variable optimization problem, which is solved by using a one-dimensional line search algorithm. Then, successive convex approximation (SCA) based secrecy rate maximization problem is proposed, where we approximate the non-convex constraint and reformulate the secrecy rate maximization problem as a convex one. Moreover, we extend our proposed schemes to the robust case by incorporating channel uncertainties. Tightness analyses for the relaxation of the secrecy rate maximization problems are provided to show the relaxed problem yields rank-one solution.

The remaining part of this paper is organized as follows. A system model is described in Section II. The secrecy rate optimization problems with SWIPT are solved to jointly optimize the transmit beamforming without AN in Section III. The secrecy rate optimization problem with SWIPT to jointly optimize the transmit beamforming with AN is investigated in Section IV. The computation complexity of the proposed algorithms is given in section V. Section VI provides simulation results to support the proposed schemes. Finally, the conclusions are presented in Section VII.

A. Notation

We use the upper case boldface letters for matrices and lower case boldface letters for vectors. $(\cdot)^T$, $(\cdot)^*$ and $(\cdot)^H$ denote the transpose, conjugate and conjugate transpose respectively. $\text{Tr}(\cdot)$ and $\mathbb{E}\{\cdot\}$ stand for trace of a matrix and the statistical expectation for random variables. $\text{Vec}(\mathbf{A})$ is the vector obtained by stacking the columns of $\mathbf{A}$ on top of one another and $\otimes$ is the Kronecker product. $\mathbf{A} \succeq \mathbf{0}$ indicates that $\mathbf{A}$ is a positive semidefinite matrix. $\mathbf{I}$ and $(\cdot)^{-1}$ denote the identity matrix with appropriate size and the inverse of a matrix respectively. $\|\cdot\|_2$ represents the Euclidean norm of a matrix. $\Re\{\cdot\}$ stands for the real part of a complex number, whereas $|\mathbf{A}|$ denotes the determinant of $\mathbf{A}$. $[x]^+$ represents $\max\{x, 0\}$. The distribution of a circularly symmetric complex Gaussian (CSCG) vector with mean vector $\mathbf{x}$ and covariance matrix Σ is denoted by $\mathcal{CN}(\mathbf{x}, \Sigma)$, and $\sim$ means “distributed as”. The notation $\succeq_K$ denotes the following generalized inequality:

$$\begin{bmatrix} p \\ \mathbf{w} \end{bmatrix} \succeq_K \mathbf{0} \Leftrightarrow \|\mathbf{w}\|_2 \leq p.$$

II. SYSTEM MODEL

We consider a MISO secured SWIPT channel, comprising one multiantenna legitimate transmitter, one legitimate user, K eavesdroppers and L energy harvesting (EH) receivers. It is assumed that the transmitter is equipped with N_T transmit antennas, whereas the legitimate user, the eavesdroppers and the EH receivers each have a single receive antenna. The channel coefficients between the legitimate transmitter and the legitimate user, the k -th eavesdropper as well as the l -th EH receiver are denoted by $\mathbf{h}_s \in \mathbb{C}^{N_T \times 1}$, $\mathbf{h}_{e,k} \in \mathbb{C}^{N_T \times 1}$ and $\mathbf{h}_l \in \mathbb{C}^{N_T \times 1}$, respectively. The noise power at the legitimate user and the eavesdroppers are assumed to be σ_s^2 and σ_e^2 . The received signal at the legitimate user and the k -th eavesdropper can be written as

$$y_s = \mathbf{h}_s^H \mathbf{w} s + n_s, \quad y_{e,k} = \mathbf{h}_{e,k}^H \mathbf{w} s + n_{e,k}, \quad k = 1, \dots, K,$$

where s and $\mathbf{w} \in \mathbb{C}^{N_T \times 1}$ are the desired signal for the legitimate user ($\mathbb{E}\{|s|^2\} = 1$) and the transmit beamforming at the legitimate transmitter, respectively. In addition, $n_s \sim \mathcal{CN}(0, \sigma_s^2)$ and $n_{e,k} \sim \mathcal{CN}(0, \sigma_e^2)$ represent the noise of the legitimate user and the k -th eavesdropper, respectively. Thus, the achieved secrecy rate at the legitimate user is expressed as follows:

$$R_s = \left[\log \left(1 + \frac{|\mathbf{h}_s^H \mathbf{w}|^2}{\sigma_s^2} \right) - \max_k \log \left(1 + \frac{|\mathbf{h}_{e,k}^H \mathbf{w}|^2}{\sigma_e^2} \right) \right]^+, \quad \forall k. \quad (1)$$

The harvested energy at the l -th EH receiver is written as

$$E_l = \xi_l |\mathbf{h}_l^H \mathbf{w}|^2, \quad \forall l, \quad (2)$$

where $\xi_l \in (0, 1]$ is the energy conversion efficiency of the energy transducers at the l -th energy receiver that accounts for the loss in the energy transducers for converting the harvested energy to electrical energy to be stored [23]. For convenience, we assume that $\xi_l = 1$, $\forall l$, in this paper.

Remark 1: This system model consists of L EH receivers, which harvest power carried by the RF signal without AN or

with AN based on a reliable transmission scenario. These EH receivers sometimes play a “ helper ” role by employing the harvested power to introduce a jamming signal to confuse the eavesdroppers [27]. However, the efficiency of this harvest-and-jamming policy is dependant on the network topology [28]. In this paper, we mainly focus on the secrecy rate optimization without AN or with AN. The EH performance of the EH receivers is exploited, whereas how to use the harvested power is outside the scope of our paper.

III. SECRECY RATE MAXIMIZATION WITHOUT AN

In this section, we consider a MISO secrecy channel with multiple eavesdroppers and EH receivers described in Section II, where secure beamforming is designed without AN to achieve the secrecy rate maximization subject to the transmit power and the EH constraints. This optimization is written as follows:

$$\max_{\mathbf{w}} \min_k R_s, \text{ s.t. } \|\mathbf{w}\|^2 \leq P, \min_l E_l \geq E, \forall k, l, \quad (3)$$

where P is the maximum available transmit power at the legitimate transmitter, and E denotes the target harvested energy of the EH receivers. These above problems are not convex, and cannot be solved directly. Unlike existing literature [24], where rank relaxation is considered to reformulate the secrecy rate, however, it is challenging to show a rank-one solution. In this paper, we propose a novel relaxation method for the secrecy rate maximization problem to circumvent rank relaxation. The secrecy rate maximization problem (3) is not convex in terms of the nonconvex secrecy rate objective function and EH constraint, and cannot be solved directly. Thus, this problem can be solved by considering a sequence of power minimization problems, one for each target rate $R > 0$. The optimal solution of the secrecy rate maximization problem can be obtained by solving the corresponding power minimization problem with different R , which can be obtained by using bisection search over R [29], [30]. Next, we will focus on the following power minimization problem,

$$\min_{\mathbf{w}} \|\mathbf{w}\|^2, \text{ s.t. } \min_k R_s \geq R, \min_l E_l \geq E, \forall k, l. \quad (4)$$

A. Power Minimization

Now, we consider the power minimization problem based on the assumption that the transmitter has perfect CSI of the legitimate user, the eavesdroppers and the EH receivers. Thus, the problem in (4) can be relaxed as

$$\min_{\mathbf{w}} \|\mathbf{w}\|^2, \text{ s.t. } \log \left(1 + \frac{|\mathbf{h}_s^H \mathbf{w}|^2}{\sigma_s^2} \right) - \log \left(1 + \frac{|\mathbf{h}_{e,k}^H \mathbf{w}|^2}{\sigma_e^2} \right) \geq R, \\ |\mathbf{h}_l^H \mathbf{w}|^2 \geq E, \forall k, l. \quad (5)$$

The above problem is not convex in terms of the non-convex secrecy rate and EH constraints. In order to circumvent these issues, the following lemma is required to tackle the power minimization problem (5):

Lemma 1: The problem in (5) is reformulated into the following form:

$$\min_{\mathbf{w}, s_1} s_1, \text{ s.t. } \begin{bmatrix} s_1 \\ \mathbf{w} \end{bmatrix} \succeq_K \mathbf{0}, \\ \mathbf{S}_k = \begin{bmatrix} \frac{1}{\sigma_s} \mathbf{w}^H \mathbf{h}_s \mathbf{I} & \begin{bmatrix} \frac{2^{\frac{R}{2}}}{\sigma_e} \mathbf{w}^H \mathbf{h}_{e,k} \\ (2^R - 1)^{\frac{1}{2}} \end{bmatrix} \\ \begin{bmatrix} \frac{2^{\frac{R}{2}}}{\sigma_e} \mathbf{w}^H \mathbf{h}_{e,k} \\ (2^R - 1)^{\frac{1}{2}} \end{bmatrix}^H & \frac{1}{\sigma_s} \mathbf{w}^H \mathbf{h}_s \end{bmatrix} \succeq \mathbf{0}, \forall k, \\ x_l = \Re\{\mathbf{w}^H \mathbf{h}_l\}, y_l = \Im\{\mathbf{w}^H \mathbf{h}_l\}, \mathbf{u}_l = [x_l \ y_l], \\ \|\mathbf{u}_l^{(n)}\|^2 + 2 \sum_{i=1}^2 \mathbf{u}_l^{(n)}(i) [\mathbf{u}_l(i) - \mathbf{u}_l^{(n)}(i)] \geq E, \forall l. \quad (6)$$

Proof: Please refer to Appendix A. ■

In problem (6), the secrecy rate constraint is reformulated into linear matrix inequality (LMI), whereas the EH constraint is approximated by a first-order Taylor series expansion, thus this problem is a convex problem for a given $\mathbf{u}_l$. An initialization value of the vector $\mathbf{u}_l$ is randomly generated and can be updated at each iteration. The algorithm converges when $\mathbf{u}_l^{(n+1)} = \mathbf{u}_l^{(n)}$ holds, and it is guaranteed to converge to a locally optimal solution (quite close to the globally optimal solution) [31], [32].

B. Robust Power Minimization

In the previous section, we have solved the power minimization problem based on the assumption that the legitimate transmitter has perfect CSI. However, it is not always possible to have perfect CSI due to the lack of cooperation as well as channel estimation and quantization errors. Thus, we consider the robust scheme by incorporating norm-bounded channel uncertainties in the following.

1) *Channel Uncertainty:* In this subsection, it is assumed that the CSI is not available at the legitimate transmitter. The channel uncertainties are modelled as

$$\mathbf{h}_s = \bar{\mathbf{h}}_s + \mathbf{e}_s, \mathbf{h}_{e,k} = \bar{\mathbf{h}}_{e,k} + \mathbf{e}_{e,k}, \forall k, \mathbf{h}_l = \bar{\mathbf{h}}_l + \mathbf{e}_l, \forall l,$$

where $\bar{\mathbf{h}}_s$, $\bar{\mathbf{h}}_{e,k}$ and $\bar{\mathbf{h}}_l$ denote the estimated channels of the legitimate user, the k -th eavesdropper and the l -th EH receiver, and $\mathbf{e}_s$, $\mathbf{e}_{e,k}$ and $\mathbf{e}_l$ represent the corresponding channel errors, which are assumed to be bounded as

$$\|\mathbf{e}_s\|_2 = \|\mathbf{h}_s - \bar{\mathbf{h}}_s\|_2 \leq \varepsilon_s, \text{ for } \varepsilon_s \geq 0, \\ \|\mathbf{e}_{e,k}\|_2 = \|\mathbf{h}_{e,k} - \bar{\mathbf{h}}_{e,k}\|_2 \leq \varepsilon_{e,k}, \text{ for } \varepsilon_{e,k} \geq 0, \forall k, \\ \|\mathbf{e}_l\|_2 = \|\mathbf{h}_l - \bar{\mathbf{h}}_l\|_2 \leq \varepsilon_l, \text{ for } \varepsilon_l \geq 0, \forall l,$$

where ε_s , $\varepsilon_{e,k}$ and ε_l represent the norm bounds of the channel errors.

2) *Robust Power Minimization with Channel Uncertainty:* Now, we solve the robust power minimization problem by incorporating the channel uncertainties. Thus, this robust problem is formulated as follows:

$$\min_{\mathbf{w}} \|\mathbf{w}\|^2, \text{ s.t. } \min_{\mathbf{e}_s} \log \left(1 + \frac{|\bar{\mathbf{h}}_s + \mathbf{e}_s)^H \mathbf{w}|^2}{\sigma_s^2} \right) - \\ \max_{\mathbf{e}_{e,k}} \log \left(1 + \frac{|\bar{\mathbf{h}}_{e,k} + \mathbf{e}_{e,k})^H \mathbf{w}|^2}{\sigma_e^2} \right) \geq R, \forall k, \quad (7a)$$

$$\min_{\mathbf{e}_l} |(\bar{\mathbf{h}}_l + \mathbf{e}_l)^H \mathbf{w}|^2 \geq E, \forall l. \quad (7b)$$

The problem (7) is not convex in terms of channel uncertainties, and cannot be solved directly. Thus, we first consider the reformulation of the secrecy rate constraint in (7a), which can be relaxed as

$$\begin{cases} \frac{1}{\sigma_s} \left(\mathbf{w}^H \bar{\mathbf{h}}_s - \varepsilon_s \|\mathbf{w}\| \right) \geq \sqrt{t_2}, \\ \left[\frac{2^{\frac{R}{2}}}{\sigma_e} (\bar{\mathbf{h}}_{e,k} + \mathbf{e}_{e,k})^H \mathbf{w} \quad (2^R - 1)^{\frac{1}{2}} \right] \left[\frac{2^{\frac{R}{2}}}{\sigma_e} \mathbf{w}^H (\bar{\mathbf{h}}_{e,k} + \mathbf{e}_{e,k}) \right] \leq t_2, \end{cases} \quad (8)$$

The first constraint in (8) is rewritten based on a first-order Taylor approximation as follows:

$$\frac{1}{\sigma_s} \Re\{\mathbf{w}^H \bar{\mathbf{h}}_s\} - \frac{\varepsilon_s}{\sigma_s} \|\mathbf{w}\| \geq f^{(n)}(t_2), \quad (9)$$

where $f^{(n)}(t_2) = \sqrt{t_2^{(n)}} + \frac{1}{2\sqrt{t_2^{(n)}}}(t_2 - t_2^{(n)})$.

Lemma 2: The second constraint in (8) can be reformulated as

$$\bar{\mathbf{S}}_k = \begin{bmatrix} \mathbf{S}_{k,1} - \lambda_k \begin{bmatrix} \mathbf{0} & -1 \end{bmatrix} \begin{bmatrix} \mathbf{0} \\ -1 \end{bmatrix} - \varepsilon_{e,k} \begin{bmatrix} \frac{2^{\frac{R}{2}}}{\sigma_e} \mathbf{w}^H \\ \mathbf{0} \\ \mathbf{0} \end{bmatrix} \\ -\varepsilon_{e,k} \begin{bmatrix} \frac{2^{\frac{R}{2}}}{\sigma_e} \mathbf{w}^H & \mathbf{0} & \mathbf{0} \end{bmatrix} & \lambda_k \mathbf{I} \end{bmatrix} \succeq \mathbf{0}, \forall k. \quad (10)$$

where

$$\mathbf{S}_{k,1} = \begin{bmatrix} f^{(n)}(t_2) \mathbf{I} & \begin{bmatrix} \frac{2^{\frac{R}{2}}}{\sigma_e} \mathbf{w}^H \bar{\mathbf{h}}_{e,k} \\ (2^R - 1)^{\frac{1}{2}} \end{bmatrix} \\ \begin{bmatrix} \frac{2^{\frac{R}{2}}}{\sigma_e} \mathbf{w}^H \bar{\mathbf{h}}_{e,k} \\ (2^R - 1)^{\frac{1}{2}} \end{bmatrix}^H & f^{(n)}(t_2) \end{bmatrix}. \quad (11)$$

Proof: Please refer to Appendix B. ■

Thus, the robust power minimization problem can be written as

$$\begin{aligned} \min_{s_2, \mathbf{w}, \lambda_k} \quad & s_2, \quad s.t. \quad \begin{bmatrix} s_2 \\ \mathbf{w} \end{bmatrix} \succeq_K \mathbf{0}, \quad \bar{\mathbf{S}}_k(\lambda_k, f^{(n)}(t_2)) \succeq \mathbf{0}, \quad \forall k, \\ & \frac{1}{\sigma_s} \mathbf{w}^H \bar{\mathbf{h}}_s - \frac{\varepsilon_s}{\sigma_s} \|\mathbf{w}\| \geq f^{(n)}(t_2), \\ & \Re\{\bar{\mathbf{h}}_l^H \mathbf{w}\} \geq E^{\frac{1}{2}} + \varepsilon_l \|\mathbf{w}\|_2, \quad \Im\{\bar{\mathbf{h}}_l^H \mathbf{w}\} = 0, \quad \forall l. \end{aligned} \quad (12)$$

The above problem is convex for a given $t_2^{(n)}$ at each iteration. Thus, an initialization of t_2 is given to solve the problem in (12) by using interior-point method, which is updated iteratively. It is easily observed that t_2 is updated to $t_2^{(n+1)} = t_2^n$ when the algorithm converges.

IV. SECURE SWIPT OF JOINT BEAMFORMING AND ARTIFICIAL NOISE DESIGN

In the previous section, we have solved the secrecy rate optimization problems to optimize the transmit beamforming without AN. In this section, we extend our attention to joint transmit beamforming and AN design in the secrecy rate maximization problem, where the legitimate transmitter sends the signal with AN in order to introduce more interference to the eavesdroppers.

A. Problem Formulation

We formulate the secrecy rate maximization problem with the transmit power and the minimum EH constraints, where the secured transmit beamforming (i.e., $\mathbf{w}$) and AN beamforming (i.e., $\mathbf{v} \sim \mathcal{CN}(0, \mathbf{V})$) are jointly designed. This optimization problem can be formulated as

$$\begin{aligned} \max_{\mathbf{w}, \mathbf{V}} \min_k \quad & \log \left(1 + \frac{\mathbf{h}_s^H \mathbf{w} \mathbf{w}^H \mathbf{h}_s}{\mathbf{h}_s^H \mathbf{V} \mathbf{h}_s + \sigma_s^2} \right) - \log \left(1 + \frac{\mathbf{h}_{e,k}^H \mathbf{w} \mathbf{w}^H \mathbf{h}_{e,k}}{\mathbf{h}_{e,k}^H \mathbf{V} \mathbf{h}_{e,k} + \sigma_e^2} \right), \\ s.t. \quad & \|\mathbf{w}\|^2 + \text{Tr}(\mathbf{V}) \leq P, \quad [\mathbf{w} \mathbf{w}^H]_{(i,i)} + [\mathbf{V}]_{(i,i)} \leq p_i, \quad \forall i, \\ & \min_l |\mathbf{h}_l^H \mathbf{w}|^2 + \mathbf{h}_l^H \mathbf{V} \mathbf{h}_l \geq E_l, \quad \forall l, \quad \mathbf{V} \succeq \mathbf{0}, \end{aligned} \quad (13)$$

where $[\mathbf{w} \mathbf{w}^H]_{(i,i)} + [\mathbf{V}]_{(i,i)}$ ($i = 1, \dots, N_T$) represents each antenna transmit power constraint.

Remark 2: The proposed relaxation method is also suitable for the scenario where the eavesdroppers and the EH receivers are equipped with multiple antennas [33, Section V-D].

This optimization problem (13) is not convex and cannot be solved directly. Thus, we propose two reformulations to make this problem tractable, one dimensional line search based two-level optimization algorithm and SCA. Unlike [25], where it was shown that the relaxed problem returns rank-two. In this paper, we provide a novel SDR for the secrecy rate maximization problem, and show the optimal solution always returns rank-one. We first employ the SDR to relax the original problem (13) by using $\mathbf{Q}_s = \mathbb{E}\{\mathbf{w} \mathbf{w}^H\}$ as follows:

$$\max_{\mathbf{Q}_s, \mathbf{V}} \log \left(1 + \frac{\mathbf{h}_s^H \mathbf{Q}_s \mathbf{h}_s}{\mathbf{h}_s^H \mathbf{V} \mathbf{h}_s + \sigma_s^2} \right) - \max_k \log \left(1 + \frac{\mathbf{h}_{e,k}^H \mathbf{Q}_s \mathbf{h}_{e,k}}{\mathbf{h}_{e,k}^H \mathbf{V} \mathbf{h}_{e,k} + \sigma_e^2} \right),$$

$$s.t. \quad \text{Tr}(\mathbf{Q}_s + \mathbf{V}) \leq P, \quad \text{Tr}[\mathbf{A}_i(\mathbf{Q}_s + \mathbf{V})] \leq p_i, \quad \forall i, \quad (14a)$$

$$\mathbf{h}_l^H (\mathbf{Q}_s + \mathbf{V}) \mathbf{h}_l \geq E_l, \quad \forall l, \quad (14b)$$

$$\mathbf{Q}_s \succeq \mathbf{0}, \mathbf{V} \succeq \mathbf{0}, \text{rank}(\mathbf{Q}_s) = 1, \quad (14c)$$

where $\mathbf{A}_i = \mathbf{a}_i \mathbf{a}_i^H$ is the given antenna design parameters to adjust each antenna power budget, and $\mathbf{a}_i$ is a unit i -th vector (i.e., $[\mathbf{a}_i]_j = 1$ for $i = j$ and $[\mathbf{a}_i]_j = 0$ for $i \neq j$). The specific applications of each antenna power constraint have already been described in [17], [23].

B. Secrecy Rate Maximization

For the secrecy rate maximization problem (13), we will provide two different algorithms to jointly optimize the transmit beamforming and AN covariance matrix: one-dimensional line search based two-level optimization algorithm and SCA.

1) *One-Dimensional Line Search Based Two-Level Optimization Algorithm:* We first introduce a slack variable t , and the problem (13) is rewritten as

$$\begin{aligned} \max_{\mathbf{Q}_s, \mathbf{V}, t} \quad & R_s + \log(t), \\ s.t. \quad & \log \left(1 + \frac{\mathbf{h}_{e,k}^H \mathbf{Q}_s \mathbf{h}_{e,k}}{\mathbf{h}_{e,k}^H \mathbf{V} \mathbf{h}_{e,k} + \sigma_e^2} \right) \leq \log\left(\frac{1}{t}\right), \quad \forall k, \end{aligned} \quad (15a)$$

$$(14a), (14b), (14c). \quad (15b)$$

The problem in (15) is still not convex in terms of the constraint (15a), and cannot be solved directly, thus, it can

be formulated as a two-stage optimization problem. The outer problem is a function of t , which can be written as

$$\max_t \log(1 + f(t)) + \log(t), \quad s.t. \quad t_{\min} \leq t \leq 1, \quad (16)$$

It is easily derived that the lower bound $t_{\min} = (1 + \frac{P\|\mathbf{h}_s\|^2}{\sigma_s^2})^{-1}$. Then, the inner problem can be recast for a given t as follows:

$$f(t) = \max_{\mathbf{Q}_s, \mathbf{V}} \frac{\mathbf{h}_s^H \mathbf{Q}_s \mathbf{h}_s}{\mathbf{h}_s^H \mathbf{V} \mathbf{h}_s + \sigma_s^2}, \quad s.t. (15a), (14a), (14b), (14c). \quad (17)$$

It is easily verified that the constraint in (15) can be reformulated as

$$\mathbf{h}_{e,k}^H \left[\mathbf{Q}_s - \left(\frac{1}{t} - 1 \right) \mathbf{V} \right] \mathbf{h}_{e,k} \leq \left(\frac{1}{t} - 1 \right) \sigma_e^2. \quad (18)$$

Then, (17) can be recast for a given t as

$$f(t) = \max_{\mathbf{Q}_s, \mathbf{V}} \frac{\mathbf{h}_s^H \mathbf{Q}_s \mathbf{h}_s}{\mathbf{h}_s^H \mathbf{V} \mathbf{h}_s + \sigma_s^2}, \quad s.t. (18), (14a), (14b), (14c). \quad (19)$$

The problem (19) is a quasi-convex problem without the nonconvex rank-one constraint, thus we consider the Charnes-Cooper transformation to convert it into a convex problem. Let us introduce δ so that $\mathbf{Q}_s = \frac{\bar{\mathbf{Q}}_s}{\delta}$ and $\mathbf{V} = \frac{\bar{\mathbf{V}}}{\delta}$ hold. Thus, we have

$$\begin{aligned} f(t) &= \max_{\bar{\mathbf{Q}}_s, \bar{\mathbf{V}}, \delta} \frac{\mathbf{h}_s^H \bar{\mathbf{Q}}_s \mathbf{h}_s}{\mathbf{h}_s^H \bar{\mathbf{V}} \mathbf{h}_s + \delta \sigma_s^2}, \quad s.t. \quad \mathbf{h}_s^H \bar{\mathbf{V}} \mathbf{h}_s + \delta \sigma_s^2 = 1, \\ &\quad \mathbf{h}_{e,k}^H \left[\bar{\mathbf{Q}}_s - \left(\frac{1}{t} - 1 \right) \bar{\mathbf{V}} \right] \mathbf{h}_{e,k} \leq \left(\frac{1}{t} - 1 \right) \delta \sigma_e^2, \quad \forall k, \\ &\quad \text{Tr}(\bar{\mathbf{Q}}_s + \bar{\mathbf{V}}) \leq \delta P, \quad \text{Tr}[\mathbf{A}_i(\bar{\mathbf{Q}}_s + \bar{\mathbf{V}})] \leq \delta p_i, \quad \forall i, \\ &\quad \mathbf{h}_l^H(\bar{\mathbf{Q}}_s + \bar{\mathbf{V}})\mathbf{h}_l \geq \delta E_l, \quad \forall l, \quad \bar{\mathbf{Q}}_s \succeq \mathbf{0}, \quad \bar{\mathbf{V}} \succeq \mathbf{0}. \quad (20) \end{aligned}$$

The problem (20) is a convex problem, and can be solved efficiently by using interior-point method [34]. Thus, the optimal solution to (19) can be obtained when $\text{rank}(\mathbf{Q}_s) = 1$ holds that will be shown in Section IV-B2, once (20) has been solved.

2) *Tightness Analyses of Rank Relaxation*: Now we investigate the tightness of the rank relaxation to (19). We assume that the optimal value $f(t)$ can be obtained by the optimal solution to (19), resulting in the following inequality,

$$\frac{\mathbf{h}_s^H \mathbf{Q}_s \mathbf{h}_s}{\mathbf{h}_s^H \mathbf{V} \mathbf{h}_s + \sigma_s^2} \geq f(t) \Rightarrow \mathbf{h}_s^H [\mathbf{Q}_s - f(t) \mathbf{V}] \mathbf{h}_s \geq f(t) \sigma_s^2, \quad (21)$$

Thus, we consider the following power minimization,

$$\min_{\mathbf{Q}_s} \text{Tr}(\mathbf{Q}_s), \quad s.t. (21), (18), (14a), (14b), (14c). \quad (22)$$

It is easily verified that the feasible solution of (22) is the optimal solution of (19) due to the constraints (21), (14a), (14b), and (14c). Thus, the following theorem is provided to show that every optimal solution to (22) is rank-one:

Theorem 1: If (19) is feasible, there always exists an optimal solution (i.e., $\mathbf{Q}_s$) that satisfies $\text{rank}(\mathbf{Q}_s) \leq 1$, which can be obtained by solving (22).

Proof: Please refer to Appendix C. ■

From *Theorem 1*, a tightness analysis has been provided so that (19) has a rank-one solution for all feasible t .

3) *Successive Convex Approximation*: In this section, we propose a SCA algorithm to jointly optimize the transmit beamforming and AN, thus, (13) can be rewritten as

$$\begin{aligned} \min_{\mathbf{Q}_s, \mathbf{V}} \max_k & \frac{\left(\sigma_e^2 + \text{Tr}[\mathbf{h}_{e,k} \mathbf{h}_{e,k}^H (\mathbf{Q}_s + \mathbf{V})] \right) \left(\sigma_s^2 + \text{Tr}(\mathbf{h}_s \mathbf{h}_s^H \mathbf{V}) \right)}{\left(\sigma_s^2 + \text{Tr}[\mathbf{h}_s \mathbf{h}_s^H (\mathbf{Q}_s + \mathbf{V})] \right) \left(\sigma_e^2 + \text{Tr}(\mathbf{h}_{e,k} \mathbf{h}_{e,k}^H \mathbf{V}) \right)} \\ s.t. & \quad \text{Tr}(\mathbf{Q}_s + \mathbf{V}) \leq P, \quad \text{Tr}[\mathbf{A}_i(\mathbf{Q}_s + \mathbf{V})] \leq p_i, \quad \forall i, \quad (23a) \\ & \quad \mathbf{h}_l^H(\mathbf{Q}_s + \mathbf{V})\mathbf{h}_l \geq E_l, \quad \forall l, \quad (23b) \\ & \quad \mathbf{Q}_s \succeq \mathbf{0}, \quad \mathbf{V} \succeq \mathbf{0}, \quad \text{rank}(\mathbf{Q}_s) = 1. \quad (23c) \end{aligned}$$

The above problem is not convex in terms of the objective function. Let us introduce the following exponential variables to equivalently convert the objective function,

$$\begin{aligned} e^{x_0} &= \sigma_s^2 + \text{Tr}[\mathbf{h}_s \mathbf{h}_s^H (\mathbf{Q}_s + \mathbf{V})], \quad e^{x_k} = \sigma_e^2 + \text{Tr}(\mathbf{h}_{e,k} \mathbf{h}_{e,k}^H \mathbf{V}), \\ e^{y_k} &= \sigma_e^2 + \text{Tr}[\mathbf{h}_{e,k} \mathbf{h}_{e,k}^H (\mathbf{Q}_s + \mathbf{V})], \quad e^{y_0} = \sigma_s^2 + \text{Tr}(\mathbf{h}_s \mathbf{h}_s^H \mathbf{V}). \quad (24) \end{aligned}$$

Thus, (23) is rewritten by introducing a slack variable τ as

$$\min_{\mathbf{Q}_s, \mathbf{V}, x_0, y_0, x_k, y_k} \tau \quad (25a)$$

$$s.t. \quad e^{y_0 - x_0 + y_k - x_k} \leq \tau, \quad (25b)$$

$$\sigma_s^2 + \text{Tr}[\mathbf{h}_s \mathbf{h}_s^H (\mathbf{Q}_s + \mathbf{V})] \geq e^{x_0}, \quad \sigma_e^2 + \text{Tr}(\mathbf{h}_{e,k} \mathbf{h}_{e,k}^H \mathbf{V}) \geq e^{x_k}, \quad (25c)$$

$$\sigma_e^2 + \text{Tr}[\mathbf{h}_{e,k} \mathbf{h}_{e,k}^H (\mathbf{Q}_s + \mathbf{V})] \leq e^{y_k}, \quad \sigma_s^2 + \text{Tr}(\mathbf{h}_s \mathbf{h}_s^H \mathbf{V}) \leq e^{y_0}, \quad (25d)$$

$$(23a), (23b), (23c), \quad \forall k, l, i. \quad (25e)$$

The above problem is not still convex in terms of the constraint (25d). Thus, a Taylor series expansion (i.e., $a^{\hat{x}} + a^{\hat{x}} \ln a(x - \hat{x}) \leq a^x$) is employed to linearise (25d) as follows:

$$\sigma_e^2 + \text{Tr}[\mathbf{h}_{e,k} \mathbf{h}_{e,k}^H (\mathbf{Q}_s + \mathbf{V})] \leq e^{\hat{y}_k} (y_k - \hat{y}_k + 1), \quad (26a)$$

$$\sigma_s^2 + \text{Tr}(\mathbf{h}_s \mathbf{h}_s^H \mathbf{V}) \leq e^{\hat{y}_0} (y_0 - \hat{y}_0 + 1), \quad (26b)$$

where $\hat{y}_0$ and $\hat{y}_k$ are approximated values such that $y_0 = \hat{y}_0$ and $y_k = \hat{y}_k$ when the approximations are tight. Thus, the secrecy rate maximization problem can be relaxed as

$$\begin{aligned} \min_{\mathbf{Q}_s, \mathbf{V}, x_0, y_0, x_k, y_k, \tau} & \tau \\ s.t. & (23a), (23b), (23c), (25b), (25c), (26), \quad \forall k, l, i. \quad (27) \end{aligned}$$

The problem (27) is convex without the nonconvex rank-one constraint for a given $(\hat{y}_0, \hat{y}_k)$, and can be solved by using an interior-point method. From SCA, the approximation with the current optimal solution can be updated iteratively until the constraints (25c) and (25d) hold with equality, which implies (23) is optimally solved. The optimal solution obtained by the SCA algorithm at the n -th iteration is assumed to be $(\mathbf{Q}_s^*(n), \mathbf{V}^*(n), x_0^*(n), y_0^*(n), x_k^*(n), y_k^*(n), \tau^*(n))$, which can achieve a stable point when the SCA algorithm converges [35]. In addition, provided that (23) is feasible for positive secrecy rates, there exists an optimal solution of rank-one, and the proof is similar to that of *Theorem 1*.

C. Robust Secrecy Rate Maximization

In this subsection, we turn our attention to the robust secrecy rate maximization, which jointly optimize the transmit beamforming and AN by incorporating channel uncertainties

shown in Section III-B1. In addition, the transmit power constraint per antenna is considered, where the Hermitian positive semidefinite (PSD) matrix $\mathbf{A}_i$ is not available at the legitimate transmitter, thus the true PSD matrix can be written as $\mathbf{A}_i = \bar{\mathbf{A}}_i + \Delta_i$, $\forall i$, where $\bar{\mathbf{A}}_i \in \mathbb{H}_+^{N_T}$ is the estimated Hermitian PSD matrix, and Δ_i is estimated error of the matrix $\bar{\mathbf{A}}_i$, which can be modelled as a spherical uncertainty with a norm-bound ϵ_i ($\|\Delta_i\|_F \leq \epsilon_i$) [20]. In the following, we relax the robust secrecy rate maximization problem by incorporating the channel uncertainties.

1) *One Dimensional Line Search Based Two-Level Optimization Algorithm:* In this subsection, a robust scheme is considered to jointly optimize transmit beamforming and AN by incorporating channel uncertainties. Thus, the two-level optimization framework discussed in the previous subsection is employed by incorporating channel uncertainties. Since the outer problem does not involve the channel uncertainties similar to Section IV-B1, thus we focus on the inner problem for a given t , which can be reformulated as

$$\begin{aligned} f(t) &= \max_{\mathbf{Q}_s, \mathbf{V}} \frac{(\bar{\mathbf{h}}_s + \mathbf{e}_s)^H \mathbf{Q}_s (\bar{\mathbf{h}}_s + \mathbf{e}_s)}{(\bar{\mathbf{h}}_s + \mathbf{e}_s)^H \mathbf{V} (\bar{\mathbf{h}}_s + \mathbf{e}_s) + \sigma_s^2}, \\ s.t. \quad & (\bar{\mathbf{h}}_{e,k} + \mathbf{e}_{e,k})^H \left[\mathbf{Q}_s - \left(\frac{1}{t} - 1 \right) \mathbf{V} \right] (\bar{\mathbf{h}}_{e,k} + \mathbf{e}_{e,k}) \leq \left(\frac{1}{t} - 1 \right) \sigma_e^2, \\ & \text{Tr}(\mathbf{Q}_s + \mathbf{V}) \leq P, \quad \max_{\Delta_i} \text{Tr}[(\bar{\mathbf{A}}_i + \Delta_i)(\mathbf{Q}_s + \mathbf{V})] \leq p_i, \\ & (\bar{\mathbf{h}}_l + \mathbf{e}_l)^H (\mathbf{Q}_s + \mathbf{V}) (\bar{\mathbf{h}}_l + \mathbf{e}_l) \geq E_l, \quad \forall l, \\ & \mathbf{Q}_s \succeq \mathbf{0}, \mathbf{V} \succeq \mathbf{0}, \text{rank}(\mathbf{Q}_s) = 1. \end{aligned} \quad (28)$$

The above problem is not convex due to channel uncertainties. Thus, we employ *S-Procedure* to solve this robust secrecy rate maximization problem, which can be written as

$$\begin{aligned} f(t) &= \max_{\mathbf{Q}_s, \mathbf{V}, \lambda_{e,k}, \alpha_l} \frac{(\bar{\mathbf{h}}_s + \mathbf{e}_s)^H \mathbf{Q}_s (\bar{\mathbf{h}}_s + \mathbf{e}_s)}{(\bar{\mathbf{h}}_s + \mathbf{e}_s)^H \mathbf{V} (\bar{\mathbf{h}}_s + \mathbf{e}_s) + \sigma_s^2}, \\ s.t. \quad & \text{Tr}(\mathbf{Q}_s + \mathbf{V}) \leq P, \text{Tr}[\bar{\mathbf{A}}_i (\mathbf{Q}_s + \mathbf{V})] + \epsilon_i \|\mathbf{Q}_s + \mathbf{V}\|_F \leq p_i, \quad (29a) \\ & \begin{bmatrix} \lambda_{e,k} \mathbf{I} - [\mathbf{Q}_s - (\frac{1}{t} - 1) \mathbf{V}] & -[\mathbf{Q}_s - (\frac{1}{t} - 1) \mathbf{V}] \bar{\mathbf{h}}_{e,k} \\ -\bar{\mathbf{h}}_{e,k}^H [\mathbf{Q}_s - (\frac{1}{t} - 1) \mathbf{V}] & c_k \end{bmatrix} \succeq \mathbf{0}, \quad (29b) \\ & \begin{bmatrix} \alpha_l \mathbf{I} + (\mathbf{Q}_s + \mathbf{V}) & (\mathbf{Q}_s + \mathbf{V}) \bar{\mathbf{h}}_l \\ \bar{\mathbf{h}}_l^H (\mathbf{Q}_s + \mathbf{V}) & \bar{\mathbf{h}}_l^H (\mathbf{Q}_s + \mathbf{V}) \bar{\mathbf{h}}_l - E_l - \alpha_l \varepsilon_l^2 \end{bmatrix} \succeq \mathbf{0}, \quad (29c) \\ & \mathbf{Q}_s \succeq \mathbf{0}, \mathbf{V} \succeq \mathbf{0}, \text{rank}(\mathbf{Q}_s) = 1, \quad \forall i, k, l, \quad (29d) \end{aligned}$$

where $c_k = -\bar{\mathbf{h}}_{e,k}^H [(\mathbf{Q}_s - \frac{1}{t} - 1) \mathbf{V}] \bar{\mathbf{h}}_{e,k} + (\frac{1}{t} - 1) \sigma_e^2 - \lambda_{e,k} \varepsilon_{e,k}^2$. Let us introduce a slack variable τ to relax the objective function to (29), and by exploiting *S-Procedure* and Charnes-Cooper transformation, we have

$$\begin{aligned} f(t) &= \max_{\mathbf{Q}_s, \bar{\mathbf{V}}, \lambda_s, \mu_s, \lambda_{e,k}, \alpha_l, \delta, \tau} \tau, \\ s.t. \quad & \begin{bmatrix} \lambda_s \mathbf{I} + \bar{\mathbf{Q}}_s & \bar{\mathbf{Q}}_s \bar{\mathbf{h}}_s \\ \bar{\mathbf{h}}_s^H \bar{\mathbf{Q}}_s & \bar{\mathbf{h}}_s^H \bar{\mathbf{Q}}_s \bar{\mathbf{h}}_s - \tau - \lambda_s \varepsilon_s^2 \end{bmatrix} \succeq \mathbf{0}, \\ & \begin{bmatrix} \mu_s \mathbf{I} - \bar{\mathbf{V}} & -\bar{\mathbf{V}} \bar{\mathbf{h}}_s \\ -\bar{\mathbf{h}}_s^H \bar{\mathbf{V}} & -\bar{\mathbf{h}}_s^H \bar{\mathbf{V}} \bar{\mathbf{h}}_s - \delta \sigma_s^2 + 1 - \mu_s \varepsilon_s^2 \end{bmatrix} \succeq \mathbf{0}, \\ & \begin{bmatrix} \lambda_{e,k} \mathbf{I} - [\bar{\mathbf{Q}}_s - (\frac{1}{t} - 1) \bar{\mathbf{V}}] & -[\bar{\mathbf{Q}}_s - (\frac{1}{t} - 1) \bar{\mathbf{V}}] \bar{\mathbf{h}}_{e,k} \\ -\bar{\mathbf{h}}_{e,k}^H [\bar{\mathbf{Q}}_s - (\frac{1}{t} - 1) \bar{\mathbf{V}}] & \bar{c}_k \end{bmatrix} \succeq \mathbf{0}, \\ & \begin{bmatrix} \alpha_l \mathbf{I} + (\bar{\mathbf{Q}}_s + \bar{\mathbf{V}}) & (\bar{\mathbf{Q}}_s + \bar{\mathbf{V}}) \bar{\mathbf{h}}_l \\ \bar{\mathbf{h}}_l^H (\bar{\mathbf{Q}}_s + \bar{\mathbf{V}}) & \bar{\mathbf{h}}_l^H (\bar{\mathbf{Q}}_s + \bar{\mathbf{V}}) \bar{\mathbf{h}}_l - \delta E_l - \alpha_l \varepsilon_l^2 \end{bmatrix} \succeq \mathbf{0}, \\ & \text{Tr}[\bar{\mathbf{A}}_i (\bar{\mathbf{Q}}_s + \bar{\mathbf{V}})] + \epsilon_i \|\bar{\mathbf{Q}}_s + \bar{\mathbf{V}}\|_F \leq \delta p_i, \quad \forall i, \\ & \text{Tr}(\bar{\mathbf{Q}}_s + \bar{\mathbf{V}}) \leq \delta P, \bar{\mathbf{Q}}_s \succeq \mathbf{0}, \bar{\mathbf{V}} \succeq \mathbf{0}, t \geq 0. \end{aligned} \quad (30)$$

where $\bar{c}_k = -\bar{\mathbf{h}}_{e,k}^H [\bar{\mathbf{Q}}_s - (\frac{1}{t} - 1) \bar{\mathbf{V}}] \bar{\mathbf{h}}_{e,k} + \delta (\frac{1}{t} - 1) \sigma_e^2 - \lambda_{e,k} \varepsilon_{e,k}^2$. Without the nonconvex rank constraint, (30) is convex, and can be solved by using interior-point method. By solving the problem (30), we can obtain the optimal value $f(t)^*$, which can be written based on channel uncertainties as

$$\begin{aligned} \frac{(\bar{\mathbf{h}}_s + \mathbf{e}_s)^H \mathbf{Q}_s (\bar{\mathbf{h}}_s + \mathbf{e}_s)}{(\bar{\mathbf{h}}_s + \mathbf{e}_s)^H \mathbf{V} (\bar{\mathbf{h}}_s + \mathbf{e}_s) + \sigma_s^2} &\geq f(t)^*, \\ \Rightarrow (\bar{\mathbf{h}}_s + \mathbf{e}_s)^H [\mathbf{Q}_s - f(t)^* \mathbf{V}] (\bar{\mathbf{h}}_s + \mathbf{e}_s) &\geq f(t)^* \sigma_s^2, \end{aligned} \quad (31)$$

Thus, the associated power minimization problem is considered as

$$\begin{aligned} \min_{\mathbf{Q}_s, \mathbf{V}, \alpha_l, \beta_s, \lambda_{e,k}} \quad & \text{Tr}(\mathbf{Q}_s), \\ s.t. \quad & (29a) - (29c), \quad (32a) \\ & \begin{bmatrix} \beta_s \mathbf{I} + [\mathbf{Q}_s - f(t)^* \mathbf{V}] & [\mathbf{Q}_s - f(t)^* \mathbf{V}] \bar{\mathbf{h}}_s \\ \bar{\mathbf{h}}_s^H [\mathbf{Q}_s - f(t)^* \mathbf{V}] & d_s \end{bmatrix} \succeq \mathbf{0}, \quad (32b) \end{aligned}$$

where $d_s = \bar{\mathbf{h}}_s^H [\mathbf{Q}_s - f(t)^* \mathbf{V}] \bar{\mathbf{h}}_s - f(t)^* \sigma_s^2 - \beta_s \varepsilon_s^2$. It is easily verified that the feasible solution to (32) is optimal for (29), which is derived from (32a) and (32b). Thus, the following theorem holds to show that the optimal solution to (29) is rank-one:

Theorem 2: Provided that (29) is feasible, its optimal solution always returns rank-one, which can be obtained by solving (32).

Proof: Please refer to Appendix D. $\blacksquare$

2) *Successive Convex Approximation:* Now, we consider the second reformulation based on SCA for the secrecy rate maximization problem to jointly optimize transmit beamforming and AN covariance matrix. The optimization framework can also be reformulated as a convex form by incorporating channel uncertainties. Thus, this robust secrecy rate maximization problem can be rewritten as

$$\begin{aligned} \min_{\mathbf{Q}_s, \mathbf{V}} \max_k \quad & \frac{t_{e,k} r_s}{t_s r_{e,k}} \quad (33a) \\ s.t. \quad & \text{Tr}(\mathbf{Q}_s + \mathbf{V}) \leq P, \text{Tr}[(\bar{\mathbf{A}}_i + \Delta_i)(\mathbf{Q}_s + \mathbf{V})] \leq p_i, \quad \forall i, \quad (33b) \\ & \mathbf{h}_l^H (\mathbf{Q}_s + \mathbf{V}) \mathbf{h}_l \geq E_l, \quad \forall l, \quad (33c) \\ & \mathbf{Q}_s \succeq \mathbf{0}, \mathbf{V} \succeq \mathbf{0}, \text{rank}(\mathbf{Q}_s) = 1. \quad (33d) \end{aligned}$$

where $t_{e,k} = \sigma_e^2 + (\bar{\mathbf{h}}_{e,k} + \mathbf{e}_{e,k})^H (\mathbf{Q}_s + \mathbf{V}) (\bar{\mathbf{h}}_{e,k} + \mathbf{e}_{e,k})$, $r_s = \sigma_s^2 + (\bar{\mathbf{h}}_s + \mathbf{e}_s)^H \mathbf{V} (\bar{\mathbf{h}}_s + \mathbf{e}_s)$, $t_s = \sigma_s^2 + (\bar{\mathbf{h}}_s + \mathbf{e}_s)^H (\mathbf{Q}_s + \mathbf{V}) (\bar{\mathbf{h}}_s + \mathbf{e}_s)$ and $r_{e,k} = \sigma_e^2 + (\bar{\mathbf{h}}_{e,k} + \mathbf{e}_{e,k})^H \mathbf{V} (\bar{\mathbf{h}}_{e,k} + \mathbf{e}_{e,k})$. Let us introduce the following relations for (33a)

$$e^{x_0} \leq \sigma_s^2 + \min_{\mathbf{e}_s} (\bar{\mathbf{h}}_s + \mathbf{e}_s)^H (\mathbf{Q}_s + \mathbf{V}) (\bar{\mathbf{h}}_s + \mathbf{e}_s), \quad (34a)$$

$$e^{x_k} \leq \sigma_e^2 + \min_{\mathbf{e}_{e,k}} (\bar{\mathbf{h}}_{e,k} + \mathbf{e}_{e,k})^H \mathbf{V} (\bar{\mathbf{h}}_{e,k} + \mathbf{e}_{e,k}), \quad (34b)$$

$$e^{y_k} \geq \sigma_e^2 + \max_{\mathbf{e}_{e,k}} (\bar{\mathbf{h}}_{e,k} + \mathbf{e}_{e,k})^H (\mathbf{Q}_s + \mathbf{V}) (\bar{\mathbf{h}}_{e,k} + \mathbf{e}_{e,k}), \quad (34c)$$

$$e^{y_0} \geq \sigma_s^2 + \max_{\mathbf{e}_s} (\bar{\mathbf{h}}_s + \mathbf{e}_s)^H \mathbf{V} (\bar{\mathbf{h}}_s + \mathbf{e}_s), \quad (34d)$$

By employing the slack variables (i.e., τ , u_s , $u_{e,k}$, v_s , and $v_{e,k}$) for (33a), (34a)-(34d), respectively, (33) can be equivalently

modified as

$$\begin{aligned}
& \min_{\Omega} \tau, \text{ s.t. } e^{y_0+y_k-x_0-x_k} \leq \tau, \quad (33b), (33c), (33d), \\
& e^{x_0} \leq \sigma_s^2 + u_s, \min_{\mathbf{e}_s} (\bar{\mathbf{h}}_s + \mathbf{e}_s)^H [\mathbf{Q}_s + \mathbf{V}] (\bar{\mathbf{h}}_s + \mathbf{e}_s) \geq u_s, \quad (35a) \\
& e^{x_k} \leq \sigma_e^2 + u_{e,k}, \min_{\mathbf{e}_{e,k}} (\bar{\mathbf{h}}_{e,k} + \mathbf{e}_{e,k})^H \mathbf{V} (\bar{\mathbf{h}}_{e,k} + \mathbf{e}_{e,k}) \geq u_{e,k}, \quad (35b) \\
& e^{y_k} \geq \sigma_e^2 + v_{e,k}, \max_{\mathbf{e}_{e,k}} (\bar{\mathbf{h}}_{e,k} + \mathbf{e}_{e,k})^H (\mathbf{Q}_s + \mathbf{V}) (\bar{\mathbf{h}}_{e,k} + \mathbf{e}_{e,k}) \leq v_{e,k}, \quad (35c) \\
& e^{y_0} \geq \sigma_s^2 + v_s, \max_{\mathbf{e}_s} (\bar{\mathbf{h}}_s + \mathbf{e}_s)^H \mathbf{V} (\bar{\mathbf{h}}_s + \mathbf{e}_s) \leq v_s, \quad (35d) \\
& \{\mathbf{Q}_s, \mathbf{V}, \mathbf{e}_s, \mathbf{e}_{e,k}, x_0, y_0, x_k, y_k, u_s, u_{e,k}, v_s, v_{e,k}\} \in \Omega, \forall k, l, i. \quad (35e)
\end{aligned}$$

By exploiting *S-Procedure* and a first-order Taylor series approximation, we have

$$\begin{aligned}
& \min_{\Omega} \tau, \\
& \text{s.t. } e^{y_0+y_k-x_0-x_k} \leq \tau, \quad e^{x_0} \leq \sigma_s^2 + u_s, \quad e^{x_k} \leq \sigma_e^2 + u_{e,k}, \quad (36a) \\
& e^{\bar{y}_k} (y_k - \bar{y}_k + 1) \geq \sigma_e^2 + v_{e,k}, \quad e^{\bar{y}_0} (y_0 - \bar{y}_0 + 1) \geq \sigma_s^2 + v_s, \quad (36b) \\
& \begin{bmatrix} \lambda_s \mathbf{I} + (\mathbf{Q}_s + \mathbf{V}) & (\mathbf{Q}_s + \mathbf{V}) \bar{\mathbf{h}}_s \\ \bar{\mathbf{h}}_s^H (\mathbf{Q}_s + \mathbf{V}) & \bar{\mathbf{h}}_s^H (\mathbf{Q}_s + \mathbf{V}) \bar{\mathbf{h}}_s - u_s - \lambda_s \varepsilon_s^2 \end{bmatrix} \succeq \mathbf{0}, \quad (36c) \\
& \begin{bmatrix} \lambda_{e,k} \mathbf{I} + \mathbf{V} & \mathbf{V} \bar{\mathbf{h}}_{e,k} \\ \bar{\mathbf{h}}_{e,k}^H \mathbf{V} & \bar{\mathbf{h}}_{e,k}^H \mathbf{V} \bar{\mathbf{h}}_{e,k} - u_{e,k} - \lambda_{e,k} \varepsilon_{e,k}^2 \end{bmatrix} \succeq \mathbf{0}, \quad (36d) \\
& \begin{bmatrix} \beta_s \mathbf{I} - (\mathbf{Q}_s + \mathbf{V}) & -(\mathbf{Q}_s + \mathbf{V}) \bar{\mathbf{h}}_{e,k} \\ -\bar{\mathbf{h}}_{e,k}^H (\mathbf{Q}_s + \mathbf{V}) & -\bar{\mathbf{h}}_{e,k}^H (\mathbf{Q}_s + \mathbf{V}) \bar{\mathbf{h}}_{e,k} + v_{e,k} - \beta_{e,k} \varepsilon_{e,k}^2 \end{bmatrix} \succeq \mathbf{0}, \quad (36e) \\
& \begin{bmatrix} \beta_s \mathbf{I} - \mathbf{V} & -\mathbf{V} \bar{\mathbf{h}}_s \\ -\bar{\mathbf{h}}_s^H \mathbf{V} & -\bar{\mathbf{h}}_s^H \mathbf{V} \bar{\mathbf{h}}_s + v_s - \beta_s \varepsilon_s^2 \end{bmatrix} \succeq \mathbf{0}, \quad (36f) \\
& \begin{bmatrix} \alpha_l \mathbf{I} + (\mathbf{Q}_s + \mathbf{V}) & (\mathbf{Q}_s + \mathbf{V}) \bar{\mathbf{h}}_l \\ \bar{\mathbf{h}}_l^H (\mathbf{Q}_s + \mathbf{V}) & \bar{\mathbf{h}}_l^H (\mathbf{Q}_s + \mathbf{V}) \bar{\mathbf{h}}_l - E_l - \alpha_l \varepsilon_l^2 \end{bmatrix} \succeq \mathbf{0}, \quad (36g) \\
& \text{Tr}(\mathbf{Q}_s + \mathbf{V}) \leq P, \quad \text{Tr}[\bar{\mathbf{A}}_i (\mathbf{Q}_s + \mathbf{V})] + \epsilon_i \|\mathbf{Q}_s + \mathbf{V}\|_F \leq p_i, \\
& \{\mathbf{Q}_s \succeq \mathbf{0}, \mathbf{V} \succeq \mathbf{0}, x_0, y_0, x_k, y_k, u_s, u_{e,k}, v_s, v_{e,k}, \\
& \lambda_s \geq 0, \lambda_{e,k} \geq 0, \beta_s \geq 0, \beta_{e,k} \geq 0, \alpha_l \geq 0\} \in \Omega, \quad \forall k, l, i. \quad (36h)
\end{aligned}$$

The above problem is convex for a given $\bar{y}_k$ and $\bar{y}_0$ at each iteration, and can be solved by using the interior-point method to update the solution for the next iteration until the algorithm converges. On the other hand, there exists a rank-one solution to (36), and the proof is similar to that of *Theorem 2*.

V. COMPUTATION COMPLEXITY ANALYSIS

In this section, we provide the computation complexity analysis for our proposed algorithms in Section III and Section IV, which is analysed by applying the basic elements of complexity analysis as used in [36].

First, we consider the secrecy rate maximization problem without AN in perfect and imperfect CSI, where a bisection search is employed to solve (6) and (12), where $M_1^{\max}$ and T_1 are defined as the iteration number of the Taylor approximation and bisection search, respectively. The problem (6) has one second-order cone (SOC) constraint of dimension $N_T + 1$, K LMI constraints of size 3, and L linear constraints. Here, the number of decision variables n is on the order of $N_T + 2L + 1$. While (12) involves $L + 2$ SOCs, including 2 SOCs with dimension $N_T + 1$, L SOCs with dimension N_T , K LMI constraints of size $N_T + 3$, and L linear constraints. The

number of variables n is on the order of $N_T + K + 2$.

Then, we provide the computation complexity for the secrecy rate maximization problems (20) and (27), which are solved by employing a one-dimensional line search and SCA. Thus, T_2 and $M_2^{\max}$ are defined as the iteration number of the one-dimensional line search and SCA, respectively. For problem (20), which involves 2 LMI constraints with size N_T , and $N_T + L + K + 2$ linear constraints. The number of variables n is on the order of $2N_T + 1$. Problem (27) involves 2 LMI constraint with size N_T , and $N_T + L + 3K + 4$ linear constraints. The number of variables n is on the order of $2N_T + 2K + 3$.

Finally, we consider the computation complexity for the robust secrecy rate problems (30) and (36) by incorporating channel uncertainties. The problem (30) has N_T SOCs with dimension $2N_T + 1$, $K + L + 2$ LMI constraints with size $N_T + 1$, 2 LMI constraints with size N_T , and $L + K + 3$ linear constraints. The number of variables n is on the order of $2N_T + K + L + 3$. While problem (36) involves N_T with dimension $2N_T + 1$, $2K + L + 2$ LMI constraints with size $N_T + 1$, and $5K + L + 5$ linear constraints. The number of variables n is on the order of $2N_T + 6K + L + 6$. Based on the aforementioned analysis, the computation complexities for all of our proposed algorithms are shown in Table (I).

VI. NUMERICAL RESULTS

In this section, we provide simulation results to validate our proposed algorithms. We consider a MISO secrecy system in the presence of three eavesdroppers and two EH receivers. The legitimate transmitter is equipped with four transmit antennas (i.e., $N_T = 4$), whereas the other receivers (i.e., legitimate user, eavesdroppers and EH receivers) are equipped with a single antenna. We assume channel models with both large-scale fading and small-scale fading. The simplified large-scale fading model is given by $D = A_0 \left(\frac{d}{d_r} \right)^{-\alpha}$, for $d \geq d_r$, where $A_0 = 1$, d represents the distance between the transmitter and all receivers (i.e., legitimate user d_s , passive eavesdroppers d_e , and the energy receivers d_l), d_r denotes a reference distance set to be 20 meters, and $\alpha = 3$ is the path loss exponent. The small scale fading channel coefficients are assumed to be Rician fading with Rician factor 5 dB. Note that for the involved line-of-sight (LOS) component is modelled as the far-field uniform linear antenna array [37]. In addition, we assume that $\sigma_s^2 = \sigma_e^2 = -40$ dBm, and the distances between the transmitter and the legitimate user, the passive eavesdroppers, as well as the energy receivers are set to be 100, 50, 25 meters unless specified. The target transmit power is assumed to be 30 dBm or 1w, and the target harvested power is set to be 1mw. All error bounds (i.e., ε_s , $\varepsilon_{e,k}$ and ε_l) are replaced by ε for convenience, which is set to be 0.1 or 0.2 unless specified.

We first provide the simulation results for the case without AN. Fig. 1 shows the achieved secrecy rate with different transmit powers, where it is easily observed that the achieved secrecy rate increases with transmit power, and our proposed scheme achieves the same performance with SDR based scheme in terms of achieved secrecy rate. In order to improve the security in SWIPT, AN assisted secrecy rate

TABLE I: Computation Complexity Analysis of Proposed Algorithms

Algorithms	Complexity Order (suppressing $\ln(\frac{1}{\epsilon})$, where ϵ denotes the accuracy requirement.)
Problem (6)	$\mathcal{O}\left(nT_1 M_1^{\max} \sqrt{2N_T + 2 + 3K + L[K(3^3 + n3^2) + L + (N_T + 1)^2 + n^2]}\right)$, where $n = \mathcal{O}(N_T + 2L + 1)$.
Problem (12)	$\mathcal{O}\left(nT_1 M_1^{\max} \sqrt{KN_T + 4 + 3K + 3L[K((N_T + 3)^3 + n(N_T + 3)^2) + 2(N_T + 1)^2 + L(N_T)^2 + L + n^2]}\right)$, where $n = \mathcal{O}(N_T + K + 2)$.
Problem (20)	$\mathcal{O}\left(nT_2 \sqrt{3N_T + K + L + 2[2(N_T^3 + nN_T^2) + N_T + L + K + 2 + n^2]}\right)$, where $n = \mathcal{O}(2N_T + 1)$.
Problem (27)	$\mathcal{O}\left(nM_2^{\max} \sqrt{3N_T + L + 3K + 4[2(N_T^3 + nN_T^2) + N_T + L + 3K + 4 + n^2]}\right)$, where $n = \mathcal{O}(2N_T + 2K + 3)$.
Problem (30)	$\mathcal{O}\left(nT_2 \sqrt{\Theta[(K + L + 2)((N_T + 1)^3 + n(N_T + 1)^2) + 2(N_T^3 + nN_T^2) + N_T(2N_T + 1)^2 + L + K + 3 + n^2]}\right)$, where $\Theta = KN_T + LN_T + 6N_T + 2K + 2L + 5$, and $n = \mathcal{O}(2N_T + K + L + 3)$.
Problem (36)	$\mathcal{O}\left(nM_2^{\max} \sqrt{\Theta[(2KL + L + 2)((N_T + 1)^3 + n(N_T + 1)^2) + 5K + L + 5 + N_T(2N_T + 1)^2 + n^2]}\right)$, where $\Theta = 2KLN_T + 7KL + 4N_T + 7$, and $n = \mathcal{O}(2N_T + 6K + L + 6)$.

Fig. 1: Achieved secrecy rate with different transmit powers.

Fig. 2: AN assisted achieved secrecy rate with different transmit powers.

versus transmit power is plotted in Fig. 2 based on two of our proposed schemes: one-dimensional search based two-level optimization algorithm and SCA. From this result, we can observe that the two proposed schemes increase with transmit power, and both schemes have a similar performance in terms of secrecy rate. In addition, in lower transmit power regime, the SCA based scheme outperforms one-dimensional search based two-level optimization scheme ('1D').

Then, we evaluate the security performance with energy

Fig. 3: AN assisted achieved secrecy rate with target harvested power.

harvesting. Fig. 3 shows the achieved secrecy rate versus the target harvested power, where it can be observed that the secrecy rate decreases with the target harvested power based on perfect and imperfect CSI. Also, we compare our proposed schemes ('1D' and 'SCA') with the scheme shown in [25] ('1D Benchmark'), one-dimensional line search based scheme with Gaussian randomization ('1D GR'), two-dimensional search based scheme ('2D'), and the case without AN ('NO AN'), in which our proposed SCA based scheme outperforms our proposed 1D scheme, 1D Benchmark scheme, 1D GR scheme, and NO AN scheme. The SCA based scheme has a similar performance to 2D based scheme in terms of secrecy rate. Fig. 4 shows the percentage of AN power consumption in the

Fig. 4: The proportion of AN power consumption with different transmit powers.

total transmit power P with different transmit powers, which shows the proportion of AN power consumed to confuse the eavesdroppers or for energy harvesting. One can observe that this proportion increases and then declines after approximately 26 dBm due to the low SNRs at the legitimate user and passive eavesdroppers at the low transmit power regime. Therefore, it is not necessary to consume a large amount of AN power. With the increase in transmit power, the percentage of consumed AN power should increase which ensures secure communications and satisfies the EH constraint. When transmit power is high enough, in order to further increase the secrecy rate required, more power should be allocated to the message-bearing signals so that the AN power may get decreased. The scheme without EH receivers has a lower proportion than the scheme with EN receivers, since the AN is introduced to interfere with the passive eavesdropper only in the system without EH receiver.

Finally, we evaluate the secrecy rate and the EH per-

Fig. 5: Achieved secrecy rate with different distances between the transmitter and the legitimate user.

formance versus the distances between the transmitter and the legitimate user (i.e., d_s), as well as the EH receivers

Fig. 6: Harvested power with different distances between the transmitter and the energy receivers.

(i.e., d_l), respectively, when $P = 20$ dBm. Fig. 5 shows the secrecy rate versus d_s , where one can observe that the secrecy rate decreases with d_s . In addition, the SCA based scheme outperforms the 1D based scheme in terms of secrecy rate. Fig. 6 shows the EH performance versus d_l . From this result, the harvested power decreases with d_l , approaching zero after $d_s = 40$ m.

VII. CONCLUSIONS

In this paper, we have investigated the secrecy rate maximization problem for a MISO secrecy channel with SWIPT in the presence of multiple eavesdroppers and EH receivers. We first proposed a novel reformulation to optimize the transmit beamforming without AN based on perfect CSI and imperfect CSI. Then, joint optimization for transmit beamforming with AN have been considered for the secrecy rate maximization problem based on both perfect and imperfect CSI. We reformulated this optimization problem by using one-dimensional line search based two-level optimization and SCA based schemes, respectively. Furthermore, we provided a tightness analysis for this optimization problem, which shows the optimal solution of this secrecy rate maximization problem exactly returns rank-one. Simulation results have been provided to validate the performance of our proposed schemes.

APPENDIX

A. Proof of Lemma 1

In order to prove *Lemma 1*, we first rewrite the secrecy rate constraint in (5) as

$$\frac{1}{\sigma_s^2} |\mathbf{w}^H \mathbf{h}_s|^2 \geq \left[\frac{\frac{2^{\frac{R}{2}}}{\sigma_e} \mathbf{w}^H \mathbf{h}_{e,k}}{(2^R - 1)^{\frac{1}{2}}} \right]^H \left[\frac{\frac{2^{\frac{R}{2}}}{\sigma_e} \mathbf{w}^H \mathbf{h}_{e,k}}{(2^R - 1)^{\frac{1}{2}}} \right] \quad (37)$$

By exploiting the *Schur complement* [34], (37) can be reformulated as

$$\begin{bmatrix} \frac{1}{\sigma_s} \mathbf{w}^H \mathbf{h}_s \mathbf{I} & \left[\frac{\frac{2^{\frac{R}{2}}}{\sigma_e} \mathbf{w}^H \mathbf{h}_{e,k}}{(2^R - 1)^{\frac{1}{2}}} \right]^H \\ \left[\frac{\frac{2^{\frac{R}{2}}}{\sigma_e} \mathbf{w}^H \mathbf{h}_{e,k}}{(2^R - 1)^{\frac{1}{2}}} \right]^H & \frac{1}{\sigma_s} \mathbf{w}^H \mathbf{h}_s \end{bmatrix} \succeq \mathbf{0}, \quad (38)$$

In addition, we consider the reformulation of the EH constraint in (5). In order to express this constraint clearly, we introduce two variables (i.e., $x_l \in \mathbb{R}$ and $y_l \in \mathbb{R}$) such that this constraint can be equivalently modified as

$$x_l^2 + y_l^2 \geq E, \quad (39a)$$

$$x_l = \Re\{\mathbf{w}^H \mathbf{h}_l\}, \quad y_l = \Im\{\mathbf{w}^H \mathbf{h}_l\}, \quad \forall l. \quad (39b)$$

The constraint (39b) is convex (linear), whereas (39a) is not convex, thus, a first-order Taylor approximation is considered to obtain the desired upper bound.

Setting $\mathbf{u}_l = [x_l \ y_l]^T$, gives, $x_l^2 + y_l^2 = \mathbf{u}_l^T \mathbf{u}_l$. $\mathbf{u}_l^{(n)}$ is the n -th iteration of the vector $\mathbf{u}_l$. Thus, (39a) can be approximated as

$$\mathbf{u}_l^T \mathbf{u}_l \approx \|\mathbf{u}_l^{(n)}\|^2 + 2 \sum_{i=1}^2 \mathbf{u}_l^{(n)}(i) [\mathbf{u}_l(i) - \mathbf{u}_l^{(n)}(i)], \quad (40)$$

where i denotes the i -th element of the vector $\mathbf{u}_l$.

This completes *Lemma 1*. ■

B. Proof of Lemma 2

The second constraint in (8) can be rewritten by exploiting the *Schur complement* as

$$\mathbf{S}'_k = \begin{bmatrix} f^{(n)}(t_2) \mathbf{I} & \begin{bmatrix} \frac{2^{\frac{R}{\sigma_e}} \mathbf{w}^H (\bar{\mathbf{h}}_{e,k} + \mathbf{e}_{e,k})}{(2^R - 1)^{\frac{1}{2}}} \end{bmatrix} \\ \begin{bmatrix} \frac{2^{\frac{R}{\sigma_e}} \mathbf{w}^H (\bar{\mathbf{h}}_{e,k} + \mathbf{e}_{e,k})}{(2^R - 1)^{\frac{1}{2}}} \end{bmatrix}^H & f^{(n)}(t_2) \end{bmatrix} \succeq \mathbf{0}, \quad (41)$$

where $f^{(n)}(t_2)$ has been defined in (9). In order to remove the impact of the channel uncertainties, we employ [38, Proposition 2], and the constraint in (41) is written as

$$\mathbf{S}_k \succeq \begin{bmatrix} \frac{2^{\frac{R}{\sigma_e}} \mathbf{w}^H}{\sigma_e} \\ \mathbf{0} \\ \mathbf{0} \end{bmatrix} \mathbf{e}_{e,k} [\mathbf{0} \ -1] + \begin{bmatrix} \mathbf{0} \\ -1 \end{bmatrix} \mathbf{e}_{e,k}^H \begin{bmatrix} \frac{2^{\frac{R}{\sigma_e}} \mathbf{w}}{\sigma_e} \ \mathbf{0} \ \mathbf{0} \end{bmatrix}, \quad (42)$$

where

$$\mathbf{S}_k = \begin{bmatrix} f^{(n)}(t_2) \mathbf{I} & \begin{bmatrix} \frac{2^{\frac{R}{\sigma_e}} \mathbf{w}^H \bar{\mathbf{h}}_{e,k}}{(2^R - 1)^{\frac{1}{2}}} \end{bmatrix} \\ \begin{bmatrix} \frac{2^{\frac{R}{\sigma_e}} \mathbf{w}^H \bar{\mathbf{h}}_{e,k}}{(2^R - 1)^{\frac{1}{2}}} \end{bmatrix}^H & f^{(n)}(t_2) \end{bmatrix} \quad (43)$$

Thus, the robust secrecy rate constraint can be reformulated as

$$\bar{\mathbf{S}}_k = \begin{bmatrix} \mathbf{S}_k - \lambda_k [\mathbf{0} \ -1] \begin{bmatrix} \mathbf{0} \\ -1 \end{bmatrix} - \varepsilon_{e,k} \begin{bmatrix} \frac{2^{\frac{R}{\sigma_e}} \mathbf{w}^H}{\sigma_e} \\ \mathbf{0} \\ \mathbf{0} \end{bmatrix} \\ -\varepsilon_{e,k} \begin{bmatrix} \frac{2^{\frac{R}{\sigma_e}} \mathbf{w}^H}{\sigma_e} \ \mathbf{0} \ \mathbf{0} \end{bmatrix} & \lambda_k \mathbf{I} \end{bmatrix} \succeq \mathbf{0}, \quad \forall k. \quad (44)$$

This completes *Lemma 2*. ■

C. Proof of Theorem 1

In order to show *Theorem 1*, we check the Karush-Kuhn-Tucker (KKT) conditions of (22). First, its Lagrange dual function can be written as

$$\begin{aligned} \mathcal{L}(\mathbf{Q}_s, \mathbf{V}, \mathbf{Y}, \mathbf{Z}, \lambda, \mu, \eta_i, \nu_l, \tau_k) = & \text{Tr}(\mathbf{Q}_s) \\ & - \lambda \left[\text{Tr}[\mathbf{h}_s \mathbf{h}_s^H (\mathbf{Q}_s - f(t) \mathbf{V})] - \sigma_s^2 f(t) \right] + \mu \left[\text{Tr}(\mathbf{Q}_s + \mathbf{V}) - P \right] \\ & + \sum_{i=1}^{N_T} \eta_i \left[\text{Tr}[\mathbf{A}_i (\mathbf{Q}_s + \mathbf{V})] - p_i \right] - \sum_{l=1}^L \nu_l \left[\text{Tr}[\mathbf{h}_l \mathbf{h}_l^H (\mathbf{Q}_s + \mathbf{V})] \right. \\ & \left. - E_l \right] + \sum_{k=1}^K \tau_k \left[\text{Tr}[\mathbf{h}_{e,k} \mathbf{h}_{e,k}^H (\mathbf{Q}_s - (t-1) \mathbf{V})] - (t-1) \sigma_e^2 \right] \\ & - \text{Tr}(\mathbf{Y} \mathbf{Q}_s) - \text{Tr}(\mathbf{Z} \mathbf{V}), \end{aligned} \quad (45)$$

where $\mathbf{Y} \in \mathbb{H}_+^{N_T}$, $\mathbf{Z} \in \mathbb{H}_+^{N_T}$, $\lambda \in \mathbb{R}_+$, $\mu \in \mathbb{R}_+$, $\eta_i \in \mathbb{R}_+$, $\nu_l \in \mathbb{R}_+$, $\tau_k \in \mathbb{R}_+$ denote the dual variables of $\mathbf{Q}_s$, $\mathbf{V}$, (21), (14a), (14b), and (18), respectively. Then, we consider the following related KKT conditions:

$$\begin{aligned} \frac{\partial \mathcal{L}}{\partial \mathbf{Q}_s} = \mathbf{0} \Rightarrow \mathbf{Y} = & \mathbf{I} - \lambda \mathbf{h}_s \mathbf{h}_s^H + \mu \mathbf{I} + \sum_{i=1}^{N_T} \eta_i \mathbf{A}_i - \sum_{l=1}^L \nu_l \mathbf{h}_l \mathbf{h}_l^H \\ & + \sum_{k=1}^K \tau_k \mathbf{h}_{e,k} \mathbf{h}_{e,k}^H, \end{aligned} \quad (46a)$$

$$\begin{aligned} \frac{\partial \mathcal{L}}{\partial \mathbf{V}} = \mathbf{0} \Rightarrow \mathbf{Z} = & \lambda f(t) \mathbf{h}_s \mathbf{h}_s^H + \mu \mathbf{I} + \sum_{i=1}^{N_T} \eta_i \mathbf{A}_i - \sum_{l=1}^L \nu_l \mathbf{h}_l \mathbf{h}_l^H \\ & - \sum_{k=1}^K \tau_k (t-1) \mathbf{h}_{e,k} \mathbf{h}_{e,k}^H, \end{aligned} \quad (46b)$$

$$\mathbf{Q}_s \mathbf{Y} = \mathbf{0}, \mathbf{Z} \succeq \mathbf{0}, \lambda \geq 0, \forall i, l, k. \quad (46c)$$

By subtracting (46b) from (46a), we have

$$\begin{aligned} \mathbf{Y} - \mathbf{Z} = & \mathbf{I} - \lambda(1 + f(t)) \mathbf{h}_s \mathbf{h}_s^H + \sum_{k=1}^K \tau_k t \mathbf{h}_{e,k} \mathbf{h}_{e,k}^H, \\ \Rightarrow \mathbf{Y} = & \mathbf{A} - \lambda(1 + f(t)) \mathbf{h}_s \mathbf{h}_s^H, \end{aligned} \quad (47)$$

where $\mathbf{A} = \mathbf{I} + \mathbf{Z} + \sum_{k=1}^K \tau_k t \mathbf{h}_{e,k} \mathbf{h}_{e,k}^H$. From (47), one can easily observe that $\mathbf{A}$ is positive definite, and $\text{rank}(\mathbf{A}) = N_T$, whereas $\text{rank}(\mathbf{Y}) = N_T$ or $N_T - 1$. However, if $\text{rank}(\mathbf{Y}) = N_T$, then it violates $\mathbf{Q}_s \neq \mathbf{0}$. Thus, $\text{rank}(\mathbf{Y}) = N_T - 1$ always holds, which implies $\mathbf{Q}_s$ lies in the null space of $\mathbf{Y}$ from (46c), thus $\text{rank}(\mathbf{Q}_s) = 1$.

This completes *Theorem 1*. ■

D. Proof of Theorem 2

We first write the dual function to (32) as follows:

$$\begin{aligned} \mathcal{L}(\mathbf{Q}_s, \mathbf{V}, \mathbf{Y}, \mathbf{Z}, \lambda, \gamma_i, \mathbf{T}_s, \mathbf{T}_{e,k}, \mathbf{T}_l) = & \text{Tr}(\mathbf{Q}_s) - \text{Tr}(\mathbf{Y} \mathbf{Q}_s) \\ & - \text{Tr}(\mathbf{Z} \mathbf{V}) + \lambda [\text{Tr}(\mathbf{Q}_s + \mathbf{V}) - P] + \sum_{i=1}^{N_T} \gamma_i \left[\text{Tr}[\bar{\mathbf{A}}_i (\mathbf{Q}_s + \mathbf{V})] \right. \\ & \left. + \epsilon_i \|\mathbf{Q}_s + \mathbf{V}\|_F - p_i \right] - \text{Tr}(\mathbf{T}_s \mathbf{A}_1) - \text{Tr}[\mathbf{T}_s \mathbf{H}_s^H (\mathbf{Q}_s - f(t) \mathbf{V}) \mathbf{H}_s] \\ & - \sum_{k=1}^K \text{Tr}(\mathbf{T}_{e,k} \mathbf{B}_k) + \sum_{k=1}^K \text{Tr} \left[\mathbf{T}_{e,k} \mathbf{H}_{e,k}^H [\mathbf{Q}_s - (t^{-1} - 1) \mathbf{V}] \mathbf{H}_{e,k} \right] \\ & - \sum_{l=1}^L \text{Tr}(\mathbf{T}_l \mathbf{C}_l) - \sum_{l=1}^L \text{Tr}[\mathbf{T}_l \mathbf{H}_l^H (\mathbf{Q}_s + \mathbf{V}) \mathbf{H}_l], \end{aligned} \quad (48)$$

where $\mathbf{Y} \in \mathbb{H}_+^{N_T}$, $\mathbf{Z} \in \mathbb{H}_+^{N_T}$, $\lambda \in \mathbb{R}_+$, $\gamma_i \in \mathbb{R}_+$, $\mathbf{T}_s \in \mathbb{H}_+^{N_T+1}$, $\mathbf{T}_{e,k} \in \mathbb{H}_+^{N_T+1}$ and $\mathbf{T}_l \in \mathbb{H}_+^{N_T+1}$ are dual variables of $\mathbf{Q}_s$, $\mathbf{V}$, (29a), (29c) and (29b), respectively. In addition,

$$\begin{aligned} \mathbf{A}_1 &= \begin{bmatrix} \beta_s \mathbf{I} & \mathbf{0} \\ \mathbf{0}^H & -f(t)\sigma_s^2 - \beta_s \varepsilon_s^2 \end{bmatrix}, \quad \mathbf{H}_s = [\mathbf{I}_{N_T} \quad \bar{\mathbf{h}}_s], \\ \mathbf{B}_k &= \begin{bmatrix} \lambda_{e,k} \mathbf{I} & \mathbf{0} \\ \mathbf{0}^H & (t^{-1}-1)\sigma_e^2 - \lambda_{e,k} \varepsilon_{e,k}^2 \end{bmatrix}, \quad \mathbf{H}_{e,k} = [\mathbf{I}_{N_T} \quad \bar{\mathbf{h}}_{e,k}], \\ \mathbf{C}_l &= \begin{bmatrix} \alpha_l \mathbf{I} & \mathbf{0} \\ \mathbf{0}^H & -E_l - \alpha_l \varepsilon_l^2 \end{bmatrix}, \quad \mathbf{H}_l = [\mathbf{I}_{N_T} \quad \bar{\mathbf{h}}_l]. \end{aligned}$$

The related KKT conditions are considered as follows:

$$\frac{\partial \mathcal{L}}{\partial \mathbf{Q}_s} = \mathbf{0}, \Rightarrow \mathbf{Y} = \mathbf{I} + \lambda \mathbf{I} + \sum_{i=1}^{N_T} \gamma_i [\bar{\mathbf{A}}_i + \epsilon_i \|\mathbf{Q}_s + \mathbf{W}\|_F^{-1} \mathbf{I}] - \mathbf{H}_s \mathbf{T}_s \mathbf{H}_s^H + \sum_{k=1}^K \mathbf{H}_{e,k} \mathbf{T}_{e,k} \mathbf{H}_{e,k}^H - \sum_{l=1}^L \mathbf{H}_l \mathbf{T}_l \mathbf{H}_l^H, \quad (49a)$$

$$\frac{\partial \mathcal{L}}{\partial \mathbf{V}} = \mathbf{0}, \Rightarrow \mathbf{Z} = \lambda \mathbf{I} + \sum_{i=1}^{N_T} \gamma_i [\bar{\mathbf{A}}_i + \epsilon_i \|\mathbf{Q}_s + \mathbf{W}\|_F^{-1} \mathbf{I}] + f(t) \mathbf{H}_s \mathbf{T}_s \mathbf{H}_s^H - \sum_{k=1}^K (t^{-1}-1) \mathbf{H}_{e,k} \mathbf{T}_{e,k} \mathbf{H}_{e,k}^H - \sum_{l=1}^L \mathbf{H}_l \mathbf{T}_l \mathbf{H}_l^H, \quad (49b)$$

$$\mathbf{Q}_s \mathbf{Y} = \mathbf{0}, \mathbf{Z} \succeq \mathbf{0}, \quad \forall i, k, l, \quad (49c)$$

$$[\mathbf{A}_1 + \mathbf{H}_s^H (\mathbf{Q}_s - f(t) \mathbf{V}) \mathbf{H}_s] \mathbf{T}_s = \mathbf{0}. \quad (49d)$$

By subtracting (49b) from (49a), we have

$$\begin{aligned} \mathbf{Y} - \mathbf{Z} &= \mathbf{I} - [1 + f(t)] \mathbf{H}_s \mathbf{T}_s \mathbf{H}_s^H + \sum_{k=1}^K t^{-1} \mathbf{H}_{e,k} \mathbf{T}_{e,k} \mathbf{H}_{e,k}^H, \\ \Rightarrow \mathbf{Y} + [1 + f(t)] \mathbf{H}_s \mathbf{T}_s \mathbf{H}_s^H &= \mathbf{I} + \mathbf{Z} + \sum_{k=1}^K t^{-1} \mathbf{H}_{e,k} \mathbf{T}_{e,k} \mathbf{H}_{e,k}^H. \end{aligned} \quad (50)$$

We premultiply (50) by $\mathbf{Q}_s$,

$$\mathbf{Q}_s \left(\mathbf{I} + \mathbf{Z} + \sum_{k=1}^K t^{-1} \mathbf{H}_{e,k} \mathbf{T}_{e,k} \mathbf{H}_{e,k}^H \right) = [1 + f(t)] \mathbf{Q}_s \mathbf{H}_s \mathbf{T}_s \mathbf{H}_s^H. \quad (51)$$

The following rank relation holds:

$$\begin{aligned} \text{rank}(\mathbf{Q}_s) &= \text{rank} \left[\mathbf{Q}_s \left(\mathbf{I} + \mathbf{Z} + \sum_{k=1}^K t^{-1} \mathbf{H}_{e,k} \mathbf{T}_{e,k} \mathbf{H}_{e,k}^H \right) \right] \\ &= \text{rank}(\mathbf{Q}_s \mathbf{H}_s \mathbf{T}_s \mathbf{H}_s^H) \\ &\leq \min\{\text{rank}(\mathbf{H}_s \mathbf{T}_s \mathbf{H}_s^H), \text{rank}(\mathbf{Q}_s)\} \end{aligned} \quad (52)$$

Based on the above rank relation, we need to show $\text{rank}(\mathbf{H}_s \mathbf{T}_s \mathbf{H}_s^H) \leq 1$ if we claim $\text{rank}(\mathbf{Q}_s) \leq 1$, thus, we consider the following two facts:

$$[\mathbf{I}_{N_T} \quad \mathbf{0}] \mathbf{H}_s^H = \mathbf{I}_{N_T}, \quad [\mathbf{I}_{N_T} \quad \mathbf{0}] \mathbf{A}_1 = \beta_s (\mathbf{H}_s - [\mathbf{0}_{N_T} \quad \bar{\mathbf{h}}_s]).$$

Premultiplying $[\mathbf{I}_{N_T} \quad \mathbf{0}]$ and postmultiplying $\mathbf{H}_s^H$ by (49d), respectively, and applying the above two equalities, we have

$$\begin{aligned} \beta_s (\mathbf{H}_s - [\mathbf{0}_{N_T} \quad \bar{\mathbf{h}}_s]) \mathbf{T}_s \mathbf{H}_s^H + [\mathbf{Q}_s - f(t) \mathbf{V}] \mathbf{H}_s \mathbf{T}_s \mathbf{H}_s^H &= \mathbf{0}, \\ \Rightarrow (\beta_s \mathbf{I} + [\mathbf{Q}_s - f(t) \mathbf{V}]) \mathbf{H}_s \mathbf{T}_s \mathbf{H}_s^H &= \beta_s [\mathbf{0}_{N_T} \quad \bar{\mathbf{h}}_s] \mathbf{T}_s \mathbf{H}_s^H. \end{aligned} \quad (53)$$

Lemma 3: If a block hermitian matrix $\mathbf{P} = \begin{bmatrix} \mathbf{P}_1 & \mathbf{P}_2 \\ \mathbf{P}_3 & \mathbf{P}_4 \end{bmatrix} \succeq \mathbf{0}$, then the main diagonal matrices $\mathbf{P}_1$ and $\mathbf{P}_4$ must be positive definite (PSD) matrices [39].

By applying Lemma 3, we can claim $\beta_s \mathbf{I} + [\mathbf{Q}_s - f(t) \mathbf{V}] \succeq \mathbf{0}$ and is nonsingular, thus pre(post)multiplying by a nonsingular matrix will not change the matrix rank. Thus, the following rank relation holds:

$$\begin{aligned} \text{rank}(\mathbf{H}_s \mathbf{T}_s \mathbf{H}_s^H) &= \text{rank}([\mathbf{0}_{N_T} \quad \bar{\mathbf{h}}_s] \mathbf{T}_s \mathbf{H}_s^H) \\ &\leq \text{rank}([\mathbf{0}_{N_T} \quad \bar{\mathbf{h}}_s]) \leq 1. \end{aligned} \quad (54)$$

This completes Theorem 2. $\blacksquare$

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networks, wireless power transfer, convex optimization techniques and game theory.

Zheng Chu received the B.Eng. degree from School of Electric and Information Engineering, Zhengzhou University of Light Industry (ZZULI), in 2007, and the M.Sc. Degree from School of Electric and Electronic Engineering, North China Electrical Power University (NCEPU), in 2011. He also obtained M.Sc. Degree (with distinction) from School of Electrical and Electronic Engineering, Newcastle University, UK, in 2012, where he is currently pursuing towards the Ph.D. degree. His research interests include physical layer security, wireless cooperative

ing algorithms for wireless communications and data storage devices.

Stphane Y. Le Goff received the BSc, MSc, and PhD degrees, all in electrical engineering, from the University of Western Brittany, Brest, Brittany, France, in 1990, 1991, and 1995, respectively. From 1995 to 1997, he worked as a teacher at the Institut Suprieur d'Electronique de Bretagne, Brest. During 1999-2003, Dr. Le Goff was an Assistant Professor at the Emirates Telecommunications Corporation (Etisalat) College of Engineering, UAE. In 2003, he joined the Department of Physics and Electronics at the University of Waikato, Hamilton, New Zealand as a Senior Lecturer in Electronics. Since 2005, he has been a Lecturer in the School of Electrical and Electronic Engineering at Newcastle University, UK. Dr. Le Goff also held visiting positions at the Eastern Mediterranean University, Cyprus, during the Academic Year 1998-1999 and at the Sultan Qaboos University, Oman, from September to December 2004. His research interests include information theory, channel coding, and wireless communication systems.