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Research Article

AN-Aided Transmit Beamforming Design for Secured Cognitive Radio Networks with SWIPT

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We investigate multiple-input single-output secured cognitive radio networks relying on simultaneous wireless information and power transfer (SWIPT), where a multiantenna secondary transmitter sends confidential information to multiple single-antenna secondary users (SUs) in the presence of multiple single-antenna primary users (PUs) and multiple energy-harvesting receivers (ERs). In order to improve the security of secondary networks, we use the artificial noise (AN) to mask the transmit beamforming. Optimization design of AN-aided transmit beamforming is studied, where the transmit power of the information signal is minimized subject to the secrecy rate constraint, the harvested energy constraint, and the total transmit power. Based on a successive convex approximation (SCA) method, we propose an iterative algorithm which reformulates the original problem as a convex problem under the perfect channel state information (CSI) case. Also, we give the convergence of the SCA-based iterative algorithm. In addition, we extend the original problem to the imperfect CSI case with deterministic channel uncertainties. Then, we study the robust design problem for the case with norm-bounded channel errors. Also, a robust SCA-based iterative algorithm is proposed by adopting the $\mathcal{S}$-Procedure. Simulation results are presented to validate the performance of the proposed algorithms.

1. Introduction

The fifth-generation (5G) wireless technology is expected to satisfy an increasing demand for wireless device, such as high data service and radio coverage [1, 2]. However, the explosive increase of mobile terminal has resulted in severe scarcity of radio spectrum resources, which has become an outstanding problem [3–5]. As one of the most efficient ways to alleviate the problem of spectrum scarcity for green communications and networks, cognitive radio (CR) is a promising approach for heightening the spectrum utilization ratio [6, 7]. In CR networks, so long as the interference produced by the secondary transmitter (ST) is tolerable to each primary user (PU), a secondary user (SU) can employ the licensed spectrum of the primary system [8]. Although CR technology can significantly increase in the spectrum efficiency, the energy scarcity still give rise to a major bottleneck problem for the quality of service (QoS) and the long lifetime of wireless users [9].

Recently, a promising technique, simultaneous wireless information and power transfer (SWIPT), has been proposed to use the radio frequency- (RF-) enabled signal harvesting power in wireless networks, which can greatly help to solve the bottleneck problem of energy scarcity [10–18]. Compared to the conventional energy harvesting techniques, such as solar power and wind, there is an advantage for SWIPT in providing more stable and controllable energy to portable wireless devices [10]. For the SWIPT operation, the work [16] examined colocated receivers which employ a power splitter for energy harvesting (EH) and information decoding (ID). Therefore, it is really important to research the combining SWIPT with CR, which has the dual function of improving both the energy efficiency and spectrum efficiency, and it has attracted more attention in [19–28]. In SWIPT-based CR system, the energy efficiency optimization was considered in [19, 20]. Moreover, the SWIPT approach for CR schemes was investigated in cooperative relay networks [21], a thresholding-based antenna selection multiple-input multiple-output (MIMO) systems [22], multiuser MISO system [23–25, 27], cooperative nonorthogonal multiple access networks [26], and sensing-Based wideband CR [28].

On the other hand, secrecy transmission has gained attentions in communication systems [29]. Unlike traditional cryptographic methods which are normally adopted in the network layer, physical layer security was developed from information theoretical aspects to improve the secrecy capacity of wireless transmission systems [30]. In the conventional SWIPT systems, since the energy-harvesting receivers (ERs) are normally assumed to be closer to the transmitter compared with information receivers (IRs), this results in a new information security issue. In such a situation, ERs have a possibility of eavesdropping the information sent to the IRs and thus can become potential eavesdroppers [31]. As a result, physical layer security has been recognized as an important issue for SWIPT systems [32]. Moreover, a few techniques have been proposed for multiple antenna secrecy systems to cause more interference to eavesdroppers [31, 33]. In SWIPT operation, artificial noise (AN) was embedded in the transmit beamforming signal to confuse the eavesdroppers and harvest power simultaneously [33].

In addition, due to the inherent characteristics of CR with SWIPT, ERs may illegitimately access the PU bands and change the radio environment. In this case, the legitimate SU is unable to use frequency bands of the PU. Thus, in order to satisfy secure communication and EH requirement, the security of CR SWIPT with ERs is also of great importance [34–38]. In [34], an outage-constrained secrecy rate maximization (SRM) problem has been investigated in an underlay MIMO CR network where the secondary transmitter (ST) provides SWIPT to all receivers. In order to guarantee secure communication and energy harvesting in MISO CR network with SWIPT, [35] studied a robust secure AN-aided beamforming and power splitting (PS) design under imperfect channel state information (CSI). For a CR network consisting of a PS-based to decode information and harvest energy simultaneously, [36] analyzed the behavior of the nodes by using game theoretic techniques and proved the existence of a unique Nash equilibrium (NE) strategy. Considering a system with ERs acting as potential eavesdroppers in CR-based SWIPT, [37] has derived a closed-form analytical expression for the exact secrecy outage probability. In a CR MIMO-SWIPT broadcast channel, [38] studied the SRM problem by designing secrecy AN-aided precoding.

Motivated by the above observations, in this paper, we study secrecy transmission over a MISO CR system with SWIPT, which consists of one primary transmitter-receiver pair (denoted as PT and PU), one multiantenna ST, multiple SUs, and multiple ERs (potentially eavesdropper). Under the perfect CSI case, we formulate a transmit power of the information signal minimization (TPISM) problem subject to the secrecy rate constraint for SUs and PU, the harvested energy constraint for ERs, and total transmit power constraint. We seek to jointly design strategies of secure beamforming and AN for MISO CR with SWIPT wiretap channels. Then, the framework is extended to robust designs for the imperfect CSI case by adopting deterministic CSI uncertainties. The main contributions for this paper are summarized as follows:

(i) For the two different types of channel models, the secrecy rate constraint with linear fractional programming is equivalently converted into several constraints with exponential form by introducing exponential variables.

(ii) For the perfect CSI case at ST and PT, unlike the conventional semidefinite relaxation (SDR), we propose a novel reformulation of the TPISM problem. A successive convex approximation- (SCA-) based iterative algorithm is proposed, where the nonconvex constraint is approximated as a convex one.

(iii) For the imperfect CSI case, we use the norm-bounded channel uncertainty to model channel. First, by applying the triangle inequality, the original constraints can be transformed as the infinitely inequality constraints. Then, by employing $\mathcal{S}$-Procedure we convert these infinitely inequality constraints into finite linear matrix inequalities (LMIs). At last, by utilizing a SCA method, the recast TPISM problem is transformed to a semidefinite programming (SDP) problem, which can be directly solved to obtain a local optimal solution. A robust SCA-based iterative algorithm is proposed.

The rest of this paper is organized as follows: Section 2 presents the system model and problem formulation. In Section 3, the SCA-based iterative algorithm is proposed with perfect CSI case. Robust SCA-based iterative algorithm is developed with imperfect CSI case in Section 4. Section 5 illustrates the simulation results. Finally, we conclude the paper in Section 6.

Notation. Vectors and matrices are denoted by bold lowercase and uppercase letters, respectively. $(\cdot)^H$ represents the Hermitian transpose. For a vector $\boldsymbol{x}$, $\|\boldsymbol{x}\|$ indicates the Euclidean norm. $|\cdot|$ defines the absolute value of a complex scalar. $\mathbb{C}^{M\times L}$ and $\mathbb{H}^{M\times L}$ describe the space of $M\times L$ complex matrices and Hermitian matrices, respectively. For a matrix $\mathbf{A}$, $\mathbf{A}\succeq\mathbf{0}$ means that $\mathbf{A}$ is positive semidefinite, and $\mathrm{tr}(\mathbf{A})$ indicate the trace, respectively. $\mathbb{E}\{\cdot\}$ describes the mathematical expectation. $\mathfrak{R}\{\cdot\}$ stands for the real part of a complex number. $[x]^+$ equals $\max\{x,0\}$. $\mathbf{I}$ denote the identity matrix with appropriate size.

2. System Model and Problem Formulation

In this section, we consider a MISO secured SWIPT cognitive radio networks, which consists of one PT, one PU, one multiantenna ST, K SU, and L ERs, as shown in Figure 1. We assume that the ST is equipped with N_S transmit antennas and each ER and each SU has one receive antenna. This system operates as follows: the primary network shares their frequency spectrum with the secondary network, whereas the confidential messages from the PT and the ST are intercepted by the eavesdroppers.

In order to achieve secure transmission, the ST employs transmit beamforming with AN, which acts as interference to

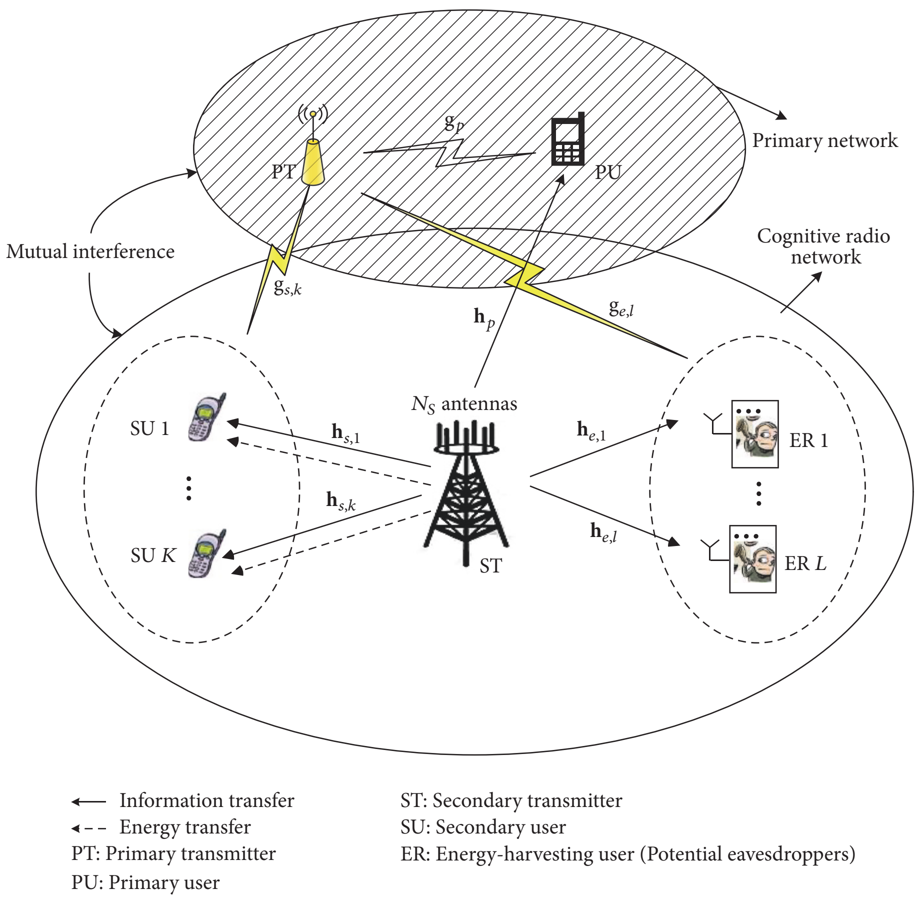

Figure 1: MISO Secured cognitive radio networks with SWIPT.

the ERs and provides energy to the SUs. The transmit signal vector $\mathbf{x}_s$ from the ST can be written as

$$\mathbf{x}_s = \sum_{j=1}^{K} \mathbf{w}_j s_j + \mathbf{z}, \tag{1}$$

where $\mathbf{w}_j \in \mathbb{C}^{N_s}$ defines the transmit beamforming vector, s_j with $\mathbb{E}\{s_j^2\} = 1$ is the information-bearing signal intended for the SUs, and $\mathbf{z}$ represents the energy-carrying AN.

We assume a frequency-flat slow-fading channel. Therefore, the received signal at the PU, the kth SU, and the lth ER can be given by, respectively,

$$y_p = \sqrt{P_p} g_p s_p + \mathbf{h}_p^H \mathbf{x}_s + n_p, \tag{2}$$

$$y_k = \sqrt{P_p} g_{s,k} s_p + \mathbf{h}_{s,k}^H \mathbf{x}_s + n_{s,k}, \quad k = 1, \ldots, K, \tag{3}$$

$$y_{e,l} = \sqrt{P_p} g_{e,l} s_p + \mathbf{h}_{e,l}^H \mathbf{x}_s + n_{e,l}, \quad l = 1, \ldots, L. \tag{4}$$

where $g_p \in \mathbb{C}$ and $\mathbf{h}_p \in \mathbb{C}^{N_S}$ are denotes by the channel between the PT and PU as well as that between the ST and PU, $g_{s,k} \in \mathbb{C}$ and $\mathbf{h}_{s,k} \in \mathbb{C}^{N_S}$ indicate the channel between the PT and the kth SU as well as that between the ST and the kth SU, $g_{e,l} \in \mathbb{C}$ and $\mathbf{h}_{e,l} \in \mathbb{C}^{N_S}$ are the channel between the PT and the lth ER as well as that between the ST and the lth ER, s_p is confidential information-bearing signal for the PU from the PT satisfying $\mathbb{E}\{s_p^2\} = 1$, and P_p represents the transmitting power from the PT. In addition, $n_p \sim \mathscr{CN}(0, \sigma_p^2)$, $n_{s,k} \sim \mathscr{CN}(0, \sigma_{s,k}^2)$, and $n_{e,l} \sim \mathscr{CN}(0, \sigma_{e,l}^2 \mathbf{I})$ denote the complex Gaussian noise at the PU, the kth SU, and the lth ER, respectively.

Thus, the channel capacity of the kth SU can be written as

$$R_{s,k} = \log\left(1 + \frac{\mathbf{h}_{s,k}^H \mathbf{w}_k \mathbf{w}_k^H \mathbf{h}_{s,k}}{\mathbf{h}_{s,k}^H \left(\sum_{j \neq k} \mathbf{w}_j \mathbf{w}_j^H + \mathbf{Z}\right) \mathbf{h}_{s,k} + P_p \left|g_{s,k}\right|^2 + \sigma_{s,k}^2}\right). \tag{5}$$

where $\mathbf{Z} = \mathbf{z}\mathbf{z}^H$. According to [3, 25], it is assumed that the kth SU can successfully decode the information from the PT by exploiting the successive interference cancellation and, thus, (5) can be rewritten as

$$\widetilde{R}_{s,k} = \log\left(1 + \frac{\mathbf{h}_{s,k}^H \mathbf{w}_k \mathbf{w}_k^H \mathbf{h}_{s,k}}{\mathbf{h}_{s,k}^H \left(\sum_{j \neq k} \mathbf{w}_j \mathbf{w}_j^H + \mathbf{Z}\right) \mathbf{h}_{s,k} + \sigma_{s,k}^2}\right). \tag{6}$$

Moreover, the channel capacity of the lth ER for decoding the desired signal of the kth SU can be represented as

$$R_{e,lk} = \log\left(1 + \frac{\mathbf{h}_{e,l}^H \mathbf{w}_k \mathbf{w}_k^H \mathbf{h}_{e,l}}{\sigma_{e,l}^2 + \mathbf{h}_{e,l}^H \left(\sum_{j\neq k} \mathbf{w}_j \mathbf{w}_j^H + \mathbf{Z}\right)\mathbf{h}_{e,l} + P_p \left|g_{e,l}\right|^2}\right). \quad (7)$$

Thus, the secrecy capacity of the kth SU can be written as

$$R_{su,k} = \left[\widetilde{R}_{s,k} - \max_l R_{e,lk}\right]^+, \quad \forall k, l. \quad (8)$$

In order to achieve the more reliable secrecy capacity (i.e., the minimum channel capacity at the k-th SU), (7) can be thus rewritten as

$$\widetilde{R}_{e,lk} = \log\left(1 + \frac{\mathbf{h}_{e,l}^H \mathbf{w}_k \mathbf{w}_k^H \mathbf{h}_{e,l}}{\sigma_{e,l}^2 + \mathbf{h}_{e,l}^H \mathbf{Z} \mathbf{h}_{e,l}}\right). \quad (9)$$

Then, we can obtain a lower bound of the secrecy capacity of the kth SU as follows:

$$R_{su,k}^{min} = \left[\widetilde{R}_{s,k} - \max_l \widetilde{R}_{e,lk}\right]^+, \quad \forall k, l. \quad (10)$$

Additionally, the channel capacity of the PU can be expressed as

$$R^{pu} = \log\left(1 + \frac{P_p \left|g_p\right|^2}{\mathbf{h}_p^H \left(\sum_{k=1}^K \mathbf{w}_k \mathbf{w}_k^H + \mathbf{Z}\right)\mathbf{h}_p + \sigma_p^2}\right). \quad (11)$$

The channel capacity of the lth ER for decoding the PU is given as

$$R_{e,l}^{pu} = \log\left(1 + \frac{P_p \left|g_{e,l}\right|^2}{\mathbf{h}_{e,l}^H \mathbf{Z} \mathbf{h}_{e,l} + \sigma_{e,l}^2}\right). \quad (12)$$

Hence, the secrecy capacity of the PU under the considered worst case scenario can be written as

$$R_s^{pu} = \left[R^{pu} - \max_l R_{e,l}^{pu}\right]^+, \quad \forall l. \quad (13)$$

Moreover, the harvested power at the lth ER is expressed as, respectively,

$$E_l^e = \eta_{e,l}\left(\mathbf{h}_{e,l}^H \left(\sum_{j=1}^K \mathbf{w}_j \mathbf{w}_j^H + \mathbf{Z}\right)\mathbf{h}_{e,l} + P_p \left|g_{e,l}\right|^2 + \sigma_{e,l}^2\right), \quad \forall l, \quad (14)$$

where $0 \le \eta_{e,l} \le 1$ denote the energy conversion efficiency at the lth ER.

In this paper, our aim is to minimize the transmit power of the information signal subject to the secrecy rate constraint at the SUs, the harvested energy constraint at the ERs, and the total transmit power constraint. Based on the system models, the TPISM problem is formulated as

$$\min_{\mathbf{w}_k, \mathbf{Z}} \quad \sum_{k=1}^K \left\|\mathbf{w}_k\right\|^2 \quad (15a)$$

$$\text{s.t.} \quad \min_k R_{su,k}^{min} \ge \overline{R}^{su}, \quad \forall k, \quad (15b)$$

$$R_s^{pu} \ge \overline{R}^{pu}, \quad \forall l, \quad (15c)$$

$$\min_l E_l^e \ge \overline{E}^e, \quad \forall l, \quad (15d)$$

$$\sum_{k=1}^K \left\|\mathbf{w}_k\right\|^2 + \operatorname{tr}(\mathbf{Z}) \le P, \quad \forall k, \quad (15e)$$

$$\mathbf{Z} \succeq \mathbf{0}. \quad (15f)$$

where P is the total transmit power, $\overline{R}^{su}$ and $\overline{R}^{pu}$ denote the secrecy capacity requirement of the kth SU and the PU, and $\overline{E}^e$ mean the harvested power requirement of the lth ER, respectively. The constraints (15b) and (15c) guarantee that the minimum secrecy rate should be achieved by the kth SU and the PU, respectively. The constraint (15d) guarantees that the minimum harvested power at the lth ER is no less than $\overline{E}^e$, respectively. The constraint (15e) limits the total transmit power of the ST. It is seen that problem (15a) are nonconvex, difficult to be solved directly.

3. Proposed Algorithm with Perfect CSI

In this section, we investigate a joint design of the transmit beamforming and AN for systems under the assumption that the PT and ST can obtain perfect CSI. Problems (15a)–(15f) can be rewritten as

$$\min_{\mathbf{w}_k, \mathbf{Z}} \quad \sum_{k=1}^K \left\|\mathbf{w}_k\right\|^2 \quad (16a)$$

$$\text{s.t.} \quad \log\left(1 + \frac{\mathbf{h}_{s,k}^H \mathbf{w}_k \mathbf{w}_k^H \mathbf{h}_{s,k}}{\mathbf{h}_{s,k}^H \left(\sum_{j\neq k} \mathbf{w}_j \mathbf{w}_j^H + \mathbf{Z}\right)\mathbf{h}_{s,k} + \sigma_{s,k}^2}\right) - \log\left(1 + \frac{\mathbf{h}_{e,l}^H \mathbf{w}_k \mathbf{w}_k^H \mathbf{h}_{e,l}}{\sigma_{e,l}^2 + \mathbf{h}_{e,l}^H \mathbf{Z} \mathbf{h}_{e,l}}\right) \ge \overline{R}^{su}, \quad \forall l, k, \quad (16b)$$

$$\log\left(1 + \frac{P_p \left|g_p\right|^2}{\sum_{j=1}^K \mathbf{h}_p^H \mathbf{w}_j \mathbf{w}_j^H \mathbf{h}_p + \mathbf{h}_p^H \mathbf{Z} \mathbf{h}_p + \sigma_p^2}\right) - \log\left(1 + \frac{P_p \left|g_{e,l}\right|^2}{\mathbf{h}_{e,l}^H \mathbf{Z} \mathbf{h}_{e,l} + \sigma_{e,l}^2}\right) \ge \overline{R}^{pu}, \quad \forall l, k, \quad (16c)$$

$$\eta_{e,l}\left(\mathbf{h}_{e,l}^H \left(\sum_{j=1}^K \mathbf{w}_j \mathbf{w}_j^H + \mathbf{Z}\right)\mathbf{h}_{e,l} + P_p \left|g_{e,l}\right|^2 + \sigma_{e,l}^2\right) \ge \overline{E}^e, \quad \forall l, \quad (16d)$$

$$(15\text{e}), (15\text{f}). \quad (16e)$$

In order to solve the nonconvex problems (16a)–(16e), we firstly define $\mathbf{W}_k \triangleq \mathbf{w}_k\mathbf{w}_k^H$ and denote $\mathbf{W}_Z = \sum_{j=1}^{K}\mathbf{w}_j\mathbf{w}_j^H + \mathbf{Z}$. Then, the constraints (16b) and (16c) can be reformulated as

$$\log\left(\frac{\mathbf{h}_{s,k}^H\left(\sum_{j\neq k}\mathbf{W}_j+\mathbf{Z}\right)\mathbf{h}_{s,k}+\sigma_{s,k}^2+\mathbf{h}_{s,k}^H\mathbf{W}_k\mathbf{h}_{s,k}}{\mathbf{h}_{s,k}^H\left(\sum_{j\neq k}\mathbf{W}_j+\mathbf{Z}\right)\mathbf{h}_{s,k}+\sigma_{s,k}^2}\right) - \log\left(\frac{\sigma_{e,l}^2+\mathbf{h}_{e,l}^H\mathbf{Z}\mathbf{h}_{e,l}+\mathbf{h}_{e,l}^H\mathbf{W}_k\mathbf{h}_{e,l}}{\sigma_{e,l}^2+\mathbf{h}_{e,l}^H\mathbf{Z}\mathbf{h}_{e,l}}\right) \geq \overline{R}^{su}, \tag{17a}$$

$$\log\left(\frac{\mathbf{h}_p^H\mathbf{W}_Z\mathbf{h}_p+\sigma_p^2+P_p\left|g_p\right|^2}{\mathbf{h}_p^H\mathbf{W}_Z\mathbf{h}_p+\sigma_p^2}\right) - \log\left(\frac{\mathbf{h}_{e,l}^H\mathbf{Z}\mathbf{h}_{e,l}+\sigma_{e,l}^2+P_p\left|g_{e,l}\right|^2}{\mathbf{h}_{e,l}^H\mathbf{Z}\mathbf{h}_{e,l}+\sigma_{e,l}^2}\right) \geq \overline{R}^{pu}, \tag{17b}$$

where they can be also rewritten as

$$\frac{\left(\mathbf{h}_{s,k}^H\mathbf{W}_Z\mathbf{h}_{s,k}+\sigma_{s,k}^2\right)\left(\sigma_{e,l}^2+\mathbf{h}_{e,l}^H\mathbf{Z}\mathbf{h}_{e,l}\right)}{\left(\mathbf{h}_{s,k}^H\left(\sum_{j\neq k}\mathbf{W}_j+\mathbf{Z}\right)\mathbf{h}_{s,k}+\sigma_{s,k}^2\right)\left(\sigma_{e,l}^2+\mathbf{h}_{e,l}^H\left(\mathbf{Z}+\mathbf{W}_k\right)\mathbf{h}_{e,l}\right)} \geq 2^{\overline{R}^{su}}, \quad \forall l,k, \tag{18a}$$

$$\frac{\left(\mathbf{h}_p^H\mathbf{W}_Z\mathbf{h}_p+\sigma_p^2+P_p\left|g_p\right|^2\right)\left(\mathbf{h}_{e,l}^H\mathbf{Z}\mathbf{h}_{e,l}+\sigma_{e,l}^2\right)}{\left(\mathbf{h}_p^H\mathbf{W}_Z\mathbf{h}_p+\sigma_p^2\right)\left(\mathbf{h}_{e,l}^H\mathbf{Z}\mathbf{h}_{e,l}+\sigma_{e,l}^2+P_p\left|g_{e,l}\right|^2\right)} \geq 2^{\overline{R}^{pu}}, \quad \forall l,k. \tag{18b}$$

For solving linear fractional programming (18a) and (18b), we can introduce the following exponential variables to equivalently convert. Then, we introduce slack variables x_k, y_l, t_k, $r_{l,k}$, x_p, u_l, t_p, and s_l. Equations (18a) and (18b) can be transformed as follows, respectively:

$$e^{x_k+y_l-t_k-r_{l,k}} \geq 2^{\overline{R}^{su}}, \tag{19a}$$

$$\mathbf{h}_{s,k}^H\mathbf{W}_Z\mathbf{h}_{s,k}+\sigma_{s,k}^2 \geq e^{x_k}, \tag{19b}$$

$$\sigma_{e,l}^2+\mathbf{h}_{e,l}^H\mathbf{Z}\mathbf{h}_{e,l} \geq e^{y_l}, \tag{19c}$$

$$\mathbf{h}_{s,k}^H\left(\sum_{j\neq k}\mathbf{W}_j+\mathbf{Z}\right)\mathbf{h}_{s,k}+\sigma_{s,k}^2 \leq e^{t_k}, \tag{19d}$$

$$\sigma_{e,l}^2+\mathbf{h}_{e,l}^H\left(\mathbf{Z}+\mathbf{W}_k\right)\mathbf{h}_{e,l} \leq e^{r_{l,k}}. \tag{19e}$$

$$e^{x_p+u_l-t_p-s_l} \geq 2^{\overline{R}^{pu}}, \tag{20a}$$

$$\mathbf{h}_p^H\mathbf{W}_Z\mathbf{h}_p+\sigma_p^2+P_p\left|g_p\right|^2 \geq e^{x_p}, \tag{20b}$$

$$\mathbf{h}_{e,l}^H\mathbf{Z}\mathbf{h}_{e,l}+\sigma_{e,l}^2 \geq e^{u_l}, \tag{20c}$$

$$\mathbf{h}_p^H\mathbf{W}_Z\mathbf{h}_p+\sigma_p^2 \leq e^{t_p}, \tag{20d}$$

$$\mathbf{h}_{e,l}^H\mathbf{Z}\mathbf{h}_{e,l}+\sigma_{e,l}^2+P_p\left|g_{e,l}\right|^2 \leq e^{s_l}. \tag{20e}$$

It is noted that the aforementioned constraints (19a), (19d), (19e), (20a), (20d), and (20e) are not still convex. Firstly, (19a) and (20a) can be reshaped respectively as the following convex constraints:

$$e^{-x_k-y_l+t_k+r_{l,k}} \leq 2^{-\overline{R}^{su}}, \quad \forall k,\ \forall l, \tag{21a}$$

$$e^{-x_p-u_l+t_p+s_l} \leq 2^{-\overline{R}^{pu}}, \quad \forall l. \tag{21b}$$

Secondly, an SCA method is used to jointly design the secure beamforming and AN matrix. Let us define $t_k(n)$, $r_{l,k}(n)$, $t_p(n)$, and $s_l(n)$ as the variables t_k, $r_{l,k}$, t_p, and s_l at the nth iteration for the SCA method. By adopting a Taylor series expansion $e^{x_l(n)}(x_l - x_l(n) + 1) \leq e^{x_l}$, we can convert the nonconvex constraints (19d), (19e), (20d), and (20e) to their corresponding convex approximations as

$$\mathbf{h}_{s,k}^H\left(\sum_{j\neq k}\mathbf{W}_j+\mathbf{Z}\right)\mathbf{h}_{s,k}+\sigma_{s,k}^2 \leq e^{t_k(n)}\left(t_k-t_k(n)+1\right), \tag{22a}$$

$$\sigma_{e,l}^2+\mathbf{h}_{e,l}^H\left(\mathbf{Z}+\mathbf{W}_k\right)\mathbf{h}_{e,l} \leq e^{r_{l,k}(n)}\left(r_{l,k}-r_{l,k}(n)+1\right), \tag{22b}$$

$$\mathbf{h}_p^H\mathbf{W}_Z\mathbf{h}_p+\sigma_p^2 \leq e^{t_p(n)}\left(t_p-t_p(n)+1\right), \tag{22c}$$

$$\mathbf{h}_{e,l}^H\mathbf{Z}\mathbf{h}_{e,l}+\sigma_{e,l}^2+P_p\left|g_{e,l}\right|^2 \leq e^{s_l(n)}\left(s_l-s_l(n)+1\right). \tag{22d}$$

At last, we consider the constraints (16d) and (15e), which can be converted as

$$\mathbf{h}_{e,l}^H\mathbf{W}_Z\mathbf{h}_{e,l}+P_p\left|g_{e,l}\right|^2+\sigma_e^2 \geq \frac{\overline{E}^e}{\eta_{e,l}}, \quad \forall l, \tag{23a}$$

$$\sum_{k=1}^{K}\operatorname{tr}\left(\mathbf{W}_k\right)+\operatorname{tr}\left(\mathbf{Z}\right) \leq P, \quad \forall k. \tag{23b}$$

According to equations from (16a) to (23b), an SCA-based iterative algorithm is proposed. At the $(n+1)$th iteration, by removing the nonconvex rank-one constraint $\operatorname{rank}(\mathbf{W}_k) = 1$, $\forall k$, problems (16a)–(16e) can be thus reformed as

$$\begin{aligned}\min_{\Omega}\quad & \sum_{k=1}^{K}\operatorname{tr}\left(\mathbf{W}_k\right)\\ \text{s.t.}\quad & (15\text{f}), (19\text{b}), (19\text{c}), (20\text{b}), (20\text{c}), (21\text{a}), (21\text{b}), (22\text{a}), (22\text{b}), (22\text{c}), (22\text{d}), (23\text{a}), (23\text{b}), (23\text{c}), \quad \mathbf{W}_k \succeq \mathbf{0},\\ & \Omega = \left\{\mathbf{W}_k, \mathbf{Z}, x_k, y_l, t_k, r_{l,k}, x_p, u_l, t_p, s_l\right\}.\end{aligned} \tag{24}$$

Set $n = 0$ and initialize $\Psi(0) = \{t_k(0), r_{l,k}(0), t_p(0), s_l(0)\}$.
Repeat
(i) Solve problem (24) with $\{t_k(n), r_{l,k}(n), t_p(n), s_l(n)\}$
and denote a solution by $\{t_k(n+1), r_{l,k}(n+1), t_p(n+1), s_l(n+1)\}$.
(ii) Update $n \longleftarrow n+1$.
Until Convergence

Algorithm 1: SCA-based iterative algorithm with perfect CSI.

For given $\Psi(n) = \{t_k(n), r_{l,k}(n), t_p(n), s_l(n)\}$ as the optimal solution obtained at the nth iteration, problem (24) is convex by removing the nonconvex $\text{rank}(\mathbf{W}_k) = 1$ constraint, which can be solved by using an CVX tools [39]. From SCA method, the convex approximation with the current solution is iteratively updated until the constraints (22a)–(22d) hold with equality, which implies that (16a)–(16e) can be optimally solved. The optimal solution obtained by the proposed SCA-based iterative algorithm at the nth iteration is assumed to be ($t_k(n)$, $r_{l,k}(n)$, $t_p(n)$, and $s_l(n)$), which can achieve a stable point until the SCA-based iterative algorithm converges [35], and this is summarized in Algorithm 1.

4. Proposed Algorithm with Imperfect CSI

Because of channel estimation and quantization errors, it may not be possible to have perfect CSI in practice. In this section, we extend the proposed algorithm to more practical scenarios with imperfect CSI. First, we introduce one scenario of the norm-bounded channel uncertainty and then provide the problem formulation based on the norm-bounded channel uncertainty. Moreover, we consider a joint robust design of transmit beamforming and AN.

4.1. Norm-Bounded Channel Uncertainty. Now, we adopt imperfect CSI based on the deterministic model [31, 35]. In particular, we assume that the actual channel vector $\mathbf{h}_{s,k}$ lies within a ball with the radius $\varepsilon_{s,k}$ around the estimated channel vector $\overline{\mathbf{h}}_{s,k}$ from the BS to the kth user, i.e.,

$$\begin{aligned}
\mathbf{h}_{s,k} &\in \mathscr{H}_{s,k} = \left\{\overline{\mathbf{h}}_{s,k} + \Delta\mathbf{h}_{s,k} \mid \left\|\Delta\mathbf{h}_{s,k}\right\| \le \varepsilon_{s,k}\right\}, \quad \forall l, \\
\mathbf{h}_{e,l} &\in \mathscr{H}_{e,l} = \left\{\overline{\mathbf{h}}_{e,l} + \Delta\mathbf{h}_{e,l} \mid \left\|\Delta\mathbf{h}_{e,l}\right\| \le \varepsilon_{e,l}\right\}, \quad \forall l, \\
\mathbf{h}_{p} &\in \mathscr{H}_{p} = \left\{\overline{\mathbf{h}}_{p} + \Delta\mathbf{h}_{p} \mid \left\|\Delta\mathbf{h}_{p}\right\| \le \varepsilon_{p}\right\}, \quad \forall l, \\
g_p &\in \widehat{\mathscr{G}}_p = \left\{\overline{g}_p + \Delta g_p \mid \left|\Delta g_p\right| \le \gamma_p\right\}, \\
g_{s,k} &\in \widehat{\mathscr{G}}_{s,k} = \left\{\overline{g}_{s,k} + \Delta g_{s,k} \mid \left|\Delta g_{s,k}\right| \le \gamma_{s,k}\right\}, \quad \forall k, \\
g_{e,l} &\in \widehat{\mathscr{G}}_{e,l} = \left\{\overline{g}_{e,l} + \Delta g_{e,l} \mid \left|\Delta g_{e,l}\right| \le \gamma_{e,l}\right\}, \quad \forall l.
\end{aligned} \tag{25}$$

where $\overline{\mathbf{h}}_{s,k}$, $\overline{\mathbf{h}}_{e,l}$, $\overline{\mathbf{h}}_{p}$, $\overline{g}_p$, $\overline{g}_{s,k}$, and $\overline{g}_{e,l}$ are the estimated channel available, the channel estimation errors $\Delta\mathbf{h}_{s,k}$, $\Delta\mathbf{h}_{e,l}$, $\Delta\mathbf{h}_p$, Δg_p, $\Delta g_{s,k}$, and $\Delta g_{e,l}$ are bounded by $\varepsilon_{s,k}$, $\varepsilon_{e,l}$, ε_p, γ_p, $\gamma_{s,k}$, and $\gamma_{e,l}$, respectively.

By taking the norm-bounded channel uncertainty model into account, the TPISM problem can be rewritten as

$$\min_{\mathbf{w}_k, \mathbf{Z}} \quad \sum_{k=1}^{K} \left\|\mathbf{w}_k\right\|^2 \tag{26a}$$

$$\begin{aligned}
\text{s.t.} \quad & \log\left(1 + \frac{\left(\overline{\mathbf{h}}_{s,k} + \Delta\mathbf{h}_{s,k}\right)^H \mathbf{w}_k\mathbf{w}_k^H \left(\overline{\mathbf{h}}_{s,k} + \Delta\mathbf{h}_{s,k}\right)}{\left(\overline{\mathbf{h}}_{s,k} + \Delta\mathbf{h}_{s,k}\right)^H \left(\sum_{j\neq k} \mathbf{w}_j\mathbf{w}_j^H + \mathbf{Z}\right)\left(\overline{\mathbf{h}}_{s,k} + \Delta\mathbf{h}_{s,k}\right) + \sigma_{s,k}^2}\right) \\
& - \log\left(1 + \frac{\left(\overline{\mathbf{h}}_{e,l} + \Delta\mathbf{h}_{e,l}\right)^H \mathbf{w}_k\mathbf{w}_k^H \left(\overline{\mathbf{h}}_{e,l} + \Delta\mathbf{h}_{e,l}\right)}{\sigma_{e,l}^2 + \left(\overline{\mathbf{h}}_{e,l} + \Delta\mathbf{h}_{e,l}\right)^H \mathbf{Z}\left(\overline{\mathbf{h}}_{e,l} + \Delta\mathbf{h}_{e,l}\right)}\right) \ge \overline{R}^{su}, \quad \forall l, k,
\end{aligned} \tag{26b}$$

$$\begin{aligned}
& \log\left(1 + \frac{P_p\left|\overline{g}_p + \Delta g_p\right|^2}{\left(\overline{\mathbf{h}}_{p} + \Delta\mathbf{h}_{p}\right)^H \left(\sum_{j=1}^{K} \mathbf{w}_j\mathbf{w}_j^H + \mathbf{Z}\right)\left(\overline{\mathbf{h}}_{p} + \Delta\mathbf{h}_{p}\right) + \sigma_p^2}\right) \\
& - \log\left(1 + \frac{P_p\left|\overline{g}_{e,l} + \Delta g_{e,l}\right|^2}{\left(\overline{\mathbf{h}}_{e,l} + \Delta\mathbf{h}_{e,l}\right)^H \mathbf{Z}\left(\overline{\mathbf{h}}_{e,l} + \Delta\mathbf{h}_{e,l}\right) + \sigma_{e,l}^2}\right) \ge \overline{R}^{pu}, \quad \forall l, k,
\end{aligned} \tag{26c}$$

$$\eta_{e,l}\left(\left(\overline{\mathbf{h}}_{e,l}+\Delta\mathbf{h}_{e,l}\right)^{H}\mathbf{W}_{Z}\left(\overline{\mathbf{h}}_{e,l}+\Delta\mathbf{h}_{e,l}\right)+P_{p}\left|\overline{g}_{e,l}+\Delta g_{e,l}\right|^{2}+\sigma_{e}^{2}\right)\geq\overline{E}^{e},\quad\forall l, \tag{26d}$$

$$(15e), (15f). \tag{26e}$$

Utilizing a similar methodology in (17a)–(18b), the constraints (26b) and (26c) can be reformulated as

$$\frac{\left(\left(\overline{\mathbf{h}}_{s,k}+\Delta\mathbf{h}_{s,k}\right)^{H}\left(\sum_{j=1}^{K}\mathbf{W}_{j}+\mathbf{Z}\right)\left(\overline{\mathbf{h}}_{s,k}+\Delta\mathbf{h}_{s,k}\right)+\sigma_{s,k}^{2}\right)\left(\sigma_{e,l}^{2}+\left(\overline{\mathbf{h}}_{e,l}+\Delta\mathbf{h}_{e,l}\right)^{H}\mathbf{Z}\left(\overline{\mathbf{h}}_{e,l}+\Delta\mathbf{h}_{e,l}\right)\right)}{\left(\left(\overline{\mathbf{h}}_{s,k}+\Delta\mathbf{h}_{s,k}\right)^{H}\left(\sum_{j\neq k}\mathbf{W}_{j}+\mathbf{Z}\right)\left(\overline{\mathbf{h}}_{s,k}+\Delta\mathbf{h}_{s,k}\right)+\sigma_{s,k}^{2}\right)\left(\sigma_{e,l}^{2}+\left(\overline{\mathbf{h}}_{e,l}+\Delta\mathbf{h}_{e,l}\right)^{H}\left(\mathbf{Z}+\mathbf{W}_{k}\right)\left(\overline{\mathbf{h}}_{e,l}+\Delta\mathbf{h}_{e,l}\right)\right)}\geq 2^{\overline{R}^{su}}, \tag{27a}$$

$$\frac{\left(\left(\overline{\mathbf{h}}_{p}+\Delta\mathbf{h}_{p}\right)^{H}\mathbf{W}_{Z}\left(\overline{\mathbf{h}}_{p}+\Delta\mathbf{h}_{p}\right)+\sigma_{p}^{2}+P_{p}\left|\overline{g}_{p}+\Delta g_{p}\right|^{2}\right)\left(\left(\overline{\mathbf{h}}_{e,l}+\Delta\mathbf{h}_{e,l}\right)^{H}\mathbf{Z}\left(\overline{\mathbf{h}}_{e,l}+\Delta\mathbf{h}_{e,l}\right)+\sigma_{e,l}^{2}\right)}{\left(\left(\overline{\mathbf{h}}_{p}+\Delta\mathbf{h}_{p}\right)^{H}\mathbf{W}_{Z}\left(\overline{\mathbf{h}}_{p}+\Delta\mathbf{h}_{p}\right)+\sigma_{p}^{2}\right)\left(\left(\overline{\mathbf{h}}_{e,l}+\Delta\mathbf{h}_{e,l}\right)^{H}\mathbf{Z}\left(\overline{\mathbf{h}}_{e,l}+\Delta\mathbf{h}_{e,l}\right)+\sigma_{e,l}^{2}+P_{p}\left|\overline{g}_{e,l}+\Delta g_{e,l}\right|^{2}\right)}\geq 2^{\overline{R}^{pu}}. \tag{27b}$$

Then, by introducing $\widehat{x}_k$, $\widehat{y}_l$, $\widehat{t}_k$, $\widehat{r}_{l,k}$, $\widehat{x}_p$, $\widehat{u}_l$, $\widehat{t}_p$, and $\widehat{s}_l$ as slack variables, we equivalently convert the linear fractional programming (27a) and (27b) as follows, respectively:

$$e^{\widehat{x}_k+\widehat{y}_l-\widehat{t}_k-\widehat{r}_{l,k}}\geq 2^{\overline{R}^{su}},\quad\forall k,\ \forall l, \tag{28a}$$

$$\min_{\|\Delta\mathbf{h}_{s,k}\|\leq\varepsilon_{s,k}}\left(\overline{\mathbf{h}}_{s,k}+\Delta\mathbf{h}_{s,k}\right)^{H}\mathbf{W}_{Z}\left(\overline{\mathbf{h}}_{s,k}+\Delta\mathbf{h}_{s,k}\right)+\sigma_{s,k}^{2}\geq e^{\widehat{x}_k},\quad\forall k, \tag{28b}$$

$$\min_{\|\Delta\mathbf{h}_{e,l}\|\leq\varepsilon_{e,l}}\sigma_{e,l}^{2}+\left(\overline{\mathbf{h}}_{e,l}+\Delta\mathbf{h}_{e,l}\right)^{H}\mathbf{Z}\left(\overline{\mathbf{h}}_{e,l}+\Delta\mathbf{h}_{e,l}\right)\geq e^{\widehat{y}_l},\quad\forall l, \tag{28c}$$

$$\max_{\|\Delta\mathbf{h}_{s,k}\|\leq\varepsilon_{s,k}}\left(\overline{\mathbf{h}}_{s,k}+\Delta\mathbf{h}_{s,k}\right)^{H}\left(\sum_{j\neq k}\mathbf{W}_{j}+\mathbf{Z}\right)\cdot\left(\overline{\mathbf{h}}_{s,k}+\Delta\mathbf{h}_{s,k}\right)+\sigma_{s,k}^{2}\leq e^{\widehat{t}_k},\quad\forall k, \tag{28d}$$

$$\max_{\|\Delta\mathbf{h}_{e,l}\|\leq\varepsilon_{e,l}}\sigma_{e,l}^{2}+\left(\overline{\mathbf{h}}_{e,l}+\Delta\mathbf{h}_{e,l}\right)^{H}\left(\mathbf{Z}+\mathbf{W}_{k}\right)\left(\overline{\mathbf{h}}_{e,l}+\Delta\mathbf{h}_{e,l}\right)\leq e^{\widehat{r}_{l,k}},\quad\forall k,\ \forall l. \tag{28e}$$

$$e^{\widehat{x}_p+\widehat{u}_l-\widehat{t}_p-\widehat{s}_l}\geq 2^{\overline{R}^{pu}},\quad\forall l, \tag{29a}$$

$$\min_{\|\Delta\mathbf{h}_{p}\|\leq\varepsilon_{p}}\left(\overline{\mathbf{h}}_{p}+\Delta\mathbf{h}_{p}\right)^{H}\mathbf{W}_{Z}\left(\overline{\mathbf{h}}_{p}+\Delta\mathbf{h}_{p}\right)+\sigma_{p}^{2}+P_{p}\left|\overline{g}_{p}+\Delta g_{p}\right|^{2}\geq e^{\widehat{x}_p}, \tag{29b}$$

$$\min_{\|\Delta\mathbf{h}_{e,l}\|\leq\varepsilon_{e,l}}\left(\overline{\mathbf{h}}_{e,l}+\Delta\mathbf{h}_{e,l}\right)^{H}\mathbf{Z}\left(\overline{\mathbf{h}}_{e,l}+\Delta\mathbf{h}_{e,l}\right)+\sigma_{e,l}^{2}\geq e^{\widehat{u}_l},\quad\forall l, \tag{29c}$$

$$\max_{\|\Delta\mathbf{h}_{p}\|\leq\varepsilon_{p}}\left(\overline{\mathbf{h}}_{p}+\Delta\mathbf{h}_{p}\right)^{H}\mathbf{W}_{Z}\left(\overline{\mathbf{h}}_{p}+\Delta\mathbf{h}_{p}\right)+\sigma_{p}^{2}\leq e^{\widehat{t}_p}, \tag{29d}$$

$$\max_{\|\Delta\mathbf{h}_{e,l}\|\leq\varepsilon_{e,l}}\left(\overline{\mathbf{h}}_{e,l}+\Delta\mathbf{h}_{e,l}\right)^{H}\mathbf{Z}\left(\overline{\mathbf{h}}_{e,l}+\Delta\mathbf{h}_{e,l}\right)+\sigma_{e,l}^{2}+P_{p}\left|\overline{g}_{e,l}+\Delta g_{e,l}\right|^{2}\leq e^{\widehat{s}_l},\quad\forall l. \tag{29e}$$

By employing the slack variables (i.e., d_k, w_l, b_k, and $f_{l,k}$) for (28b)–(28e), respectively, (28a)–(28e) can be equivalently modified as

$$\min_{\|\Delta\mathbf{h}_{s,k}\|\leq\varepsilon_{s,k}}\left(\overline{\mathbf{h}}_{s,k}+\Delta\mathbf{h}_{s,k}\right)^{H}\mathbf{W}_{Z}\left(\overline{\mathbf{h}}_{s,k}+\Delta\mathbf{h}_{s,k}\right)\geq d_k, \tag{30a}$$

$$\min_{\|\Delta\mathbf{h}_{e,l}\|\leq\varepsilon_{e,l}}\left(\overline{\mathbf{h}}_{e,l}+\Delta\mathbf{h}_{e,l}\right)^{H}\mathbf{Z}\left(\overline{\mathbf{h}}_{e,l}+\Delta\mathbf{h}_{e,l}\right)\geq w_l, \tag{30b}$$

$$\max_{\|\Delta\mathbf{h}_{s,k}\|\leq\varepsilon_{s,k}}\left(\overline{\mathbf{h}}_{s,k}+\Delta\mathbf{h}_{s,k}\right)^{H}\left(\sum_{j\neq k}\mathbf{W}_{j}+\mathbf{Z}\right)\cdot\left(\overline{\mathbf{h}}_{s,k}+\Delta\mathbf{h}_{s,k}\right)\leq z_k, \tag{30c}$$

$$\max_{\|\Delta\mathbf{h}_{e,l}\|\leq\varepsilon_{e,l}}\left(\overline{\mathbf{h}}_{e,l}+\Delta\mathbf{h}_{e,l}\right)^{H}\left(\mathbf{Z}+\mathbf{W}_{k}\right)\left(\overline{\mathbf{h}}_{e,l}+\Delta\mathbf{h}_{e,l}\right)\leq f_{l,k}, \tag{30d}$$

$$d_k+\sigma_{s,k}^{2}\geq e^{\widehat{x}_k}, \tag{30e}$$

$$\sigma_{e,l}^{2}+w_l\geq e^{\widehat{y}_l}, \tag{30f}$$

$$z_k+\sigma_{s,k}^{2}\leq e^{\widehat{t}_k}, \tag{30g}$$

$$\sigma_{e,l}^{2}+f_{l,k}\leq e^{\widehat{r}_{l,k}}. \tag{30h}$$

For the worst-case based design in (26b)–(26d), the PT channel gains are upper-bounded and lower-bounded using the following triangle inequality properties:

$$\begin{aligned} |x+y|^2 &\le (|x|+|y|)^2 = |x|^2+|y|^2+2|x||y|,\\ |x+y|^2 &\ge (|x|-|y|)^2 = |x|^2+|y|^2-2|x||y|. \end{aligned} \tag{31}$$

Applying (31), it follows that

$$\begin{aligned} g_{e,l}^{max} &\triangleq \max_{\Delta g_{e,l}\le\gamma_{e,l}} |g_{e,l}|^2 \\ &= \max_{\Delta g_{e,l}\le\gamma_{e,l}} \left(|\overline{g}_{e,l}|^2 + |\Delta g_{e,l}|^2 + 2|\overline{g}_{e,l}||\Delta g_{e,l}|\right) \\ &\le |\overline{g}_{e,l}|^2 + \varepsilon_{e,l}^2 + 2\varepsilon_{e,l}|\overline{g}_{e,l}|, \\ g_{e,l}^{min} &\triangleq \min_{\Delta g_{e,l}\le\gamma_{e,l}} |g_{e,l}|^2 \\ &= \min_{\Delta g_{e,l}\le\gamma_{e,l}} \left(|\overline{g}_{e,l}|^2 + |\Delta g_{e,l}|^2 - 2|\overline{g}_{e,l}||\Delta g_{e,l}|\right) \\ &\ge |\overline{g}_{e,l}|^2 + \varepsilon_{e,l}^2 - 2\varepsilon_{e,l}|\overline{g}_{e,l}|, \\ g_{p}^{min} &\triangleq \min_{\Delta g_{p}\le\gamma_{p}} |g_{p}|^2 \\ &= \min_{\Delta g_{p}\le\gamma_{p}} \left(|\overline{g}_{p}|^2 + |\Delta g_{p}|^2 - 2|\overline{g}_{p}||\Delta g_{p}|\right) \\ &\ge |\overline{g}_{p}|^2 + \varepsilon_{p}^2 - 2\varepsilon_{p}|\overline{g}_{p}|, \\ g_{s,k}^{min} &\triangleq \min_{\Delta g_{s,k}\le\gamma_{s,k}} |g_{s,k}|^2 \\ &= \min_{\Delta g_{s,k}\le\gamma_{s,k}} \left(|\overline{g}_{s,k}|^2 + |\Delta g_{s,k}|^2 + 2|\overline{g}_{s,k}||\Delta g_{s,k}|\right) \\ &\ge |\overline{g}_{s,k}|^2 + \varepsilon_{s,k}^2 - 2\varepsilon_{s,k}|\overline{g}_{s,k}|. \end{aligned} \tag{32}$$

Similarly, we introduce the slack variables d_p, v_l, b_p, and q_l for (29b)-(29e). Then, by substituting the above results (32) into (29b) and (29e), respectively, we can equivalently express (29a)–(29e) as

$$\min_{\|\Delta\mathbf{h}_p\|\le\varepsilon_p} \left(\overline{\mathbf{h}}_p+\Delta\mathbf{h}_p\right)^H \mathbf{W}_Z \left(\overline{\mathbf{h}}_p+\Delta\mathbf{h}_p\right) \ge d_p, \tag{33a}$$

$$\min_{\|\Delta\mathbf{h}_{e,l}\|\le\varepsilon_{e,l}} \left(\overline{\mathbf{h}}_{e,l}+\Delta\mathbf{h}_{e,l}\right)^H \mathbf{Z} \left(\overline{\mathbf{h}}_{e,l}+\Delta\mathbf{h}_{e,l}\right) \ge v_l, \tag{33b}$$

$$\max_{\|\Delta\mathbf{h}_p\|\le\varepsilon_p} \left(\overline{\mathbf{h}}_p+\Delta\mathbf{h}_p\right)^H \mathbf{W}_Z \left(\overline{\mathbf{h}}_p+\Delta\mathbf{h}_p\right) \le b_p, \tag{33c}$$

$$\max_{\|\Delta\mathbf{h}_{e,l}\|\le\varepsilon_{e,l}} \left(\overline{\mathbf{h}}_{e,l}+\Delta\mathbf{h}_{e,l}\right)^H \mathbf{Z} \left(\overline{\mathbf{h}}_{e,l}+\Delta\mathbf{h}_{e,l}\right) \le q_l, \tag{33d}$$

$$d_p + \sigma_p^2 + P_p g_p^{min} \ge e^{\widehat{x}_p}, \tag{33e}$$

$$v_l + \sigma_{e,l}^2 \ge e^{\widehat{u}_l}, \tag{33f}$$

$$b_p + \sigma_p^2 \le e^{\widehat{t}_p}, \tag{33g}$$

$$q_l + \sigma_{e,l}^2 + P_p g_{e,l}^{max} \le e^{\widehat{s}_l}. \tag{33h}$$

In order to make (26b)–(26d) more tractable, by applying $\mathcal{S}$-procedure [40], we can convert the infinitely inequality constraints (30a)-(30d) and (33a)-(33d) into finite linear matrix inequalities (LMIs). For completeness, the $\mathcal{S}$-procedure is presented in Lemma 1 in the following.

Lemma 1 ($\mathcal{S}$-procedure [40, Appendix B.2]). *Let a function $\mathbf{f}_m(\mathbf{x})$ with $\mathbf{x}\in\mathbb{C}^{N\times 1}(m=1,2)$ be defined as*

$$\mathbf{f}_m(\mathbf{x}) = \mathbf{x}^H\mathbf{A}_m\mathbf{x} + 2\mathrm{Re}\left\{\mathbf{b}_m^H\mathbf{x}\right\} + \mathbf{c}_m \tag{34}$$

where $\mathbf{A}_m\in\mathbb{H}^{N\times N}$, $\mathbf{b}_m\in\mathbb{C}^{N\times 1}$, and $\mathbf{c}_m\in\mathbb{R}^{N\times 1}$. Then, $\mathbf{f}_m(\mathbf{x})\le 0$ holds if and only if there exists $\theta\ge 0$ such that

$$\theta\begin{bmatrix}\mathbf{A}_1 & \mathbf{b}_1\\ \mathbf{b}_1^H & \mathbf{c}_1\end{bmatrix} - \begin{bmatrix}\mathbf{A}_2 & \mathbf{b}_2\\ \mathbf{b}_2^H & \mathbf{c}_2\end{bmatrix} \succeq \mathbf{0}, \tag{35}$$

provided that there is a point $\widehat{\mathbf{x}}$ which satisfies $\mathbf{f}_m(\widehat{\mathbf{x}})<0$.

To employ the $\mathcal{S}$-procedure, we rewrite the constraint (30a) as

$$\begin{aligned}&\Delta\mathbf{h}_{s,k}^H\mathbf{W}_Z\Delta\mathbf{h}_{s,k} + 2\Re\left\{\overline{\mathbf{h}}_{s,k}^H\mathbf{W}_Z\Delta\mathbf{h}_{s,k}\right\} + \overline{\mathbf{h}}_{s,k}^H\mathbf{W}_Z\overline{\mathbf{h}}_{s,k}\\ &\quad\ge d_k.\end{aligned} \tag{36}$$

According to Lemma 1, by using a slack variable $\lambda_{s,k}$, (36) can be expressed as

$$\begin{bmatrix}\lambda_{s,k}\mathbf{I}+\mathbf{W}_Z & \mathbf{W}_Z\overline{\mathbf{h}}_{s,k}\\ \overline{\mathbf{h}}_{s,k}^H\mathbf{W}_Z & \overline{\mathbf{h}}_{s,k}^H\mathbf{W}_Z\overline{\mathbf{h}}_{s,k}-d_k-\lambda_{s,k}\varepsilon_{s,k}^2\end{bmatrix}\succeq\mathbf{0}. \tag{37}$$

Using the same approach for the constraints (30b)-(30d) and (33a)-(33d), we have

$$\begin{bmatrix}\lambda_{e,l}\mathbf{I}+\mathbf{Z} & \mathbf{Z}\overline{\mathbf{h}}_{e,l}\\ \overline{\mathbf{h}}_{e,l}^H\mathbf{Z} & \overline{\mathbf{h}}_{e,l}^H\mathbf{Z}\overline{\mathbf{h}}_{e,l}-w_l-\lambda_{e,l}\varepsilon_{e,l}^2\end{bmatrix}\succeq\mathbf{0}, \tag{38a}$$

$$\begin{bmatrix} \alpha_{s,k}\mathbf{I} - \sum_{j\neq k}\mathbf{W}_j - \mathbf{Z} & -\left(\sum_{j\neq k}\mathbf{W}_j + \mathbf{Z}\right)\overline{\mathbf{h}}_{s,k} \\ -\overline{\mathbf{h}}_{s,k}^H\left(\sum_{j\neq k}\mathbf{W}_j + \mathbf{Z}\right) & -\overline{\mathbf{h}}_{s,k}^H\left(\sum_{j\neq k}\mathbf{W}_j + \mathbf{Z}\right)\overline{\mathbf{h}}_{s,k} + z_k - \alpha_{s,k}\varepsilon_{s,k}^2 \end{bmatrix} \succeq \mathbf{0}, \tag{38b}$$

$$\begin{bmatrix} \alpha_{e,l}\mathbf{I} - \mathbf{Z} - \mathbf{W}_k & -\left(\mathbf{Z} + \mathbf{W}_k\right)\overline{\mathbf{h}}_{e,l} \\ -\overline{\mathbf{h}}_{e,l}^H\left(\mathbf{Z} + \mathbf{W}_k\right) & -\overline{\mathbf{h}}_{e,l}^H\left(\mathbf{Z} + \mathbf{W}_k\right)\overline{\mathbf{h}}_{e,l} + f_{l,k} - \alpha_{e,l}\varepsilon_{e,l}^2 \end{bmatrix} \succeq \mathbf{0}, \tag{38c}$$

$$\begin{bmatrix} \beta_p\mathbf{I} + \mathbf{W}_Z & \mathbf{W}_Z\overline{\mathbf{h}}_p \\ \overline{\mathbf{h}}_p^H\mathbf{W}_Z & \overline{\mathbf{h}}_p^H\mathbf{W}_Z\overline{\mathbf{h}}_p - d_p - \beta_p\varepsilon_p^2 \end{bmatrix} \succeq \mathbf{0}, \tag{39a}$$

$$\begin{bmatrix} \beta_{e,l}\mathbf{I} + \mathbf{Z} & \mathbf{Z}\overline{\mathbf{h}}_{e,l} \\ \overline{\mathbf{h}}_{e,l}^H\mathbf{Z} & \overline{\mathbf{h}}_{e,l}^H\mathbf{Z}\overline{\mathbf{h}}_{e,l} - v_l - \beta_{e,l}\varepsilon_{e,l}^2 \end{bmatrix} \succeq \mathbf{0}, \tag{39b}$$

$$\begin{bmatrix} \alpha_p\mathbf{I} - \mathbf{W}_Z & -\mathbf{W}_Z\overline{\mathbf{h}}_p \\ -\overline{\mathbf{h}}_p^H\mathbf{W}_Z & -\overline{\mathbf{h}}_p^H\mathbf{W}_Z\overline{\mathbf{h}}_p + b_p - \alpha_p\varepsilon_p^2 \end{bmatrix} \succeq \mathbf{0}, \tag{39c}$$

$$\begin{bmatrix} \nu_{e,l}\mathbf{I} - \mathbf{Z} & -\mathbf{Z}\overline{\mathbf{h}}_{e,l} \\ -\overline{\mathbf{h}}_{e,l}^H\mathbf{Z} & -\overline{\mathbf{h}}_{e,l}^H\mathbf{Z}\overline{\mathbf{h}}_{e,l} + q_l - \nu_{e,l}\varepsilon_{e,l}^2 \end{bmatrix} \succeq \mathbf{0}, \tag{39d}$$

where $\lambda_{e,l}$, $\alpha_{s,k}$, $\alpha_{e,l}$, β_p, $\beta_{e,l}$, α_p, and $\nu_{e,l}$ are slack variables.

By using the above results of Taylor series expansion in (22a)–(22d), we can transform the nonconvex constraints (30g), (30h), (33g), and (33h) into the corresponding convex forms, respectively, as

$$z_k + \sigma_{s,k}^2 \leq e^{\hat{t}_k(m)}\left(\hat{t}_k - \hat{t}_k(m) + 1\right), \tag{40a}$$

$$\sigma_{e,l}^2 + f_{l,k} \leq e^{\hat{r}_{l,k}(m)}\left(\hat{r}_{l,k} - \hat{r}_{l,k}(m) + 1\right), \tag{40b}$$

$$b_p + \sigma_p^2 \leq e^{\hat{t}_p(m)}\left(\hat{t}_p - \hat{t}_p(m) + 1\right), \tag{40c}$$

$$q_l + \sigma_{e,l}^2 + P_p g_{e,l}^{max} \leq e^{\hat{s}_l(m)}\left(\hat{s}_l - \hat{s}_l(m) + 1\right). \tag{40d}$$

where $\hat{t}_k(m)$, $\hat{r}_{l,k}(m)$, $\hat{t}_p(m)$, and $\hat{s}_l(m)$ are the variables $\hat{t}_k$, $\hat{r}_{l,k}$, $\hat{t}_p$, and $\hat{s}_l$ at the nth iteration for the SCA method.

Here, we consider the EH constraint (30c). By use the inequalities (32) and (26d) can be rewritten as

$$\left(\overline{\mathbf{h}}_{e,l} + \Delta\mathbf{h}_{e,l}\right)^H\mathbf{W}_Z\left(\overline{\mathbf{h}}_{e,l} + \Delta\mathbf{h}_{e,l}\right) + P_p g_{e,l}^{min} + \sigma_e^2 \geq \frac{\overline{E}^e}{\eta_{e,l}}, \quad \forall l. \tag{41}$$

Introducing slack variables $\vartheta_{e,l}$, we can transform (41) as

$$\begin{bmatrix} \vartheta_{e,l}\mathbf{I} + \mathbf{W}_Z & \mathbf{W}_Z\overline{\mathbf{h}}_{e,l} \\ \overline{\mathbf{h}}_{e,l}^H\mathbf{W}_Z & \overline{\mathbf{h}}_{e,l}^H\mathbf{W}_Z\overline{\mathbf{h}}_{e,l} + P_p g_{e,l}^{min} + \sigma_e^2 - \dfrac{\overline{E}^e}{\eta_{e,l}} - \vartheta_{e,l}\varepsilon_{e,l}^2 \end{bmatrix} \succeq \mathbf{0}, \tag{42}$$

Finally, similarly to (21a) and (21b), we need to recast the nonconvex constraints (28a) and (29a) as follows:

$$e^{-\hat{x}_k - \hat{y}_l + \hat{t}_k + \hat{r}_{l,k}} \leq 2^{-\overline{R}^{su}}, \quad \forall k, \forall l, \tag{43a}$$

$$e^{-\hat{x}_p - \hat{u}_l + \hat{t}_p + \hat{s}_l} \leq 2^{-\overline{R}^{pu}}, \quad \forall l. \tag{43b}$$

Combining all the results in (27a)–(34) and (36)–(43b), (26b)–(26d) can be reformed as

$$\begin{aligned} \min_{\Phi} \quad & \sum_{k=1}^{K}\operatorname{tr}\left(\mathbf{W}_k\right) \\ \text{s.t.} \quad & (23b), (30e), (30f), (33e), (33f), (37), (38a), (38b), (38c), (39a), (39b), (39c), (39d), (40a), (40b), (40c), (40d), (42), (43a), (43b), \\ & \Phi = \left\{\mathbf{W}_k, \mathbf{Z}, \hat{x}_k, \hat{y}_l, \hat{t}_k, \hat{r}_{l,k}, \hat{x}_p, \hat{u}_l, \hat{t}_p, \hat{s}_l, d_k, w_l, z_k, f_{l,k}, d_p, v_l, b_p, q_l, \lambda_{s,k}, \lambda_{e,l}, \alpha_{s,k}, \alpha_{e,l}, \beta_p, \beta_{e,l}, \alpha_p, \nu_{e,l}, \zeta_{s,k}, \vartheta_{e,l}\right\}, \quad \mathbf{W}_k \succeq \mathbf{0}, \ \mathbf{Z} \succeq \mathbf{0}. \end{aligned} \tag{44}$$

For given $\{\hat{t}_k(m), \hat{r}_{l,k}(m), \hat{t}_p(m), \hat{s}_l(m)\}$ at the mth iteration, problem (44) is a convex SDP form without the nonconvex rank-one constraint $\operatorname{rank}(\mathbf{W}_k) = 1, \forall k$, which can be solved by convex optimization packages such as CVX [39],

Set $m = 0$ and initialize $\Psi(0) = \{\hat{t}_k(0), \hat{r}_{l,k}(0), \hat{t}_p(0), \hat{s}_l(0)\}$.
Repeat
(i) Solve problem (44) with $\{\hat{t}_k(m), \hat{r}_{l,k}(m), \hat{t}_p(m), \hat{s}_l(m)\}$
and denote a solution by $\{\hat{t}_k(m+1), \hat{r}_{l,k}(m+1), \hat{t}_p(m+1), \hat{s}_l(m+1)\}$.
(ii) Update $m \longleftarrow m + 1$.
Until Convergence

Algorithm 2: Robust SCA-based iterative algorithm with imperfect CSI.

to update the solution for the $m+1$-th iteration until the algorithm converges. In addition, the proposed robust SCA-based iterative algorithm with imperfect CSI is summarized in Algorithm 2.

5. Simulation Results

In this section, we provide the simulation results to validate the performance of our proposed algorithms. We consider a system with two SUs and two ERs. The ST is equipped with six transmit antennas ($N_S = 6$). We define $d_{SU_k}^{ST} = 5$ m, $d_{ER_l}^{ST} = 3$ m, and $d_{PU}^{ST} = 10$ m as the distance between the ST and the kth SU, the lth ER, and the PU, respectively. Also, we fix $d_{SU_k}^{PT} = 4$ m, $d_{ER_l}^{PT} = 3$ m, and $d_{PU}^{PT} = 2$ m as the distance between the PT and the kth SU, the lth ER, and the PU, respectively, unless otherwise specified. Thus, the estimated channels $\overline{\mathbf{h}}_{s,k}$, $\overline{\mathbf{h}}_{e,l}$, $\overline{\mathbf{h}}_p$, $\overline{g}_p$, $\overline{g}_{s,k}$, and $\overline{g}_{e,l}$, are respectively, modelled as $\overline{\mathbf{h}}_{s,k} = H(d_{SU_k}^{ST})\overline{\mathbf{h}}_I$, $\overline{\mathbf{h}}_{e,l} = H(d_{ER_l}^{ST})\overline{\mathbf{h}}_I$, $\overline{\mathbf{h}}_p = H(d_{PU}^{ST})\overline{\mathbf{h}}_I$, $\overline{g}_{s,k} = H(d_{SU_k}^{ST})\overline{g}_I$, $\overline{g}_{e,l} = H(d_{ER_l}^{ST})\overline{g}_I$, and $\overline{g}_p = H(d_{PU}^{ST})\overline{g}_I$, where $H(d) = (c/4\pi f_c)(1/d)^{\kappa/2}$, $\overline{\mathbf{h}}_I \sim \mathcal{CN}(0, \mathbf{I})$, and $\overline{g}_I \sim \mathcal{CN}(0, 1)$, and we set the speed of light, the carrier frequency, and the path loss exponent as $c = 3 \times 10^8 \mathrm{ms}^{-1}$, $f_c = 900$ MHz, and $\kappa = 2.7$, respectively. In addition, the noise power at the PU, SU, and ER is assumed to be $\sigma_p^2 = \sigma_{s,k}^2 = \sigma_{e,l}^2 = -90$dBm. Also the additional noise power of all the SUs is $\delta_{a,k}^2 = -50$ dBm, $\forall k$. We fix the channel error bound for the deterministic model as $\varepsilon = \varepsilon_{s,k} = \varepsilon_{e,l} = \varepsilon_p, \forall k, \forall l$ and $\gamma = \gamma_p = \gamma_{s,k} = \gamma_{e,l}, \forall k, \forall l$. The EH efficiency coefficients are set to $\eta_{c,l} = \eta_{e,k} = 0.3$. In our simulations, we compare the following transmit designs: the perfect CSI case, robust SCA-based scheme, no-AN scheme which is obtained by setting $\mathbf{Z} = \mathbf{0}$, and the nonrobust scheme which assumes no uncertainty in the CSI.

Figure 2 illustrates the convergence performance of the proposed SCA-aided iterative algorithm with respect to (w.r.t.) iteration numbers. Here, we set $\overline{R}^{su} = \overline{R}^{pu} = 0.5$ bps/Hz, $E = \overline{E}^e = 1$ dBm, $P_p = 20$ dBm, and $\varepsilon = \gamma = 0.01$. It is easily seen from the plots that the convergence of all perfect CSI cases can be quickly achieved within 5 iterations. It is observed that robust SCA-based scheme converges slower than the perfect CSI case regardless of E. This is due to the fact that the number of variables in the robust SCA-based scheme is greater than the perfect CSI case.

Figure 3 compares the average transmit power of the information signal w.r.t. the target secrecy rate at SU with $\overline{R}^{pu} = 0.5$ bps/Hz, $P_p = 20$ dBm and $E = 3$ dBm. It is observed that the performance gaps of perfect CSI scheme with $\varepsilon = 0.01$ and 0.1 over the robust SCA-aided iterative algorithm are 0.5 dB and 1.1 dB at all target secrecy rate region, respectively. Also, the transmit power for the no-AN scheme grows faster than the robust schemes as $\overline{R}^{su}$ increases. We can see that, for $\varepsilon = 0.01$ and 0.1, the robust SCA-aided iterative algorithm outperforms the no-AN scheme and nonrobust scheme. This is due to the help of the AN.

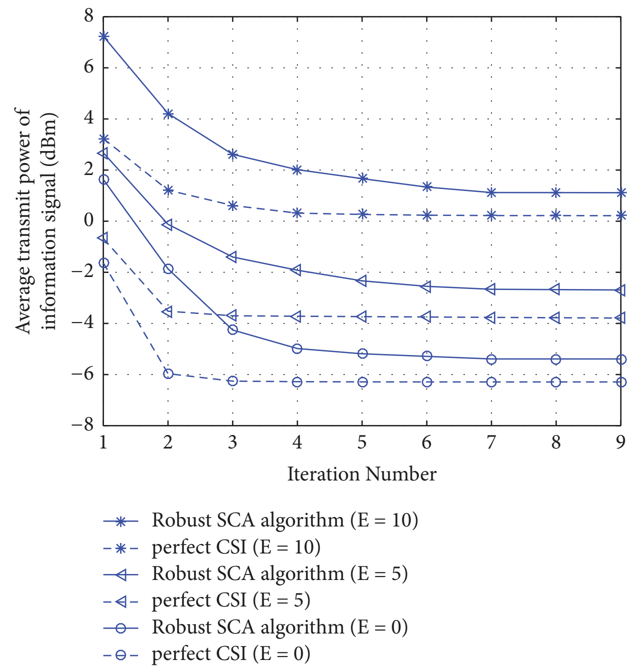

Figure 2: Average transmit power of the information signal w.r.t. iteration numbers with various E.

Moreover, the transmit power of the information signal performance is plotted in Figure 4 with $\overline{R}^{su} = 0.5$ bps/Hz, $P_p = 20$ dBm, and $\overline{E}^e = 5$ dBm. One can observe from Figure 4 that the average transmit power of the information signal increases as the target secrecy rate at PU becomes large. Also, the performance gap between the robust SCA-aided iterative algorithm and the no-AN scheme becomes large at high secrecy rate region. Also, there are 0.4 dB and 0.9 dB gaps between perfect CSI and robust SCA-aided iterative algorithm curves for $\varepsilon = 0.01$ and 0.1, respectively.

Finally, in Figure 5, the transmit power of the information signal w.r.t. the target harvested power is illustrated with

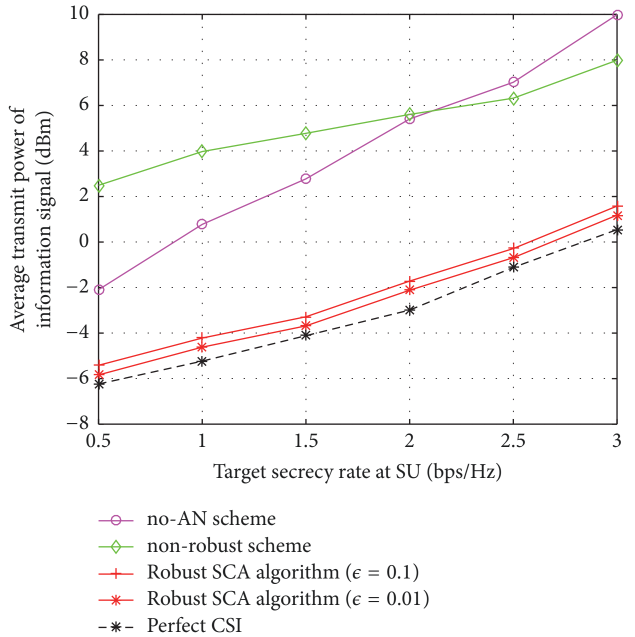

Figure 3: Average transmit power of the information signal w.r.t. the target secrecy rate at SU.

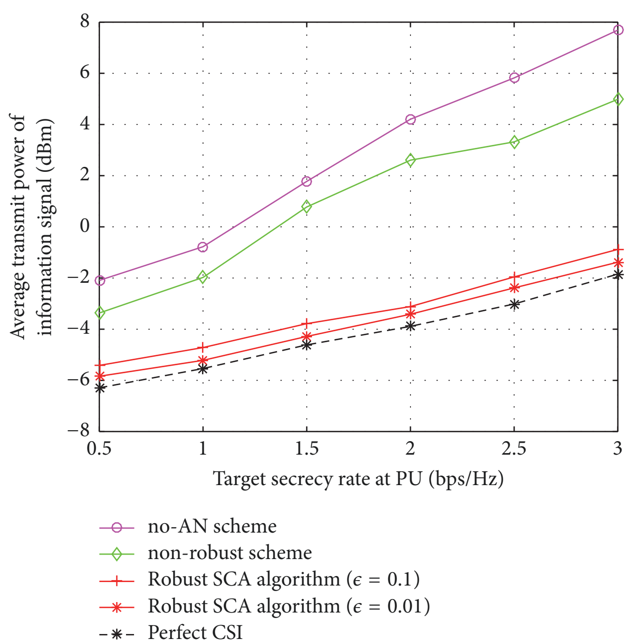

Figure 4: Average transmit power of the information signal w.r.t. the target secrecy rate at PU.

$\overline{R}^{su} = \overline{R}^{pu} = 1$ bps/Hz and $P_p = 30$ dBm. We can see that the robust SCA-aided iterative algorithm with $\varepsilon = 0.01$ outperforms the nonrobust scheme by 3.6 dB and the performance gains of the robust SCA-aided iterative algorithm over the no-AN scheme become larger as the target harvested power increases. Similarly, when $\overline{E}^{e} \leq 0$ dBm, the performance of the proposed algorithms changes slowly. This is due to the introduction of AN for the CR system.

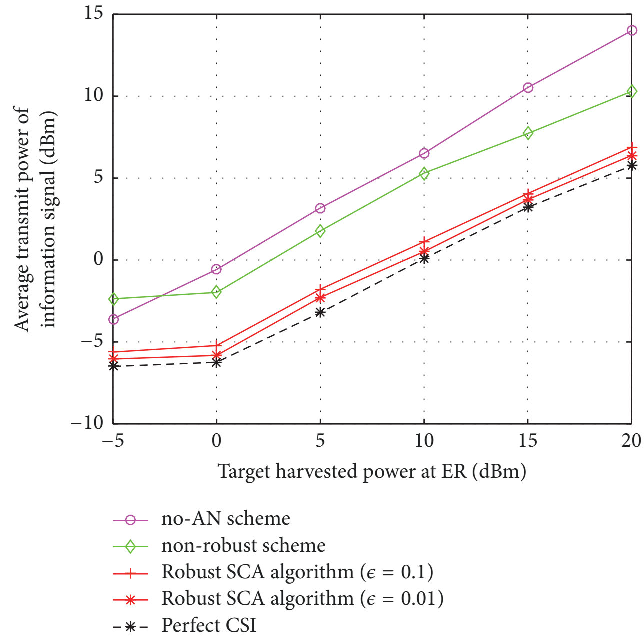

Figure 5: Average transmit power of the information signal w.r.t. the harvested power.

6. Conclusion

In this paper, we have studied AN-aided secure beamforming designs for MISO Secured CR networks with SWIPT. Our aim is to minimize the transmit power of the information signal subject to the secrecy rate constraint, the harvested energy constraint, and total transmit power constraint. As the original problem is nonconvex, we recast the original problem as a convex form by using SCA method. Then, we have proposed an SCA-based iterative algorithm for the perfect CSI case. Moreover, we have extended the proposed algorithm to the norm-bounded channel uncertainty model. Finally, simulation results have been given to validate the performance of our proposed algorithms.

Data Availability

The original code of this paper cannot be made available.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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