Robust Design of Secure IRS-aided MISO Broadcasting for SWIPT and Spectrum Sharing

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Abstract—We consider an intelligent reflecting surface (IRS)-aided secondary multiple-input single-output (MISO) broadcast system for simultaneous wireless information and power transfer (SWIPT) in a spectrum underlay setup. The secondary transmitter (ST) regards the primary receivers (PR) as possible eavesdroppers. We propose an inter-system coordination protocol that enables acquisition at the ST of control information to facilitate interference management. We assume availability of imperfect channel state information (CSI) regarding the relevant direct and IRS-cascaded links at the ST. We aim at jointly optimizing the transmit precoding, artificial noise (AN) covariance, and reflect beamforming matrices, so that the transmit power of the ST is minimized subject to the quality-of-service (QoS) requirements of the information decoding and energy harvesting secondary receivers (IDR/EHR), the security and interference constraints of the PRs, and the unit-modulus constraints of the IRS phase shifts. We obtain convex approximations of the probabilistic constraints by employing Bernstein-type and first-order Taylor inequalities. We derive a robust outage-constrained design by developing an alternating minimization algorithm that makes use of the semi-definite relaxation (SDR) method and the penalty convex-concave procedure (CCP). Our design takes into account the additional interference incurred at the PRs by the IRS-reflected transmissions of the primary transmitter (PT) itself, which serves its users in an IRS-blind manner. Numerical simulation results reveal the performance gains of the proposed scheme over benchmark strategies and highlight the impact of the system parameters on the performance.

Index Terms—Spectrum underlay, simultaneous wireless information and power transfer (SWIPT), intelligent reflecting surface (IRS), physical layer security, robust optimization.

I. INTRODUCTION

Fifth generation (5G) and beyond 5G (B5G) wireless communication systems should support the connectivity of a massive number of energy-constrained terminals, ranging from smartphones to wireless sensors and Internet-of-Things (IoT) nodes [1], in a cost-effective and energy-efficient manner. Therefore, they should be able to accommodate the traffic explosion attributed to the proliferation of user equipment [1], despite the scarcity of available sub-6 GHz radio spectrum, and prolong the limited lifetime of the end user devices. At the same time, it is of utmost importance to provide quality-of-service (QoS) and security guarantees to the end users.

The realization of this vision is challenging and requires synergy among a number of technologies. In this paper, we propose the adoption of the following strategies: i) coordinated spectrum underlay, which extends the usable spectrum via non-orthogonal spectrum sharing [2], [3]; ii) simultaneous wireless information and power transfer (SWIPT), which integrates wireless power supply in the downlink (DL) [4]; iii) physical-layer security, which exploits the randomness of the wireless channel to impose secure communication [5]; and iv) intelligent reflecting surface (IRS), which leverages a large number of passive reflecting elements to achieve high spectral efficiency gains via passive beamforming [6].

The ability of IRSs to increase the received signal power at target users, suppress the interference at non-intended users, and reconfigure the wireless propagation environment enables us to mitigate the forward inter-system interference (FISI) that the secondary transmitter (ST) induces to the primary receivers (PR) and compensate for the reverse ISI (RISI) that the primary transmitter (PT) induces to the secondary receivers (SR) in spectrum underlay setups; boost the energy harvesting (EH) performance in SWIPT systems, which is deteriorated by the distance-dependent path loss; and enhance the security by degrading the quality of the channels with the eavesdroppers.

In [7], a semi-definite relaxation (SDR)-based alternating optimization algorithm that maximizes the rate of a secondary point-to-point multiple-input single-output (MISO) system is proposed, whereas in [8] the authors derive a robust design that minimizes the transmit power in a secondary MISO broadcast system, assuming availability of imperfect channel state information (CSI) at the ST regarding the ST-PR link. The studies [9], [10] consider a multi-user MISO setting for SWIPT and tackle the problem of maximizing the weighted sum-power at the EH receivers (EHR) or minimizing the transmit power by developing an SDR- or a penalty-based algorithm, respectively. The works [11], [12] employ fractional programming or the majorization-minimization (MM) method to maximize the secrecy rate of a single-user MISO or multiple-input multiple-output (MIMO) system in the presence of a single- or multi-antenna eavesdropper, respectively.

In this paper, in accordance with the previous discussion, we consider a secondary IRS-aided MISO broadcasting system for SWIPT in a spectrum underlay setup where the ST regards the PRs as potential eavesdroppers and embeds artificial noise (AN) to the transmit signal in order to enhance the communication security. We assume availability of imperfect CSI at the ST regarding the relevant direct and IRS-cascaded links due to channel estimation errors [13], [14]. Under this context, we propose an inter-system coordination protocol that enables acquisition of control information by the ST to...
facilitate interference management. Next, we derive a robust outage-constrained design that jointly optimizes the transmit precoding, AN covariance, and reflect beamforming matrices, so that the transmit power of the ST is maximized subject to the QoS constraints of the SRs, the security and interference constraints of the PRs, and the unit-modulus constraints of the IRS phase shifts. The PT serves its users in a spectrum-sharing-agnostic and, therefore, IRS-blind fashion, as if the primary system were isolated. Hence, the proposed scheme takes into account the additional intra-system inter-user interference (IUI) and self-interference (SI) at the PRs caused by the reception at these nodes of IRS-reflected interfering and useful data signals, respectively, sent by the PT.

The paper is organized as follows: Sec. II introduces the system model and the coordination protocol. Sec. III presents the proposed robust design. Sec. IV provides the numerical simulation results. Our conclusions are given in Sec. V.

Notation: $x$ or $X$: a scalar; $x$: a column vector; $X$: a matrix; $||\cdot||$: the Euclidean norm; $(\cdot)^*$, $(\cdot)^T$, and $(\cdot)^\dagger$: the complex conjugate, transpose, and complex conjugate transpose operator; $\text{Tr}(X)$, $\text{Rank}(X)$, and $\text{vec}(X)$: the trace, rank, and vectorization of $X$; $\text{diag}(x)$: a diagonal matrix whose main diagonal entries are the elements of $x$; $\text{diag}(X)$: a vector whose elements are the main diagonal entries of $X$; $X \succeq 0$: a positive semi-definite (PSD) matrix; $O_N$: the $N$-dimensional null vector; $I_N$: the $N \times N$ identity matrix; $\otimes$: the Kronecker product operator; $Re\{\cdot\}$: the real part of a complex scalar; $CN(\cdot, \cdot)$: the complex Gaussian distribution; $\text{Pr}(\cdot)$: the probability of an event; $E\{\cdot\}$: the expectation operator.

II. SYSTEM MODEL AND COORDINATION PROTOCOL

A. System Model

The considered spectrum underlay setup is illustrated in Fig. 1. We see that the PT and the ST have $L$ and $M$ antennas, respectively. The former serves $U$ PRs, while the latter serves $K_I$ information decoding receivers (IDR) and $K_E$ EH receivers with the assistance of an IRS that has $N$ reflecting elements. All active receivers are equipped with a single antenna each.

The transmit signals from the ST and the PT, $x_{ST} \in \mathbb{C}^M$ and $x_{PT} \in \mathbb{C}^L$, respectively, are expressed as

$$x_{ST} = \sum_{i \in K_I} w_i s_i + \eta; \quad x_{PT} = \sum_{u \in U} f_u c_u,$$

where $w_i \in \mathbb{C}^M$ and $f_u \in \mathbb{C}^L$ are the transmit precoding vectors assigned to IDR $i$ and PR $u$, respectively; $s_i \in \mathbb{C}$ with $E\{s_i|^2\} = 1$ and $c_u \sim CN(0, 1)$ denote the corresponding transmitted data symbols; and $\eta \in \mathbb{C}^M$ with $\eta \sim CN(0, \Sigma)$, $\Sigma \in \mathbb{C}^{M \times M}$, $\Sigma \succeq 0$, represents the AN vector applied at the ST, $i \in K_I \triangleq \{1, \ldots, K_I\}$, $u \in U \triangleq \{1, \ldots, U\}$.

We consider quasi-static, flat fading channel models. We denote the ST-IRS, ST-IRD $i$, ST-EHR $j$, and ST-PR $u$ baseband channels as $H \in \mathbb{C}^{N \times M}$, $h_{d,i}^T \in \mathbb{C}^M$, $g_{d,j}^T \in \mathbb{C}^M$, $G_j \in \mathbb{C}^{N \times M}$, and $V_u \in \mathbb{C}^{N \times U}$, respectively. Next, we derive a robust interference management. Next, we derive a robust interference management.
represents the harvested power threshold of EHR pattern phases accordingly. In the DL and it is followed by a DL information and power transmission channel estimation phase, which is divided into two sub-phases. The primary and secondary systems operate over shared spectrum in time-division duplex (TDD) mode. Hence, pilot-linear and, in general, monotonically increasing EH function. At the output of the EH circuit, where

\[ E_{RF} = \sum_{i \in K_I} \left| g_i^j w_i \right|^2 + g_i^j \Sigma g_i + I_j, \forall j \in K_E. \]  

Let \( E_{DC} = F \left( E_{RF} \right) \) be the harvested direct current (DC) power at the output of the EH circuit, where \( F (\cdot) \) denotes a non-linear and, in general, monotonically increasing EH function. We want to satisfy the EH constraints \( E_{DC} \geq \bar{Q}_j \), where \( \bar{Q}_j > 0 \) represents the harvested power threshold of EHR node. These are equivalent to \( E_{RF} \geq F^{-1} ( \bar{Q}_j ) \geq Q_j \), where \( Q_j > 0 \) denotes the minimum required received RF power at EHR j.

### B. Inter-System Coordination Protocol

The primary and secondary systems operate over shared spectrum in time-division duplex (TDD) mode. Hence, pilot-assisted, reciprocity-based estimation of the intra- and inter-system, direct and IRS-cascaded DL channels applies. The system operation is divided into an uplink (UL) training and channel estimation phase, which is divided into two sub-phases and it is followed by a DL information and power transmission phase. The two systems are perfectly synchronized. All pilot sequences are mutually-orthogonal to each other. In the DL transmission phase, the ST computes the passive beamforming matrix based on its knowledge of relevant channels and feeds it to the digital controller of the IRS, which then adjusts the phase shifts accordingly.

The proposed inter-system coordination protocol in the UL training and channel estimation phase is described as follows:

i) In the first sub-phase, the ST selects a predefined radiation pattern \( \bar{v} \) and forwards it to both the IRS and the PT. The IDRs, the EHRs, and the PRs transmit known pilot signals to the ST, which then estimates its effective channels with them using standard methods. Similarly, the PRs transmit known pilot signals to the PT, thus enabling it to estimate its effective channels with them. ii) In the second sub-phase, the IRS is switched off and the actions of the previous steps are repeated. Hence, the ST and the PT estimate the respective IRS-cascaded channels and, thus, compute the corresponding IRS-cascaded channels. Also, the PT forwards the CSI of its IRS-cascaded links with the PRs to the ST and the PRs transmit to the ST their IPTs. The obtained channel knowledge at the ST suffices for jointly optimizing its transmit precoding matrix and the IRS beamforming matrix.

### C. Stochastic CSI Error Model

Due to the imperfect CSI at the ST, the actual direct and IRS-cascaded ST–IDR i, ST–EHR j, and ST–PR u baseband channels, as well as the actual IRS-cascaded PT–PR u baseband channels are given by

\[ \mathbf{h}_{d,i} = \mathbf{h}_{d,i} + \Delta \mathbf{h}_{d,i}, \quad \mathbf{h}_{i} = \mathbf{H}_{i} + \Delta \mathbf{H}_{i}, \quad \mathbf{g}_{d,j} = \mathbf{g}_{d,j} + \Delta \mathbf{g}_{d,j}, \quad \mathbf{G}_{j} = \mathbf{G}_{j} + \Delta \mathbf{G}_{j}; \]

\[ \mathbf{v}_{d,u} = \mathbf{v}_{d,u} + \Delta \mathbf{v}_{d,u}, \quad \mathbf{V}_{u} = \mathbf{V}_{u} + \Delta \mathbf{V}_{u}; \quad \mathbf{Z}_{u} = \mathbf{Z}_{u} + \Delta \mathbf{Z}_{u}, \quad \mathbf{Q}_{j} = \mathbf{Q}_{j} + \Delta \mathbf{Q}_{j} \]

represent the minimum and the maximum required received SINR constraints. We seek to satisfy the SINR constraints

\[ \text{SINR} \geq \gamma, \quad \forall \mathbf{u} \in U. \]

The optimization problem under study is formulated as:

\[ (\text{P1}): \min_{\{w_i\}} \sum_{i \in K_I} \left\| w_i \right\|^2 + \text{Tr} (\Sigma), \quad \text{s.t.} \quad \text{Pr} (\text{SINR} \geq \gamma) \geq 1 - p_u, \quad \forall i \in K_I, \]

\[ \text{Pr} \left( E_{RF} \geq Q_j \right) \geq 1 - q_j, \quad \forall j \in K_E, \]

\[ \text{Pr} \left( \text{FISI}_{I, u} \leq P_{\text{FI}} \right) \geq 1 - g_u, \quad \forall u \in U, \]

\[ \text{Pr} \left( \text{CIUSI}_{I, u} \right. \leq P_{\text{CI}} \left. \right) \geq 1 - w_u, \quad \forall u \in U, \]

\[ \sum_{u} V_{u} \leq 0, \]

where \( \{p_u, q_j, g_u, w_u\} \in [0, 1] \) are the corresponding maximum tolerable outage probabilities and \( \nu_u \approx e^{\theta_u} \). In order to solve this challenging non-convex optimization problem, we adopt the alternating minimization approach and employ the SDR method. Furthermore, we apply Bernstein-type inequalities (BTI) to obtain convex approximations of the probabilistic constraints.

III. PROPOSED ROBUST DESIGN

A. Problem Formulation

The optimization problem under study is formulated as:

\[ (\text{P1}): \min_{\{w_i\}} \sum_{i \in K_I} \left\| w_i \right\|^2 + \text{Tr} (\Sigma), \quad \text{s.t.} \quad \text{Pr} (\text{SINR} \geq \gamma) \geq 1 - p_u, \quad \forall i \in K_I, \]

\[ \text{Pr} \left( E_{RF} \geq Q_j \right) \geq 1 - q_j, \quad \forall j \in K_E, \]

\[ \text{Pr} \left( \text{FISI}_{I, u} \leq P_{\text{FI}} \right) \geq 1 - g_u, \quad \forall u \in U, \]

\[ \text{Pr} \left( \text{CIUSI}_{I, u} \right. \leq P_{\text{CI}} \left. \right) \geq 1 - w_u, \quad \forall u \in U, \]

\[ \sum_{u} V_{u} \leq 0, \]

where \( \{p_u, q_j, g_u, w_u\} \in [0, 1] \) are the corresponding maximum tolerable outage probabilities and \( \nu_u \approx e^{\theta_u} \). In order to solve this challenging non-convex optimization problem, we adopt the alternating minimization approach and employ the SDR method. Furthermore, we apply Bernstein-type inequalities (BTI) to obtain convex approximations of the probabilistic constraints.
B. Transmit Precoding and Artificial Noise Optimization

For fixed reflection phase shifts, problem (P1) is reduced to

\[
\begin{align*}
\text{(P2):} \quad & \min_{\{w_i\}_{i \in K_I}} \sum_{i \in K_I} \|w_i\|^2 + \text{Tr} (\Sigma) \quad (7a) \\
\text{s.t.} \quad & \text{Eqs. (6b)–(6d), (6f), (6g).} \quad (7b)
\end{align*}
\]

By introducing the rank-one PSD matrix variables \(W_i \in \mathbb{C}^{M \times M}\) defined as \(W_i = \mathbb{E} w_i w_i^\dagger\), we can express the cost function in problem (P2) as \(\sum_{i \in K_I} \text{Tr} (W_i) + \text{Tr} (\Sigma)\). Also, we can rewrite the SINR event in Eq. (6b) as \(h_i^\dagger A_i h_i - I_i \geq 0\), i.e.,

\[
\left( h_{d,i}^\dagger + u^\dagger H_{i} \right) A_i \left( h_{d,i} + H_{i}^\dagger v \right) - I_i \geq 0, \quad \forall i \in K_I, \quad (8)
\]

where \(A_i \in \mathbb{C}^{M \times M}\) is defined as \(A_i \triangleq \left( 1 + \frac{1}{B_i} \right) W_i - \sum_{k \in K_I \setminus \{i\}} W_k - \Sigma_i A_i\) in Eq. (8) can be expressed as:

\[
\begin{align*}
A_i &= \left( h_{d,i}^\dagger + u^\dagger H_{i} \right) A_i \left( h_{d,i} + H_{i}^\dagger v \right) \\
+ 2\text{Re} \left( h_{d,i}^\dagger + u^\dagger H_{i} \right) A_i \left( \Delta h_{d,i} + \Delta H_{i}^\dagger v \right) \\
+ \left( (\Delta h_{d,i})^\dagger + u^\dagger \Delta H_{i} \right) A_i \left( \Delta h_{d,i} + (\Delta H_{i})^\dagger v \right), \quad \forall i \in K_I.
\end{align*}
\]

Let \(\Delta h_{d,i} = C_{h_{d,i}}^{1/2} h_{d,i}\) and \(\text{vec}(\Delta H_{i}) = C_{H_{i}}^{1/2} H_{i}\), where \(h_{d,i} \sim \mathcal{CN}(0_M, I_M)\) and \(H_{i} \sim \mathcal{CN}(0_{NM}, I_{NM})\). Let us also define \(\tilde{N} \triangleq (N + 1)M\). Then, we can express \(C_i\) in Eq. (9) as

\[
C_i = \mathbb{E} i_i^\dagger, \quad \forall i \in K_I, \quad (10)
\]

where \(i_i \in \mathbb{C}^{\tilde{N}}\) is defined as \(i_i \triangleq \left[ h_{i}^\dagger, i_i^\dagger \right]^\dagger\) and \(e_i \in \mathbb{C}^{\tilde{N}}\) is given by

\[
e_i \triangleq \left[ C_{h_{d,i}}^{1/2} A_i \left( h_{d,i} + H_{i}^\dagger v \right) \right]^\dagger \left( C_{H_{i}}^{1/2} \right)^T \text{vec}^\ast \left( u \left( h_{d,i} + H_{i}^\dagger v \right) A_i \right), \quad \forall i \in K_I. \quad (11)
\]

Next, we define the rank-one PSD matrix \(\Xi \triangleq \nu u^\dagger \in \mathbb{C}^{\tilde{N} \times N}\). Thus, we can express \(D_i\) in Eq. (9) as

\[
D_i = i_i^\dagger E_i i_i, \quad \forall i \in K_I, \quad (12)
\]

where \(E_i \triangleq \left[ M_{i_1}, M_{2i_2}, M_{3i_3}, M_{4i_4} \right] \in \mathbb{C}^{\tilde{N} \times \tilde{N}},\) and \(M_i \in \mathbb{C}^{M \times M}, M_2 \in \mathbb{C}^{NM \times M}, M_3 \in \mathbb{C}^{NM \times NM},\) and \(M_4 \in \mathbb{C}^{NM \times NM}\) are defined as \(M_{i_1} \triangleq C_{b_{d,i}}^{1/2} A_i \left( A_i \otimes u^\dagger \right) \left( C_{H_{i}}^{1/2} \right)^T, \)

\(M_{2i_2} \triangleq C_{h_{d,i}}^{1/2} A_i \left( A_i \otimes u^\dagger \right) \left( C_{H_{i}}^{1/2} \right)^T, \)

\(M_{3i_3} \triangleq C_{H_{i}}^{1/2} \left( A_i \otimes \Xi \right) \left( C_{H_{i}}^{1/2} \right)^\ast, \quad \forall i \in K_I.\) Finally, we denote \(e_i \triangleq B_i - I_i\). Hence, the probabilistic SINR constraints in Eq. (6b) can be rewritten as

\[
\Pr \left( \begin{bmatrix} i_i^\dagger E_i i_i + 2\Re \left\{ e_i^\dagger 1_i \right\} \end{bmatrix} + e_i \geq 0 \right) \geq 1 - p_i, \quad \forall i \in K_I. \quad (13)
\]

By using the BTI in [15], we obtain:

\[
\begin{align*}
\text{Tr} (E_i) - \sqrt{2\ln(1/p_i)} x_i + \ln(p_i) y_i + e_i & \geq 0, \quad \forall i \in K_I, \quad (14a) \\
\left\| \begin{bmatrix} \text{vec}(E_i) \end{bmatrix} \right\| & \leq x_i, \quad \forall i \in K_I, \quad (14b) \\
y_i I_N + E_i & \geq 0, \quad y_i \geq 0, \quad \forall i \in K_I, \quad (14c)
\end{align*}
\]

where \(x = [x_1, \ldots, x_{|K_I|}]^T\) and \(y = [y_1, \ldots, y_{|K_I|}]^T\) are auxiliary variables.

Let’s assume that \(C_{h_{d,i}} = e_{h_{d,i}} I_M\) and \(C_{H_{i}} = e_{H_{i}} I_{NM}\) in order to enhance the tractability of the derivations. Then, we can simplify Eq. (14) as follows:

\[
\begin{align*}
\left( e_{h_{d,i}}^2 + e_{H_{i}}^2 N \right) \text{Tr} (A_i) - \sqrt{2\ln(1/q_j)} x_j + \ln(q_j) y_j + e_i & \geq 0, \quad \forall j \in K_E, \quad (15a) \\
\left\| \begin{bmatrix} \text{vec}(A_i) \end{bmatrix} \right\| & \leq x_j, \quad \forall j \in K_E, \quad (15b) \\
y_j I_M + \left( e_{h_{d,i}}^2 + e_{H_{i}}^2 N \right) A_i & \geq 0, \quad y_j \geq 0, \quad \forall i \in K_I. \quad (15c)
\end{align*}
\]

Similarly, by assuming \(C_{g_{d,i}} = e_{g_{d,i}}^2 I_M\) and \(C_{G_{i}} = e_{G_{i}}^2 I_{NM}\), we approximate Eq. (6c) as:

\[
\begin{align*}
\left( e_{g_{d,i}}^2 + e_{G_{i}}^2 N \right) \text{Tr} (B) - \sqrt{2\ln(1/q_j)} x_j + \ln(q_j) y_j + e_i & \geq 0, \quad \forall j \in K_E, \quad (16a) \\
\left\| \begin{bmatrix} \text{vec}(B) \end{bmatrix} \right\| & \leq x_j, \quad \forall j \in K_E, \quad (16b) \\
y_j I_M + \left( e_{g_{d,i}}^2 + e_{G_{i}}^2 N \right) B & \geq 0, \quad y_j \geq 0, \quad \forall i \in K_E, \quad (16c)
\end{align*}
\]

where \(B \in \mathbb{C}^{M \times M}\) is defined as \(B = \sum_{i \in K_I} W_i + \Sigma, \quad \tilde{e}_j \triangleq \left( \tilde{g}_{d,j}^\dagger + u^\dagger \tilde{G}_j \right) B \left( \tilde{g}_{d,j} + \tilde{G}_j^\dagger v \right) + I_j, \quad \text{and} \quad \tilde{x} = [\tilde{x}_1, \ldots, \tilde{x}_{|K_E|}]^T, \quad \tilde{y} = [\tilde{y}_1, \ldots, \tilde{y}_{|K_E|}]^T\) represent auxiliary variables. By assuming, in turn, that \(C_{d_{d,u}} = e_{d_{d,u}} I_M\) and \(C_{V_{u}} = e_{V_{u}} I_{NM}\), we can approximate the chance FISI constraints in Eq. (6d) as

\[
\begin{align*}
\left( e_{d_{d,u}}^2 + e_{V_{u}}^2 N \right) \text{Tr} (B) - \sqrt{2\ln(1/t_u)} x_u + \ln(t_u) y_u + e_u & \leq 0, \quad \forall u \in U, \quad (17a) \\
\left\| \begin{bmatrix} \text{vec}(B) \end{bmatrix} \right\| & \leq x_u, \quad \forall u \in U, \quad (17b)
\end{align*}
\]
where $\hat{e}_u \triangleq \left( \hat{v}_{d,u}^* + u^* \hat{V}_u \right) B \left( \hat{v}_{d,u} + \hat{V}_u^* v \right) - P_T^{(u)}$, while $x = [\hat{x}_1, \ldots, \hat{x}_U]^T$ and $y = [\hat{y}_1, \ldots, \hat{y}_U]^T$ denote auxiliary variables. Finally, we can approximate the interception SINR outage constraints in Eq. (6f) as

$$\sum_{i \in K_i} \left[ \frac{\left( \sum_{j=1}^K H_{i,j}^* H_{j,i} \right) \nu_{i,j}}{\nu_{i,j}} \right] \leq \tilde{x}_u, \forall u \in U,$$

(18a)

where $C_u \in \mathbb{C}^{M \times M}$ is defined as $C_u \triangleq \left( 1 + \frac{1}{\nu_u} \right) W_i - \sum_{k \in K_i \setminus \{i\}} W_k - \Sigma$, $\tilde{e}_u \triangleq \left( \hat{v}_{d,u}^* + u^* \hat{V}_u \right) C_u \left( \hat{v}_{d,u} + \hat{V}_u^* v \right)$, and $\tilde{x} = [\hat{x}_1, \ldots, \hat{x}_U]^T$ and $\tilde{y} = [\hat{y}_1, \ldots, \hat{y}_U]^T$ refer to auxiliary variables.

Hence, by dropping the non-convex rank constraints $\text{Rank}(W_i) = 1$, we obtain the following robust formulation of problem (P2):

$$(\text{P3}): \min_{\left\{ W_i \right\} \Sigma, \mathcal{S}} \sum_{i \in K_i} \text{Tr}(W_i) + \text{Tr}(\Sigma)$$

subject to Eqs. (15)–(18), (6g), $W_i \succeq 0$, (19a)

where $S \triangleq \{ \hat{x}_1, \hat{y}_1, \hat{x}_j, \hat{y}_j, \tilde{x}_u, \hat{y}_u, \hat{x}_u, \hat{y}_u \}$. (P3) is a convex semi-definite programming (SDP) problem and can be solved in polynomial time by convex optimization software that utilizes interior-point methods, such as CVX [16].

C. Reflect Beamforming Optimization

For given transmit precoding and AN vectors, the objective function becomes fixed as well. Therefore, problem (P1) is reduced into a feasibility-check problem:

$$\left( \text{P4}: \right) \text{Find } u \text{ s.t. Eqs. (6b)--(6f), (6h).}$$

In order to solve this problem, we utilize the SDR- and BTTI-based derivations of Sec. III-B. We note that Eqs. (15e)–(18c) are independent of $v$. We also introduce the slack variables $\xi, \lambda, \mu, \text{and } \nu$ that are associated with the SINR, EH, FISI, and security constraints, respectively, to improve the convergence of the algorithm. In addition, we notice that $e_i, \tilde{e}_i, \hat{e}_i, \tilde{e}_u$ and are non-concave in $v$. Thus, we use first-order Taylor inequalities to obtain linear approximations of [13]:

$$e_i \approx 2 \text{Re} \left\{ u^* \hat{H}_i A_i \hat{H}_i^* v \right\} - u^* \hat{H}_i A_i \hat{H}_i^* v - 2 \text{Re} \left\{ u^* \hat{H}_i A_i \hat{H}_i^* v \right\}$$

$$+ 2 \text{Re} \left\{ u^* \hat{H}_i A_i \hat{H}_i^* v \right\} + \hat{H}_i A_i \hat{H}_i^* - I_i - \xi_i, \forall i \in K_i,$$ (21a)

$$\tilde{e}_j \approx 2 \text{Re} \left\{ u^* \hat{G}_j B_j \hat{G}_j^* v \right\} - u^* \hat{G}_j B_j \hat{G}_j^* v$$

$$+ 2 \text{Re} \left\{ u^* \hat{G}_j B_j \hat{G}_j^* v \right\} + \hat{G}_j B_j \hat{G}_j^* - I_j - \lambda_j, \forall j \in K_E,$$ (21b)

where $D \in \mathbb{C}^{M \times M}$ is defined as $D \triangleq \sum_{k \in K \setminus \{i\}} W_k + \Sigma$. Moreover, assuming $C_{\tilde{Z}_u} \triangleq \epsilon_{\tilde{Z}_u} I_{\tilde{N}}$ where $\tilde{N} \triangleq N L$ and using a similar approach as in Sec. III-B, we obtain the following convex approximation of the CIUSI outage constraints in Eq. (6e):

$$\epsilon_{\tilde{Z}_u} \text{Tr} \left( \tilde{F} \right) - \sqrt{2\ln(1/\eta_u)} \tilde{x}_u + \text{ln}(\eta_u) \tilde{x}_u + \tilde{e}_u \leq 0, \forall u \in U,$$

(22a)

where $\tilde{F} \in \mathbb{C}^{L \times L}$ is defined as $\tilde{F} \triangleq \sum_{u \in U} f_{u}^* f_u^*$. $\tilde{e}_u$ is approximated as

$$\tilde{e}_u \approx 2 \text{Re} \left\{ u^* \tilde{Z}_u F \tilde{Z}_u^* v \right\} - u^* \tilde{Z}_u F \tilde{Z}_u^* v, \forall u \in U,$$ (23)

and $\tilde{x} = [\hat{x}_1, \ldots, \hat{x}_U]^T$ and $\tilde{y} = [\hat{y}_1, \ldots, \hat{y}_U]^T$ denote auxiliary variables.

Finally, we adopt the penalty convex-concave procedure (CCP) to handle the unit-modulus constraints in Eq. (20). Specifically, we introduce the slack variable $\xi = [\xi_1, \ldots, \xi_{2N}]^T$ and write these constraints as follows [13]:

$$\left| v_n^{[r]} \right|^2 - 2 \text{Re} \left\{ v_n^{[r]} v_n^{[r]} \right\} \leq \zeta_n - 1, \forall n \in N, \forall r \in R,$$ (24a)

$$\left| v_n \right|^2 \leq 1 + \zeta_{N+n}; \quad \zeta_n \geq 0, \forall n \in N,$$ (24b)

where Eq. (24) is computed at fixed $v_n^{[r]}$, with $r \in R \triangleq \{1, \ldots, R_{\text{max}}\}$ denoting the iteration index of the penalty CCP algorithm.

Hence, we can transform problem (P4) into the following problem:

$$\left( \text{P5}: \right) \max_{\left\{ \nu \right\} \Sigma, \mathcal{S}} \sum_i \xi'_i + \sum_{j \in K_E} \lambda'_j + \sum_{u \in U} (\mu_u + \nu_u) - \varphi^{[r]} \sum_{n \in N} \zeta_n$$

subject to Eqs. (15a)–(18a), (15b)–(18b), (22), (24), (25b)

where $\Sigma \triangleq \{ \xi, \lambda, \mu, \nu, \xi, \hat{y}, \tilde{e}, \zeta \}$, and $\epsilon_i, \tilde{e}_i, \hat{e}_i, \tilde{e}_u \hat{e}_u$ in Eqs. (15a)–(18a) and Eq. (22) are given by Eq. (21) and Eq. (23). $\| \xi \|_1 \triangleq \sum_{n \in N} \zeta_n$ denotes the penalty term and $\varphi^{[r]}$ is the respective regularization factor for ensuring numerical stability. (P5) is a convex problem and can be efficiently solved by CVX.
Algorithm 1 Penalty CCP Algorithm.
1: Set initial points \( \nu^{[0]} \) and \( \nu^{[0]} > 1 \) and iteration index \( r = 0 \).
2: repeat
3: if \( r < R_{\text{max}} \) then
4: Update \( \nu^{[r+1]} \) from problem (P5).
5: \( \omega^{[r+1]} = \min \{ \eta \nu^{[r]}, \omega_{\text{max}} \} \).
6: \( r = r + 1 \).
7: else
8: Set initial points \( \nu^{[0]} \) and \( \nu^{[0]} > 1 \) and iteration index \( r = 0 \).
9: end if
10: until \( \| \nu^{[r]} - \nu^{[r-1]} \|_1 \leq \nu \).
11: Output: \( \nu^* = \nu^{[r]} \).

Algorithm 2 Alternating Optimization Algorithm for (P1).
1: Set initial point \( \Theta^{(0)} \), tolerance threshold \( 0 \leq \varepsilon \leq 1 \), maximum number of iterations \( T \), and iteration index \( t = 1 \).
2: repeat
3: Solve (P3) with given \( \nu^{(t-1)} \) to obtain \( \{ w_i^{(t)}, \Sigma^{(t)} \} \).
4: Solve (P5) with given \( \{ w_i^{(t)}, \Sigma^{(t)} \} \) to obtain \( \nu^{(t)} \).
5: Set: \( r = r + 1 \).
6: repeat
7: \( | f_t - f_{t-1} | / | f_{t-1} | \leq \varepsilon \), where \( f_t = \sum_{i \in \mathcal{K}_t} \| w_i \|^2 + \text{Tr} ( \Sigma^{(t)} ) \).
8: until \( \{ w_{i,x}, \Sigma_x, \nu_x \} = \{ w_{i,x}^{(t)}, \Sigma_x^{(t)}, \nu_x^{(t)} \} \).

D. Optimization Algorithms and Computational Complexity

In summary, we solve problem (P1) by alternating solving the convex problems (P3) and (P5) in an iterative fashion. If the optimal solutions of the SDPs are of rank one, then we can recover the optimal solutions of the respective original problems (P2) and (P4) via eigen-value decomposition; otherwise, we can closely approximate them by feasible solutions by applying Gaussian randomization [17].

The penalty CCP algorithm and the alternating optimization algorithm for solving problem (P1) are presented in Alg. 1 and 2, respectively. Note that the penalty CCP algorithm restarts from a new initial point \( \nu^{[0]} \) if a feasible solution has not been found after \( R_{\text{max}} \) iterations.

The complexity of the considered problems is dominated by the respective second order cone (SOC) or/and linear matrix inequality (LMI) constraints. Hence, we can approximate it using the approach described in [13]. Specifically, the complexity of problems (P3) and (P5) for obtaining an \( \epsilon \)-accurate solution is approximated as shown in Table I, where \( a_1 \triangleq 2K_1 + K_E + 2U + 1, b_1 \triangleq K_1 + K_E + 2U, c_1 \triangleq M ( M + 1 ), c_2 \triangleq L ( L + 1 ), \) and \( n_1 \triangleq ( K_1 + 1 ) M \).

IV. NUMERICAL RESULTS

We assume that \( M = L = 8, K_1 = K_E = U = 2, \) and \( N = 64 \). The path loss in any link of interest is given by \( L_p = C_0 ( d / d_0 )^{-\gamma} \), where \( C_0 = 30 \) dB is the path loss at a reference distance \( d_0 = 1 \) m, \( d \) is the separation distance of the considered nodes, and \( \gamma \) is the corresponding path loss exponent, which equals 2.2 for the ST-IRS, PT-IRS, ST-EHRs, and IRS–receivers links and 3.6 for any other link. The ST-IRS, ST-EHR, and IRS–EHR channels are described according to the Rician fading channel model due to the adjacency of the nodes, whereas the remaining channels are modeled by the Rayleigh fading channel model. The Rician factors equal 5 dB. We set \( \Gamma_i = \Gamma, \forall i \in K, Q_j = Q, \forall j \in K_E, \Gamma^{(c)} = \Gamma, \forall u \in \mathcal{U}, \) and \( P_{\text{th}} = 10^{-6} \). We also set the noise power at \(-90 \) dBm for all receivers and the (relative to the noise power) IPT of each PR to \( F_j(u) = 0 \) dB, \( \forall u \in \mathcal{U} \). We adopt the widely applied model EH model \( F(x) = \frac{a x}{b + x} - \frac{\bar{b}}{x} \), where \( a = 2.463, \bar{b} = 1.635, \) and \( c = 0.826 \) for all IRSs [18]. The channel uncertainty level is \( \delta = 0.01 \).

We compare the performance of the proposed optimal scheme with the cases where random phase shifts are applied at the IRS or where there is no IRS deployed, assuming two scenarios: i) the considered spectrum underlay setup, and ii) a scenario where the secondary system is isolated (stand-alone), i.e., it is not collocated with the primary system and, therefore, it is not subject to interference power and security constraints.

In Fig. 2, we plot the transmit sum-power for varying SINR targets, assuming \( Q = -20 \) dBm and \( \Gamma = 0 \) dB. We note that the proposed scheme outperforms the benchmark strategies and is, in general, more robust from them as well as that the IRS improves the performance, while the requirement for satisfying the interference constraints results in higher transmission power. The performance gains of the derived method become more prominent for more stringent SINR requirements.

In Fig. 3, we fix \( \Gamma = 0 \) dB and we vary the harvested power targets. We plot the performance of the proposed optimal strategy for different number of antennas at the ST, i.e., for \( M = 8 \) and \( M = 16 \). We note that we need more transmit power to satisfy more stringent EH constraints, as well as that the use of more transmit antennas at the ST improves the performance due to the increased number of spatial degrees-of-freedom, as expected.

A similar conclusion is drawn as we are increasing the number of IRS elements, \( N = \{ 32, 64, 96, 128 \} \), as shown in Fig. 4, thanks to the higher passive beamforming gains. We notice that the performance gains are more prominent from more stringent EH thresholds.

In Fig. 3, we also plot the corresponding results for the case where we map the obtained continuous IRS phase shifts solutions to their closest valid discrete counterparts in an actual implementation with a set of 16 discrete values. We note that there is a small performance degradation as well as a deterioration of the robustness to the channel uncertainty when we map the continuous solutions to discrete ones, since the latter are not optimal.

V. SUMMARY AND CONCLUSIONS

In this paper, we studied the joint transimt precoding, AN covariance, and IRS beamforming matrix optimization for an IRS-aided MISO broadcast system for SWIPT under QoS, interference, and security constraints. Numerical simulations demonstrated the performance gains of the proposed strategy over benchmark methods, corroborated the usefulness of the IRS, and provided useful insights regarding the impact of the operational parameters and restrictions on system performance. In the future, we plan to extend this work by considering also hardware impairments.
TABLE I
COMPUTATIONAL COMPLEXITY OF PROBLEMS (P3) AND (P5).

| Problem | Complexity |
|---------|------------|
| (P3)    | \( O \left( \ln \left( \frac{1}{\epsilon} \right) \sqrt{n_1 M + 2b_1 n_1} \left( n_1^2 + n_1 n_2 M^2 + n_1 M^3 + n_1 b_1 c_1^2 \right) \right) \) |
| (P5)    | \( O \left( \ln \left( \frac{1}{\epsilon} \right) \sqrt{2 \left( N + b_1 + U \right) N} \left( N^2 + 12 N^3 + N b_1 c_2^2 + N U c_3^2 \right) \right) \) |

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