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Power Minimization Resource Allocation for Underlay MISO-NOMA SWIPT Systems

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ABSTRACT The combination of cognitive radio and non-orthogonal multiple access (NOMA) has tremendous potential to achieve high spectral efficiency in the IoT era. In this paper, we focus on the energy-efficient resource allocation of a cognitive multiple-input single-output NOMA system with the aid of simultaneous wireless information and power transfer. Specifically, a non-linear energy harvesting (EH) model is adopted to characterize the non-linear energy conversion property. In order to achieve the green design goal, we aim for the minimization of the system power consumption by jointly designing the transmit beamformer and the receive power splitter subject to the information transmission and EH harvesting requirements of second users (SUs), and the maximum tolerable interference constraints at primary users. However, the formulated optimization problem is non-convex and hard to tackle. By exploiting the classic semi-definite relaxation and successive convex approximation, we propose a penalty function-based algorithm to solve the non-convex problem. The convergence of the proposed algorithm is further proved. Finally, simulation results demonstrate that the non-linear EH model is able to strongly reflect the property of practical energy harvester and the performance gain of the proposed algorithm than the baseline scheme.

INDEX TERMS Non-orthogonal multiple access, cognitive radio network, non-linear energy harvester.

I. INTRODUCTION

The rapid development of the internet of things (IoT) leads to the explosive increase of diverse wireless devices and the rapid growth of high-rate mobile services [1]–[3]. However, the spectrum scarcity has become a major bottleneck for the employment of the IoT. To improve the spectrum efficiency (SE), cognitive radio (CR) is a promising technique by enabling the secondary users (SUs) to share the spectrum band with the primary users (PUs) on the condition that the interference leaked to the PUs is acceptable [4]–[6]. In addition, non-orthogonal multiple access (NOMA) has been envisioned as another emerging technique to improve SE and achieve massive connectivity in IoT [7], [8]. Different from the traditional orthogonal multiple access (OMA), NOMA allows multiple users to access the same resource block by exploiting the power-domain multiplexing. Therefore, the integration of CR and NOMA has great potential to satisfy the IoT requirements, namely massive connectivity and high throughput. Despite the benefits, cognitive NOMA systems also face several design challenges including high decoding power consumption and strict interference management.

By exploiting power-domain multiplexing of NOMA, the users have to consume nonnegligible energy for powering their successive interference cancellation (SIC) decoders [9], which will largely prevents the application of the NOMA in energy-constraint IoT. Recently, simultaneous wireless information and power transfer (SWIPT) has been regarded as a hopeful technique to solve the power consumption problem in wireless networks [10]–[13]. In NOMA, since the superposition signal received by the user carries substantial energy, the IoT device may harvest a portion of this energy for powering its decoder. Nevertheless, the energy harvesting efficiency (EHE) is the major design challenge in cognitive NOMA systems [14]. The EHE depends on the resource allocation scheme based on the EH model, which is divided as two categories, namely linear model and non-linear model. The classic linear model [11], cannot accurately characterize the property of practical energy harvester. In the recent, several non-linear EH models were proposed in [15]–[18]. Among these research works, Boshkovska *et al.* [17], [18] proposed a non-linear EH model by fitting over experimental measurement data in [19]. Although the other non-linear models adopted in [15] and [16] well describe the nonlinearity of the EH, however, they cannot match with the experiments. Therefore, this paper adopts the non-linear EH model of [17] and [18] for achieving efficient resource allocation. In addition, due to the non-convex non-linear EH expression, it is very challenging to design optimal resource allocation strategy based on non-linear EH model.

In cognitive NOMA-SWIPT systems, there are two types of interference, namely inter-network interference between the primary network and the second network, and intra-network interference due to non-orthogonal nature of NOMA [20]. Furthermore, the effect of interference signals is two-sided. It is harmful for the information decoding, but it can enhance the performance of EH. Therefore, in cognitive NOMA-SWIPT systems, interference management is recognized as a essential technique to balance the interference cancellation and EH. Most existing works in cognitive NOMA systems assume that perfect CSI is available [14], [20]. However, due to the feedback delay and the channel estimation errors, it is hard to obtain the perfect CSI of the inter-network interference channel. As a result, it is very meaningful to investigate the interference management scheme of cognitive NOMA systems under the imperfect CSI.

In this paper, we consider a typical cognitive MISO-NOMA system, where the second base station (SBS) simultaneously serve multiple second users (SUs) by NOMA signaling, and meanwhile guarantee the interference received by primary users (PUs) acceptable. The SUs can harvest energy from the received superposition signal for powering them own information decoders. Furthermore, we assume that the channel state information (CSI) between SBS and the PUs are imperfect. The main contributions of this paper are summarized as follows:

- To the best of our knowledge, this is the first time utilizing radio-frequency energy harvesting to meet the extra power consumption for conducting SIC in cognitive MISO-NOMA systems. Moreover, a non-linear model is applied to characterize the non-linearity of practical energy harvester.
- We formulate a system power minimization problem by jointly optimizing the transmit beamformer at SBS and the power splitter at SUs, while satisfying the SUs' signal to interference noise ratio (SINR) thresholds and lowest power harvesting requirements, as well as the PUs' interference power constraints.
- By exploiting the successive convex approximation (SCA) and semi-definite relaxation (SDR), we develop a penalty function-based algorithm to obtain the suboptimal solution of the formulated power minimization problem. The convergence of the proposed algorithm is further proved.
- Simulation results reveal that our adopted non-linear EH model consumes lower power than the linear model when energy conversion efficiency is below 0.8. It is also shown that the proposed robust design with imperfect CSI can achieve a slightly lower power consumption when compared to the counterpart with perfect CSI. Besides, we also unveil that the proposed penalty function-based algorithm is able to converge to the optimal point within a few iterations.

The remainder of this paper are organized as follows. The related work is illustrated in Section II. Section III presents the system model. In section IV, we first introduce the system power minimization problem, and then develop optimal algorithm to solve the formulated optimization problem. In section V, we illustrate the benchmark methods. In Section VI, extensive simulation results are provided to evaluate the performance of the proposed algorithm. Section VII concludes this paper.

Notations: $\mathbf{X}^H$, $\mathrm{Tr}(\mathbf{X})$ and $\mathrm{Rank}(\mathbf{X})$ denote the Hermitian transpose, trace and rank of matrix $\mathbf{X}$, respectively. $\mathbf{X} \succeq 0$ and $\mathbf{X} \succ 0$ represent the matrix $\mathbf{X}$ is a positive semidefinite matrix and positive definite matrix, respectively.

II. RELATED WORK

A. COGNITIVE NOMA SYSTEMS

Generally speaking, there are three types of cognitive NOMA framework, namely, the underlay NOMA scheme, the overlay NOMA scheme, and the interweave NOMA scheme [14]. In underlay NOMA networks, concurrent primary and secondary transmissions are permitted, while the interference on the primary network is below a threshold value. Thus, it is recognized as a promising technique to achieve massive connectivity and low latency requirements in the IoT era. In this paper, we concentrate on the interference management and resource allocation for underlay NOMA networks. Therefore, this section highlights the state-of-the-art research works in this domain. Ding *et al.* [4] first introduce the NOMA technique into the underlay cognitive radio networks. In addition, they characterized the effect of user pairing on the throughput performance of the underlay NOMA networks. Liu *et al.* [21] evaluated the outage probability of the large-scale underlay NOMA networks. The simulation results demonstrated that NOMA can surpass the conventional OMA scheme by carefully designing the power allocation among users and the required transmission rate. Reference [22] investigated the resource allocation for an underlay NOMA network. The user clustering and power allocation are jointly designed to maximum the sum throughput, while providing interference protection for the primary users. However, the high power consumption for conducting successive interference cancellation (SIC) is the main bottleneck for the sake of employing NOMA technique to the low-power IoT. To our best knowledge, the existing works generally ignore this issue.

B. SIMULTANEOUS WIRELESS INFORMATION AND POWER TRANSFER

With the explosive growth of IoT devices, how to extend their lifetime in an efficient manner has been recognized as a popular research topic [23], [24]. Recently, simultaneous wireless information and power transfer (SWIPT) was proposed to provide stable energy supply for low-power IoT devices. In general, either time switcher or power splitter is adopted by the receiver to simultaneously collect both energy and information from the received radio-frequency (RF) signal [11], [25], [26].

The SWIPT has been extensively investigated in the existing works, which can be divided into two categories according to the EH model, i.e., linear EH model and non-linear EH model. In [27]–[29], based on conventional linear energy harvesting model, the optimal resource allocation was designed to satisfy diverse performance requirements, such as throughput, energy efficiency, and fairness, etc. Moreover, Xiong *et al.* [30] and Kim *et al.* [31], investigated the optimal cooperative transmission scheme for cognitive SWIPT systems. For the sake of delineating the non-linear feature of the practical energy harvester, Boshkovska *et al.* [17] first established a non-linear energy harvesting model according to the measurement data. In [32] and [33], the optimal interference management and resource scheduling was developed for the cognitive SWIPT networks by exploiting the non-linear EH model. The same group of authors extend the works to the scenario with imperfect CSI in [34]. Xiong *et al.* [35] explored the rate-energy region for a multiple-input multiple-output (MIMO) SWIPT system with non-linear EH model.

Different from the existing works, this paper seamlessly integrates the SWIPT technique into an underlay MISO-NOMA networks. In our model, the user splits a part of the received signal for harvesting power in order to power its SIC decoder. In addition, the energy-efficient resource allocation strategy is designed based on non-linear EH model and imperfect CSI.

III. SYSTEM MODEL

This paper investigates the optimal design of underlay MISO-NOMA systems relying on the wireless powered decoder. Specifically, a non-linear model is applied to characterize the non-linearity of practical energy harvester. As illustrated in Fig. 1, the cognitive system consists of a second base station (SBS) equipped with N antennas and K second users (SUs), which coexisting with M primary users via the underlay scheme. It is assumed that all the users are equipped with a single antenna. In order to improve the spectrum efficiency, the power-domain NOMA technique is applied in the SBS for transmitting information to the second users in the same resource block, while guaranteeing the interference leaked to the PU is tolerable. Moreover, we illustrate the key notations in TABLE 1 for easy reference.

The channel coefficients between the SBS and the i-th SU/PU are denoted by the complex vectors $\mathbf{h}_i \in \mathbb{C}^{N\times 1}$ and

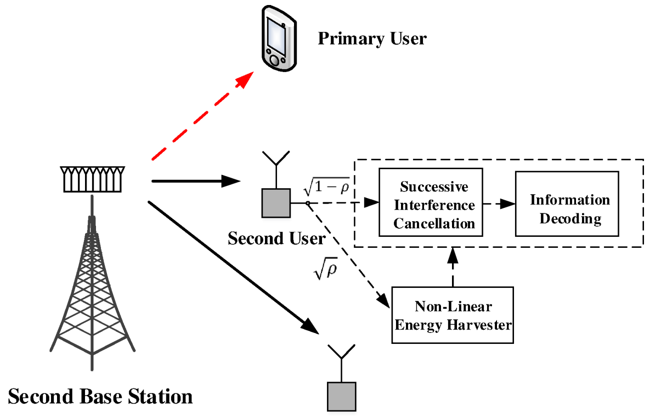

FIGURE 1. Underlay MISO-NOMA systems with wireless powered decoder.

TABLE 1. Summary of key notations.

Notation	Description
$\mathbf{h}_i/\mathbf{g}_i$	Channel coefficient between SBS and i-th SU/PU
$\widehat{\mathbf{g}}_i$	Estimate of $\mathbf{g}_i$ at SBS
$\Delta\widehat{\mathbf{g}}_i$	Channel estimate error of $\mathbf{g}_i$
$\mathbf{w}_i$	Transmit beamforming vector from SBS to i-th SU
ρ_i	Power splitting ratio at i-th SU
P_{in}^i	EH input power at i-th SU
$P_{\text{EH}}^{(nl)}$	Harvested power at i-th SU
$\text{IP}_{j,\max}$	Maximum tolerable interference power at j-th PU
$\text{P}_{i,\min}$	Power consumption of the SIC decoder at i-th SU

$\mathbf{g}_i \in \mathbb{C}^{N\times 1}$, respectively. We assume the channel uncertainties for the SBS-PU links is due to the feedback delay and the channel estimation errors [36], [37], while the channel state information (CSI) of the SBS-SU links can be perfectly obtained by the SBS from the feedback of SUs. The channels of the SBS-PU links are modelled as

$$\mathbf{g}_i = \widehat{\mathbf{g}}_i + \Delta\widehat{\mathbf{g}}_i, \tag{1}$$

where $\widehat{\mathbf{g}}_i$ represents the estimate of $\mathbf{g}_i$ at the SBS, and $\Delta\widehat{\mathbf{g}}_i$ denotes the channel estimation error, which is bounded by ϵ (known to the SBS) as

$$\|\Delta\widehat{\mathbf{g}}_i\| = \|\mathbf{g}_i - \widehat{\mathbf{g}}_i\| \le \epsilon. \tag{2}$$

The transmitted signal $\mathbf{x}$ at the SBS is expressed as

$$\mathbf{x} = \sum_{i=1}^{K} \mathbf{w}_i x_i, \tag{3}$$

where x_i denotes the desired signal for the i-th SU, and $\mathbf{w}_i \in \mathbb{C}^{N\times 1}$ is the corresponding transmit beamforming vector. The received signal at the i-th SU is written by

$$y_i = \mathbf{h}_i^H \mathbf{w}_i x_i + \sum_{k\ne i} \mathbf{h}_i^H \mathbf{w}_k x_k + z_i, \tag{4}$$

where $z_i \sim \mathcal{CN}(0, \delta_1^2)$ is the complex additive white Gaussian noise (AWGN).

In our considered system, the second user splits the received superposition signal in the power domain. One portion of the received signal is for the information decoding and the rest is for the energy harvesting. Hence, the power of the received signal for the energy harvesting at i-th SU can be expressed as

$$P_{\text{in}}^{i} = \rho_i \sum_{k=1}^{K} |\mathbf{h}_i^H \mathbf{w}_k|^2. \tag{5}$$

where $\rho_i \in (0, 1)$ represents the power splitting ratio at the i-th user. In addition, the non-linear energy harvesting model of [17] is adopted in this paper. Therefore, the harvested energy at the i-th SU is given by

$$P_{\text{EH}}^{(nl)}(P_{\text{in}}^{i}) = \frac{\Pi - a_3 \Xi}{1 - \Xi}, \quad \Xi = \frac{1}{1 + \exp(a_1 a_2)}, \quad \Pi = \frac{a_3}{1 + \exp(-a_1(P_{\text{in}}^{i} - a_2))}. \tag{6}$$

In (6), P_{in}^{i} denotes the input power of the energy harvester, and Π is the logistic function with respect to P_{in}^{i}. a_1, a_2 are the constants determined by its detailed characteristics such as capacitance, resistance, and diode turn-on voltage. a_3 represents the maximum harvested power when the energy harvester becomes saturated [17], [18], [38].

Without loss of generality, we assume that $\|\mathbf{h}_1\| \geq \|\mathbf{h}_2\| \cdots \geq \|\mathbf{h}_K\|$. According to the principle of downlink NOMA, the transmit power of the information signal of the weak user must be larger than that of the strong user, i.e.,

$$\|\mathbf{w}_1\| \leq \|\mathbf{w}_2\| \cdots \leq \|\mathbf{w}_K\|. \tag{7}$$

Note that the user with a larger channel gain is called the strong user. In the process of information decoding, the l-th second user can decode and remove the the i-th SU's signal using the SIC approach for $l < i$. Thus, the signal at the l-th user after removing the last $K - i$ SU's signals to detect the i-th user is written as

$$y_l^i = \sqrt{1 - \rho_l}(\mathbf{h}_l^H \mathbf{w}_i x_i + \sum_{k=1}^{i-1} \mathbf{h}_l^H \mathbf{w}_k x_k) + z_l. \tag{8}$$

In order to achieve SIC, the l-th second user has to successfully decode the information of all i-th ($l \leq i$) SUs' signals. Therefore, the signal to interference plus noise ratio (SINR) of the i-th user signal at the l-th user should be higher than a threshold r_i, which is expressed as

$$\text{SINR}_l^i = \frac{(1-\rho_l)|\mathbf{h}_l^H \mathbf{w}_i|^2}{(1-\rho_l) \sum_{k=1}^{i-1} |\mathbf{h}_l^H \mathbf{w}_k|^2 + \delta_l^2} \geq \mathrm{r}_i, \tag{9}$$

Furthermore, the interference signal received by the j-th PU is written as

$$s_j = \mathbf{g}_j^H \sum_{i=1}^{N} \mathbf{w}_i x_i + n_j, \tag{10}$$

where $n_j \sim \mathcal{CN}(0, \delta_1^2)$ denotes the complex AWGN at the j-th PU. Due to the uncertainty of $\mathbf{g}_j$, the interference power (IP) of the SBS-PU link is given by

$$\text{IP}_j = \max_{\|\Delta\widehat{\mathbf{g}}_j\| \leq \epsilon} \sum_{i=1}^{N} |(\widehat{\mathbf{g}}_j + \Delta\widehat{\mathbf{g}}_j)^H \mathbf{w}_i|^2. \tag{11}$$

Besides, we have $\text{IP}_{j,\max}$ denoting the maximum acceptable interference power at the j-th PU. In order to guarantee the j-th PU performance, the IP received by j-th PU cannot exceed its maximum tolerable interference power, i.e., $\text{IP}_j \leq \text{IP}_{j,\max}$.

IV. PROBLEM FORMULATION AND SOLUTION

In this paper, we aim for minimizing the total power consumption of the underlay wireless powered MISO-NOMA system by the joint design of the transmit beamformer and the receive power splitter. Due to the uncertainty of the channel between the SBS and the PU, i.e., $\Delta\widehat{\mathbf{g}}_j$, as well as the non-linear energy harvesting expression, the proposed optimization problem is non-convex. Based on successive convex approximation (SCA) and semi-definite relaxation (SDR), a penalty function-based algorithm is designed to obtain the near-optimal solution. In addition, the convergence of the proposed algorithm is proved.

Let $\mathrm{P}_{i,\min}$ be the power consumption of the information decoder at i-th SU. The total power minimization problem can be formulated as:

$$\begin{aligned}
&\min_{\{\rho_i, \mathbf{w}_i\}} \sum_{i=1}^{K} \|\mathbf{w}_i\|^2 \\
&\text{s.t.} \quad \text{C1: } \text{SINR}_l^i = \frac{(1-\rho_l)|\mathbf{h}_l^H \mathbf{w}_i|^2}{(1-\rho_l) \sum_{k=1}^{i-1} |\mathbf{h}_l^H \mathbf{w}_k|^2 + \delta_l^2} \geq \mathrm{r}_i, \ l \leq i, \\
&\qquad \text{C2: } P_{\text{EH}}^{(nl)}(P_{\text{in}}^{i}) \geq \mathrm{P}_{i,\min}, \\
&\qquad \text{C3: } \max_{\|\Delta\widehat{\mathbf{g}}_j\| \leq \epsilon} \sum_{i=1}^{N} |(\widehat{\mathbf{g}}_j + \Delta\widehat{\mathbf{g}}_j)^H \mathbf{w}_i|^2 \leq \text{IP}_{j,\max}, \\
&\qquad \text{C4: } 0 < \rho_i < 1, \\
&\qquad (7),
\end{aligned} \tag{12}$$

where C1 guarantees that the SINR of the i-th users signal at the l-th user can reach the minimum requirement for successfully decoding, C2 represents that the minimum harvested power of i-th user should be higher than its power consumption for information decoding, and C3 restricts the maximum interference power from the second base station to the PU.

It is difficult to obtain the optimal solution of problem (12) due to the non-convex constraints C1-C3. According to the triangle inequality, we have

$$\begin{aligned}
|(\widehat{\mathbf{g}}_j + \Delta\widehat{\mathbf{g}}_j)^H \mathbf{w}_i| &\leq |\widehat{\mathbf{g}}_j^H \mathbf{w}_i| + |\Delta\widehat{\mathbf{g}}_j^H \mathbf{w}_i| \\
&\overset{(\alpha)}{\leq} |\widehat{\mathbf{g}}_j^H \mathbf{w}_i| + \|\Delta\widehat{\mathbf{g}}_j\|_2 \|\mathbf{w}_i\|_2 \\
&\leq |\widehat{\mathbf{g}}_j^H \mathbf{w}_i| + \epsilon \|\mathbf{w}_i\|_2,
\end{aligned} \tag{13}$$

where (α) holds on basis of the Cauchy-Schwarz inequality, i.e., $|\Delta\widehat{\mathbf{g}}_j^H\mathbf{w}_i| \leq \|\Delta\widehat{\mathbf{g}}_j\|_2\|\mathbf{w}_i\|_2$. Then, it follows that

$$\begin{aligned}
&\max_{\|\Delta\widehat{\mathbf{g}}_j\|\leq\epsilon} \sum_{i=1}^{K} |(\widehat{\mathbf{g}}_j+\Delta\widehat{\mathbf{g}}_j)^H\mathbf{w}_i|^2 \\
&\leq \sum_{i=1}^{K} \max_{\|\Delta\widehat{\mathbf{g}}_j\|\leq\epsilon} |(\widehat{\mathbf{g}}_j+\Delta\widehat{\mathbf{g}}_j)^H\mathbf{w}_i|^2 \\
&\leq \sum_{i=1}^{K} (\widehat{\mathbf{g}}_j^H\mathbf{w}_i| + \epsilon\|\mathbf{w}_i\|_2)^2 \\
&= \sum_{i=1}^{K} (|\widehat{\mathbf{g}}_j^H\mathbf{w}_i|^2 + \epsilon^2\|\mathbf{w}_i\|_2^2 + 2\epsilon\|\mathbf{w}_i\|_2|\widehat{\mathbf{g}}_j^H\mathbf{w}_i|) \\
&\leq \sum_{i=1}^{K} (|\widehat{\mathbf{g}}_j^H\mathbf{w}_i|^2 + \epsilon^2\|\mathbf{w}_i\|_2^2 + 2\epsilon\|\mathbf{w}_i\|_2^2\|\widehat{\mathbf{g}}_j\|_2) \\
&= (\sum_{i=1}^{K}\mathbf{w}_i)^H(\widehat{\mathbf{g}}_j\widehat{\mathbf{g}}_j^H + \epsilon(\epsilon + 2\sqrt{\widehat{\mathbf{g}}_j^H\widehat{\mathbf{g}}_j})\mathbf{I}_N)(\sum_{i=1}^{K}\mathbf{w}_i). \quad (14)
\end{aligned}$$

Furthermore, the variable substitution is applied to transform the non-convex quadratic constraints to the convex counterparts. By introducing $\mathbf{W}_i = \mathbf{w}_i\mathbf{w}_i^{\mathrm{H}}$, $\mathbf{H}_i = \mathbf{h}_i\mathbf{h}_i^{\mathrm{H}}$, the original problem (12) can be converted to the following problem:

$$\begin{aligned}
\min_{\{\rho_i,\mathbf{w}_i\}} \; & \sum_{i=1}^{K} \mathrm{Tr}(\mathbf{W}_i) \\
\text{s.t.} \;\; & \text{C5: } \mathrm{Tr}(\mathbf{H}_l\mathbf{W}_i) - \mathrm{r}_i\sum_{k=1}^{i-1}\mathrm{Tr}(\mathbf{H}_l\mathbf{W}_k) \geq \frac{\delta_l^2\mathrm{r}_i}{1-\rho_l}, l \leq i, \\
& \text{C6: } \sum_{k=1}^{K}\mathrm{Tr}(\mathbf{H}_i\mathbf{W}_k) \geq \frac{\mathrm{P}_{\mathrm{in}}(\mathrm{P}_{i,\min})}{\rho_i}, \\
& \text{C7: } \sum_{k=1}^{K}\mathrm{Tr}(\mathbf{G}_j\mathbf{W}_k) \leq \mathrm{IP}_{j,\max}, \\
& \text{C8: } \mathrm{Rank}(\mathbf{W}_i) = 1, \\
& \text{C9: } \mathbf{W}_i \succeq 0, \\
& \text{C10: } \mathrm{Tr}(\mathbf{W}_1) \leq \mathrm{Tr}(\mathbf{W}_2)\cdots \leq \mathrm{Tr}(\mathbf{W}_K), \\
& \text{C4}\,, \qquad (15)
\end{aligned}$$

where

$$P_{\mathrm{in}}(\mathrm{P}_{i,\min}) = a_2 - \frac{1}{a_1}\ln(\frac{\exp(a_1a_2)(a_3 - \mathrm{P}_{i,\min})}{\exp(a_1a_2)\mathrm{P}_{i,\min} + a_3}) \quad (16)$$

and

$$\mathbf{G}_j = (\widehat{\mathbf{g}}_j\widehat{\mathbf{g}}_j^H + \epsilon(\epsilon + 2\sqrt{\widehat{\mathbf{g}}_j^H\widehat{\mathbf{g}}_j})\mathbf{I}_N. \quad (17)$$

Because of the rank-one constraint C8, the optimization problem (15) is still non-convex. In order to address this problem, this paper proposes a penalty function-based scheme. Since $\mathbf{W}_i$ is positive semi-definite matrix, thus, we have $\mathrm{Tr}(\mathbf{W}_i) \geq \lambda_{\max}(\mathbf{W}_i)$. In addition, the rank of $\mathbf{W}_i$ is 1 when its trace is equal to its maximum eigenvalue, i.e., $\mathrm{Tr}(\mathbf{W}_i) = \lambda_{\max}(\mathbf{W}_i)$. With this insight, our optimization goal is converted to minimize the sum power consumption while making the penalty function $\sum_{i=1}^{K}\mathrm{Tr}(\mathbf{W}_i) - \lambda_{\max}(\mathbf{W}_i)$ as small as possible:

$$\begin{aligned}
\min_{\{\rho_i,\mathbf{W}_i\}} \; & \sum_{i=1}^{K}\mathrm{Tr}(\mathbf{W}_i) + \kappa\sum_{i=1}^{K}(\mathrm{Tr}(\mathbf{W}_i) - \lambda_{\max}(\mathbf{W}_i)) \\
\text{s.t.} \;\; & \text{C4-C7, C9, C10,} \qquad (18)
\end{aligned}$$

where $\kappa > 0$ is a penalty factor. Obviously, a large κ will drive the resource allocation strategy to get the rank-one $\{\mathbf{W}_i\}$. Since $\lambda_{\max}(\mathbf{W}_i)$ is convex, the problem (18) is still non-convex. By exploiting the successive convex approximation (SCA) method, the non-convex problem (18) can be transformed to the following iterative optimization problem:

$$\begin{aligned}
\min_{\{\rho_i,\mathbf{W}_i\}} \; & \sum_{i=1}^{K}\mathrm{Tr}(\mathbf{W}_i^{(n+1)}) + \kappa(\sum_{i=1}^{K}\mathrm{Tr}(\mathbf{W}_i^{(n+1)}) - \lambda_{\max}(\mathbf{W}_i^{(n)}) \\
& - (\mathbf{w}_{i,\max}^{(n)})^H(\mathbf{W}_i^{(n+1)} - \mathbf{W}_i^{(n)})\mathbf{w}_{i,\max}^{(n)}) \\
\text{s.t.} \; & \text{C4-C7, C9, C10.} \qquad (19)
\end{aligned}$$

By removing the constant terms in the objective function, the problem (19) can be further reduced to

$$\begin{aligned}
\min_{\{\rho_i,\mathbf{W}_i\}} \; & \sum_{i=1}^{K}\mathrm{Tr}(\mathbf{W}_i^{(n+1)}) + \kappa(\sum_{i=1}^{K}\mathrm{Tr}(\mathbf{W}_i^{(n+1)}) \\
& -(\mathbf{w}_{i,\max}^{(n)})^H\mathbf{W}_i^{(n+1)}\mathbf{w}_{i,\max}^{(n)}) \\
\text{s.t.} \; & \text{C4-C7, C9, C10} \qquad (20)
\end{aligned}$$

When $\mathrm{Tr}(\mathbf{W}_i) - \lambda_{\max}(\mathbf{W}_i) \approx 0$, we will have $\mathbf{W}_i \approx \lambda_{\max}(\mathbf{W}_i)\mathbf{w}_{i,\max}\mathbf{w}_{i,\max}^H$, where $\mathbf{w}_{i,\max}$ represents the unit eigenvector associated with the maximum eigenvalue $\lambda_{\max}(\mathbf{W}_i)$. Therefore, we can recovery the optimal beamforming vector $\mathbf{w}_i$ by the following equation:

$$\mathbf{w}_i = (\lambda_{\max}(\mathbf{W}_i))^{\frac{1}{2}}\mathbf{w}_{i,\max}. \quad (21)$$

Algorithm 1 Penalty Function-Based Algorithm

Initialize: setting $\mathbf{W}_i^{(0)}$, penalty factor κ and tolerance value ε.
Repeat:
Solve convex optimization problem (19) by CVX [39]
to obtain $(\mathbf{W}_i^{(n+1)}, \rho_i^{(n+1)})$;
Update the iterative number $n = n + 1$;
If $\mathrm{Tr}(\mathbf{W}_i^{(n+1)}) - \lambda_{\max}(\mathbf{W}_i^{(n)}) \leq \varepsilon$
break;
End;
Return optimal power splitting ratio $\rho_i^\star$ and beamforming vector $\mathbf{w}_i^\star = (\lambda_{\max}(\mathbf{W}_i^\star))^{\frac{1}{2}}\mathbf{w}_{i,\max}^\star$.

The detailed procedure of the proposed penalty function-based algorithm is illustrated in Algorithm 1. Besides, we further analyse the convergence of the proposed algorithm in *Theorem 1*.

Lemma 1: Let $\mathbf{A}$ and $\mathbf{B}$ be positive semi-deïĄnite matrixes. According to the feature of the convex function, we have $\lambda_{\max}(\mathbf{A}) - \lambda_{\max}(\mathbf{B}) \geq \mathbf{b}_{\max}^H(\mathbf{A}-\mathbf{B})\mathbf{b}_{\max}$, where $\mathbf{b}_{\max}$ represents the eigenvector corresponding to the maximum eigenvalue of $\mathbf{B}$.

Theorem 1: The Algorithm 1 can converge to the optimal solution.

Proof: Based on *lemma 1*, we have

$$\begin{aligned}
&\sum_{i=1}^{K}\mathrm{Tr}(\mathbf{W}_i^{(n+1)}) + \kappa(\sum_{i=1}^{K}\mathrm{Tr}(\mathbf{W}_i^{(n+1)}) - \lambda_{\max}(\mathbf{W}_i^{(n+1)})) \\
&\geq \sum_{i=1}^{K}\mathrm{Tr}(\mathbf{W}_i^{(n+1)}) + \kappa(\sum_{i=1}^{K}\mathrm{Tr}(\mathbf{W}_i^{(n+1)}) - \lambda_{\max}(\mathbf{W}_i^{(n)}) \\
&\quad -(\mathbf{w}_{i,\max}^{(n)})^H(\mathbf{W}_i^{(n+1)} - \mathbf{W}_i^{(n)})\mathbf{w}_{i,\max}^{(n)}) \\
&\geq \sum_{i=1}^{K}\mathrm{Tr}(\mathbf{W}_i^{(n)}) + \kappa(\sum_{i=1}^{K}\mathrm{Tr}(\mathbf{W}_i^{(n)}) - \lambda_{\max}(\mathbf{W}_i^{(n)}) \\
&\quad -(\mathbf{w}_{i,\max}^{(n)})^H(\mathbf{W}_i^{(n)} - \mathbf{W}_i^{(n)})\mathbf{w}_{i,\max}^{(n)}) \\
&= \sum_{i=1}^{K}\mathrm{Tr}(\mathbf{W}_i^{(n)}) + \kappa(\sum_{i=1}^{K}\mathrm{Tr}(\mathbf{W}_i^{(n)}) - \lambda_{\max}(\mathbf{W}_i^{(n)})). \qquad (22)
\end{aligned}$$

Therefore, $\{\mathbf{W}_i^{(n+1)}\}$ can always achieve a lower power consumption than $\{\mathbf{W}_i^{(n)}\}$. Since the feasible set is compact, the Algorithm 1 can converge to the optimal solution according to the Cauchy theorem.

Finally, the computational complexity of the proposed Algorithm 1 is analyzed. We assume that the number of iterations for Algorithm 1 is D. The interior-point method-based solver, i.e., SDPT3, is called to solve the problem (20) in each iteration. Problem (20) is with $x = (N^2+1)K$ variables and $y = 3K + \frac{K(K+1)}{2} + M - 1$ constraints such that the worst complexity is $O((x^2y+x^3)y^{1/2}\log(\frac{1}{\varepsilon}))$ [40], where ε is the tolerance value. Therefore, the computational complexity of Algorithm 1 is shown as $O(D(x^2y+x^3)y^{1/2}\log(\frac{1}{\varepsilon}))$.

V. BENCHMARK METHODS

For performance evaluation, our optimal design are compared with the following two benchmarks.

A. PERFECT CSI

Different from the imperfect CSI scheme, we assume that the SBS can obtain the global CSI in order to design optimal resource allocation scheme. Therefore, the corresponding optimization problem can be written as:

$$\begin{aligned}
&\min_{\{\rho_i,\mathbf{w}_i\}} \sum_{i=1}^{K}\|\mathbf{w}_i\|^2 \\
&\text{s.t.}\quad \text{C10: } \sum_{i=1}^{N}|\mathbf{g}_j^H\mathbf{w}_i|^2 \leq \mathrm{IP}_{j,\max}, \\
&\qquad \text{C1, C2, C4, (7).} \qquad (23)
\end{aligned}$$

TABLE 2. Simulation parameters.

Distance between SBS and SU 1	4m
Distance between SBS and SU 2	4m
Distance between SBS and PU	3m
Path-loss exponent α	3
SINR requirement of SU 1	35dB
SINR requirement of SU 2	20dB
Noise Power δ_1^2, δ_2^2	10^{-6}W

B. LINEAR ENERGY HARVESTING MODEL

In this case, the conventional linear EH model is adopted to depict the relationship between the harvested energy and the received signal power. Let η denote the energy conversion efficiency assumed equal for all SUs. The resource allocation problem based on linear EH model is thus expressed as:

$$\begin{aligned}
&\min_{\{\rho_i,\mathbf{w}_i\}} \sum_{i=1}^{K}\|\mathbf{w}_i\|^2 \\
&\text{s.t. C11: } \eta\rho_i\sum_{k=1}^{K}|\mathbf{h}_i^H\mathbf{w}_k|^2 \geq \mathrm{P}_{i,\min}, \\
&\qquad \text{C1, C3, C4, (7).} \qquad (24)
\end{aligned}$$

Similar to the method proposed in Section IV, the problems (23)-(24) can be converted to the convex model by some variable substitutions and the relaxation. Then, a variety of efficient algorithms are able to applied to obtain the optimal solution of the corresponding convex model.

VI. PERFORMANCE EVALUATION

In this section, we evaluate the performance of the optimal resource allocation design in our considered system based on the imperfect CSI. For comparison, the performance of the system conceiving the perfect CSI is also evaluated. We consider that there are $K = 2$ SUs and $M = 1$ PU. In addition, the SBS is equipped with $N = 8$ antennas. The channel coefficient is modeled as $(d_{ij}^{-\frac{\alpha}{2}})h$, where h is the Rayleigh channel with unit mean, d_{ij} is the distance between nodes i and j, and α is the path-loss exponent. For the non-linear energy harvester, we set $a_3 = 0.024$ W, $a_1 = 150$, $a_2 = 0.014$, according to [17]. The non-linear model can accurately match experimental results from various practical energy harvester [17], [41]. The simulation parameters are summarized in TABLE 1 for easy reference.

A. PERFORMANCE COMPARISON OF DIFFERENT EH MODELS

In Fig. 2, we compare the radio-frequency (RF) to direct current (DC) power transfer functions of the linear model with energy conversion efficiency $\eta = 0.8$, the measurement data and the non-linear energy harvesting model. Fig. 2 shows that the non-linear model closely matches the measurement data provided by [19]. It also illustrates that the linear model cannot capture the non-linearity of practical energy harvester, especially in the high input RF power level.

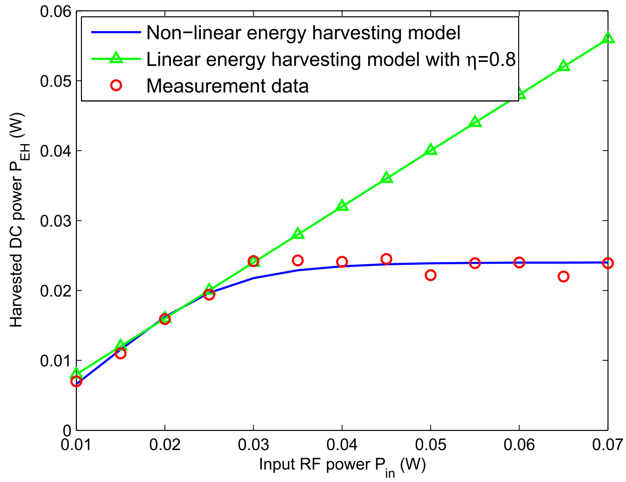

FIGURE 2. A comparison between the measurement data from [19], the RF-DC power transfer functions for linear energy harvesting model with $\eta = 0.8$, and the non-linear energy harvesting model in (8).

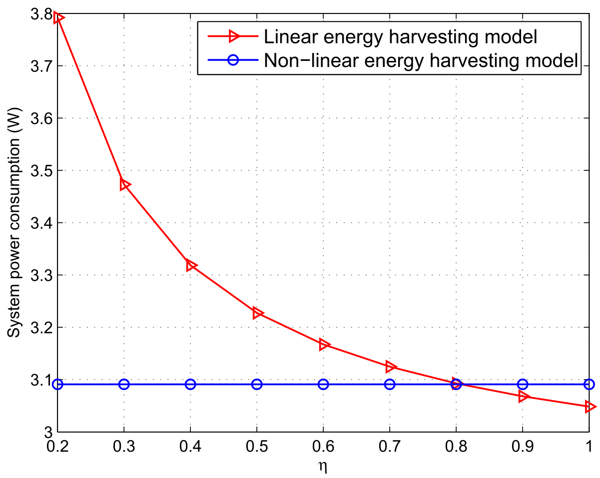

FIGURE 3. System power consumption (W) versus the linear energy conversion efficiency with $\epsilon = 0.015$.

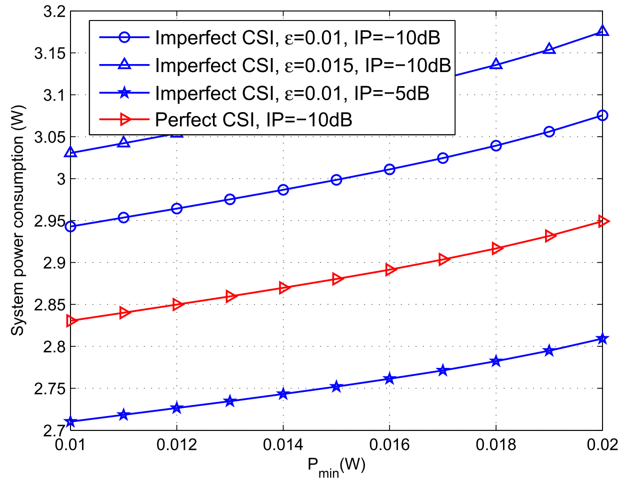

FIGURE 4. System power consumption (W) versus the decoder power consumption $P_{i,\min}$ (W).

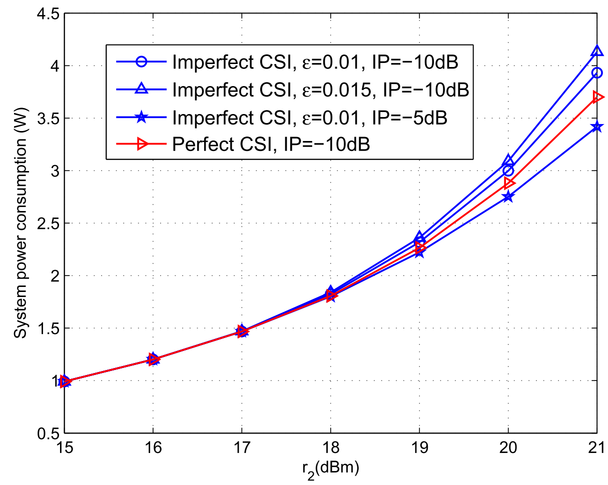

FIGURE 5. System power consumption (W) versus the target SINR at SU 2 (dB) with $P_{\min} = 0.015$ W.

In Fig. 3, we portray the total power consumption versus the energy conversion efficiency η of the linear energy harvester. Observe from Fig. 3 that conceiving the non-linear energy harvester achieve a lower power consumption than the linear model having η below 0.8. By contrast, the non-linear energy harvester results in a higher power consumption than the linear counterpart having η above 0.8.

B. EFFECT OF DIFFERENT SYSTEM PARAMETERS

In Fig. 4, we investigate the total power consumption versus the required decoding power consumption of SUs. Fig. 4 shows that the total power consumption of all the schemes increases monotonically with $P_{i,\min}$. This is because that a higher decoding power consumption requirement will promote the SBS to increase its transmission power for satisfy SUs' energy requirement. Furthermore, we can also observe that the robust scheme requires higher power consumption compared to the scheme with perfect CSI, especially in the scenario with larger channel estimation error ϵ. It reveals that the robust design generally consume more power to compensate the performance loss caused by the practical channel estimation errors.

In Fig. 5, we investigate the total power consumption against the minimum required SINR at SU 2. We observe from Fig. 5 that the total power consumption increases with the SINR threshold r_2 increases. This is due to the fact that a higher SINR requirement results in more power consumption. Besides, the system power consumption increases with the maximum tolerable IP of PU decreases. Intuitively, a larger tolerable IP implies a wider feasible domain of problem (12), which will inevitably result in the resource allocation strategy to achieve lower power consumption. In addition, the proposed robust scheme can achieve almost the same power consumption compared to the scheme with perfect CSI, when the minimum required SINR of SU 2 is low. It also unveils the effectiveness of the proposed robust scheme.

C. CONVERGENCE RATE OF ALGORITHM 1

Finally, we evaluate the convergence rate of the proposed Algorithm 1 in Fig. 6. We observe that Algorithm 1

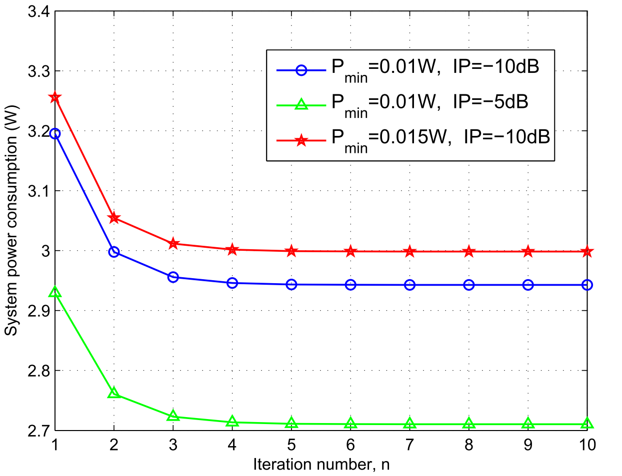

FIGURE 6. System power consumption (W) versus the iteration number *n*.

exhibits a fast convergence rate and converges typically within 5 iterations under different parameter settings. Therefore, Algorithm 1 is cost efficient in terms of computational complexity.

VII. CONCLUSION

In this paper, we investigate the minimization of the total power consumption of a underlay MISO-NOMA SWIPT system with joint transmit beamforming and the power splitting. In our model, the non-linear energy harvester and imperfect CSI are conceived. The SDR and SCA are adopted to develop a penalty function-based algorithm to obtain the optimal solution of the non-convex power consumption minimization problem. We further prove the convergence of the proposed algorithm. Finally, the performance of the proposed design is evaluated by simulation experiments. It can be observed that the non-linear energy harvester achieves a lower power consumption than the linear counterpart when η (energy conversion efficiency) is below 0.8. Moreover, the robust scheme with imperfect CSI consumes slightly high power, when compared with the corresponding strategy with perfect CSI.

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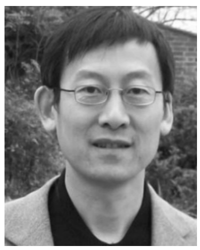

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