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Robust Secure Wireless Powered MISO Cognitive Mobile Edge Computing

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ABSTRACT Wireless power transfer (WPT) and cognitive radio (CR) are two promising techniques in designing mobile-edge computing (MEC) systems. In this paper, we study a robust secure wireless powered multiple-input single-output (MISO) cognitive MEC system, which integrates several techniques: physical-layer security, WPT, CR, underlay spectrum sharing and MEC. Three optimization problems are formulated to minimize the total transmission power (TTP) of the primary transmitter (PT) and the secondary base station (SBS) under perfect channel state information (CSI) model, bounded CSI error model and the probabilistic CSI error model, respectively. The formulated problems are nonconvex and hard to solve. Three two-phase iterative optimization algorithms combined with Lagrangian dual, semidefinite relaxation (SDR), S-Procedure and Bernstein-type inequalities are proposed to jointly optimize the beamforming vectors of the PT and the SBS, the central processing unit (CPU) frequency and the transmit power of the MD. Simulation results are provided to verify the effectiveness of the proposed algorithms.

INDEX TERMS Mobile edge computing, cognitive radio, underlay spectrum sharing, physical-layer security, wireless power transfer.

I. INTRODUCTION

In recent years, realizing the vision of smart city driven the explosive growth the mobile devices (MDs) and the new mobile applications. However, due to the finite computing and battery capacities, the MDs can not fully accomplish computation-intensive tasks, such as virtual reality (VR), augmented reality (AR) and face recognition. In light of this, the concept of mobile edge computing (MEC) has emerged. By utilizing telco, IT and cloud computing, the MEC can provide cloud-like computing capability to the MDs [1]. In MEC systems, the MDs can offload computation-intensive tasks to the proximate servers such as access points (APs) and base stations (BSs) for remote execution, which can save energy and enhance the computing capability of the MDs. Obviously, task offloading is the core of the MEC systems. Even though the offloading may decrease the energy consumption of the MDs, it still costs energy of the MDs for data transmission, especially under severe channel conditions. On the other hand, before task offloading, the MDs must have available spectrum. However, almost all the spectrum suitable for communication have been allocated. Hence, the finite battery capacity and limited spectrum resource are two challenges in designing MEC systems. These challenges can be alleviated by two technologies: 1) wireless power transfer (WPT) for powering the MDs through microwaves [2]–[7]; 2) cognitive radio (CR) for providing spectrum access opportunities for the MDs [8]–[14].

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A. RELATIVE WORK

WPT is a promising technology to provide sustainable energy supply to the MDs by transmitting energy-bearing radio-frequency (RF) signals to the MDs, which can be adopted during the MEC systems designing. In [3], an AP used WPT to charge two cooperative MDs. The two MDs cooperated with each other to overcome the doubly near-far effect. In [4], the weighted sum-rate of a multi-user wireless powered MEC

networks with binary computation offloading policy was maximized. In [5], a multiple-input single-output (MISO) MEC network was considered, the AP adopted WPT to charge the MDs. The energy consumption of the AP was minimized. An unmanned aerial vehicle (UAV) WPT-MEC system was studied in [6], the UAV acted as an AP and the computation rate of the MDs maximization problem was investigated.

It is reported that the number of the global MD devices in Internet of Things (IoT) will reach 212 billion by 2020 [15]. Allocating exclusive spectrum for such huge number of MDs is very difficult. CR is a dynamic spectrum sharing technology, which permits the unlicensed secondary users (SUs) to access the licensed primary users' (PUs') spectrum without causing severe interference to the PUs. Hence, CR can be adopted in MEC systems to provide available spectrum for the MDs for task offloading. A CR-MEC system was studied in [10], the interference power of the PU constraint was considered and the system utility was maximized. A three-layer architecture of the CR-MEC framework was proposed in [11], which adopted CR to find available spectrum for the MD.

Obviously, WPT, CR and MEC can be combined to construct a WPT-CR based MEC system, which can simultaneously alleviate the energy and the spectrum limitations of the MEC. A WPT-CR based MEC system was studied in [12], [13], [16]. In [13], the MD sensed the status of the primary transmitter (PT) and adjusted its parameters based on the sensing results to access the spectrum for WPT and task offloading. In [12], a cooperation mode was considered in WPT-CR based MEC system. The MD first harvested energy from the PT's transmission, then, it cooperatively relayed the PT's residual data in exchange for the spectrum access opportunity for WPT and task offloading. The WPT-CR based MEC framework in [12] was extended to a multi-antenna scenario in [16], in which the PT and the secondary base station (SBS) were equipped with multiple antennas. Moreover, the physical layer security of the PT's transmission was taken into consideration.

B. CONTRIBUTIONS

It is worth noting that a common assumption of above works is that the channel state information (CSI) can be perfectly obtained. However, in practical scenarios, the CSI is inevitably corrupted by estimation errors or quantization errors, which heavily deteriorate the performance of the algorithms under perfect CSI assumption [17]. Motivated by above-mentioned facts, in this paper, we consider a robust secure wireless powered MISO cognitive MEC system in perfect CSI and imperfect CSI scenarios, respectively. To the best of our knowledge, this is the first work to consider CSI uncertainties in CR based WPT-MEC systems. The main contributions of this paper are summarised as follows:

- We propose a robust secure wireless powered MISO cognitive MEC system, which consists of a multi-antenna PT, a multi-antenna SBS, a single-antenna primary receiver (PR) and a single-antenna MD. Different from [16], we consider underlay scheme, i.e., the SBS and the MD simultaneously transmit with the PT over the same spectrum. The transmission security and the interference temperature of the PT and PR, and the calculation deadline of the MD are considered.
- The total transmission power (TTP) of the PT and the SBS minimization problems are studied in perfect CSI and imperfect CSI scenarios, respectively. We consider three CSI models: perfect CSI model, bounded CSI error model (which represents the quantization error) [18] and probabilistic CSI error model (which models estimation error) [17], [18]. The beamforming vectors of the PT and the SBS, the CPU frequency and the transmit power of the MD are jointly optimized to minimize the TTP of the PT and the SBS. The formulated problems are nonconvex. Three two-phase iterative optimization algorithms based on Lagrange dual method, semidefinite relaxation (SDR), S-Procedure and Bernstein-type inequalities are proposed to solve these nonconvex problems.
- Simulation results are provided to verify the effectiveness of the proposed algorithms.

The rest of this paper is organized as follows. In Section II, we introduce the system model. Section III presents the TTP of the PT and the SBS minimization problems under perfect CSI and imperfect CSI cases, respectively. In Section IV, the formulated problems are solved through two-phase iterative optimization algorithms. Simulation results are provided in Section V. Finally, we conclude the paper in Section VI.

Notations: The scalars, vectors and matrices are denoted by lower case, boldface lower case and boldface upper case letters, respectively. For a square matrix $\mathbf{A}$, rank $(\mathbf{A})$, Tr $(\mathbf{A})$, $(\mathbf{A})^*$, $(\mathbf{A})^H$ denote its rank, trace, conjugate and conjugate transpose, respectively. $|\cdot|$ and $\|\cdot\|$ denote the complex scalar absolute value and vector Euclidean norm, respectively. $\mathbb{C}^{m\times n}$, $\mathcal{H}^n$ and $\mathcal{H}_+^n$ denote the space of $m \times n$ complex matrices, $n \times n$ complex Hermitian matrices, $n \times n$ complex Hermitian positive semidefinite matrices, respectively. $\phi(\mathbf{A})$ represents the maximum eigenvalue of matrix $\mathbf{A}$. $vec(\cdot)$ denotes the vectorization operator. $Re(\cdot)$ denotes the real part of its argument. Finally, $[x]^+ \triangleq \max(x, 0)$.

II. SYSTEM MODEL

We consider a robust secure wireless powered MISO cognitive MEC system with one PT, one PR, one SBS and one MD as shown in Fig. 1. We assume that the PT and SBS are equipped with $N_p \geq 2$ and $N_s \geq 2$ antennas and the PR and the MD has one single antenna, respectively. All nodes operate in a half-duplex mode. Let $\mathbf{H} \in \mathbb{C}^{N_s\times N_p}$ denote the PT to the SBS link, $\mathbf{h}_{pp} \in \mathbb{C}^{N_p\times 1}$ denote the PT to the PR link, $\mathbf{h}_{pm} \in \mathbb{C}^{N_s\times 1}$ denote the PT to MD link and h_{mp} denote the MD to the PR link, respectively. Let $\mathbf{h}_{sm} \in \mathbb{C}^{N_s\times 1}$ and $\mathbf{h}_{ms} \in \mathbb{C}^{N_s\times 1}$ denote the downlink and the uplink between the SBS and the MD, respectively. The system operates in a time-slotted manner with time slot length T. All channels

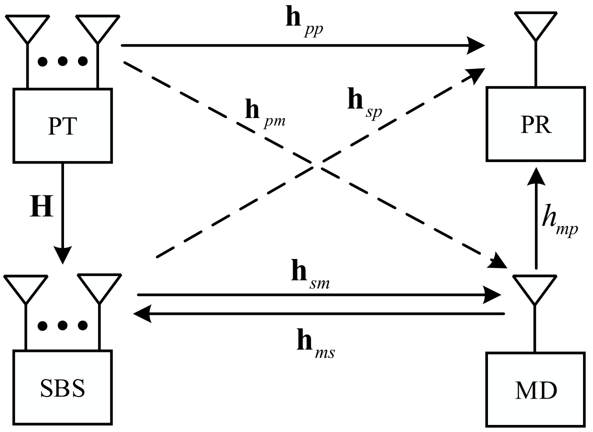

FIGURE 1. Robust secure wireless powered MISO cognitive MEC system.

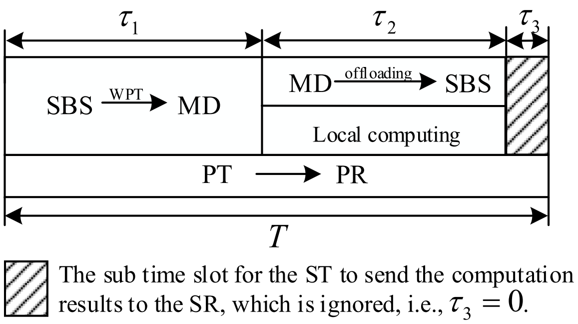

FIGURE 2. The underlay scheme for the secure MISO cognitive-based WPT-MEC system.

are modeled as independent and identically distributed (i.i.d.) block fading where the channel gains are fixed in each time slot and vary across different time slots.

A. UNDERLAY SCHEME

We adopt a underlay scheme as shown in Fig. 2. The SBS and the MD operate simultaneously with the PT over the same spectrum. The PT transmits information to the PR during the whole time slot $[0, T]$. The SBS charges the MD wirelessly by transmitting RF signal to the MD in $[0, \tau_1)$. The received signals at the PR and the MD are given as

$$y_p = \mathbf{h}_{pp}^H \mathbf{w}_1 s_1 + \mathbf{h}_{sp}^H \mathbf{w}_2 s_2 + n_p \tag{1}$$
$$y_m = \mathbf{h}_{sm}^H \mathbf{w}_2 s_2 + \mathbf{h}_{pm}^H \mathbf{w}_1 s_1 + n_m \tag{2}$$

where s_1 and s_2 are respectively the transmit signals of the PT and the SBS with $E\left[|s_i|^2\right] = 1, i = 1, 2$. $\mathbf{w}_1$ and $\mathbf{w}_2$ are the beamforming vectors of the PT and the SBS, respectively. $n_p \sim \mathcal{CN}\left(0, \sigma_p^2\right)$ and $n_m \sim \mathcal{CN}\left(0, \sigma_m^2\right)$ are the additive white Gaussian noises (AWGN) at the PR and the MD, respectively. The harvested energy of the MD is given as

$$e_h = \tau_1 \eta \left(\mathbf{w}_2^H \mathbf{h}_{sm} \mathbf{h}_{sm}^H \mathbf{w}_2 + \mathbf{w}_1^H \mathbf{h}_{pm} \mathbf{h}_{pm}^H \mathbf{w}_1 + \sigma_m^2\right) \tag{3}$$

where η is the energy harvesting efficiency.

B. COMPUTATION MODEL

After harvesting energy, the MD executes the task computation at $[\tau_1, \tau_1 + \tau_2)$. Suppose that the MD has a computation task with $\theta \geq 0$ bits, which is needed to be successfully calculated before the ending of a slot. We adopt partial offloading mode, namely, the task can be divided into two parts, one for local computing and another for offloading. Let f denote the CPU frequency of the MD, C denote the number of CPU cycles to calculate 1-bit of the task. Then, the local computing rate is $\frac{f}{C}$ bits/s. The offloading rate is given as

$$r_u = B \log_2 \left(1 + \frac{p_u \widetilde{h}_{ms}}{\|\mathbf{H}\mathbf{w}_1\|^2 + \sigma_s^2}\right) \tag{4}$$

where $\widetilde{h}_{ms} = \|\mathbf{h}_{ms}\|^2$, p_u is the transmit power of the MD, B is the channel bandwidth and σ_s^2 is the noise power at the SBS, respectively. In the end of a time slot, the MD downloads the computation result at the last time interval with length τ_3. Similar to [4], [5], we assume the computation result is small and the time interval of result downloading τ_3 can be ignored, i.e., $\tau_3 = 0$.

C. CHANNEL ERROR MODEL

As the PT and the MD, the SBS and the PR do not interact with each other frequently, hence, the CSI of $\mathbf{h}_{pm}$ and $\mathbf{h}_{sp}$ may not be perfect obtained. We consider two channel error models: bounded CSI error model and probabilistic CSI error model. The bounded CSI models for $\mathbf{h}_{pm}$ and $\mathbf{h}_{sp}$ are given as

$$\mathbf{h}_{pm} = \widehat{\mathbf{h}}_{pm} + \Delta\mathbf{h}_{pm} \tag{5a}$$
$$\Psi_{pm} \triangleq \left\{\Delta\mathbf{h}_{pm} \in C^{N_p \times 1} : \left\|\Delta\mathbf{h}_{pm}\right\|^2 \leq \xi_{pm}\right\} \tag{5b}$$
$$\mathbf{h}_{sp} = \widehat{\mathbf{h}}_{sp} + \Delta\mathbf{h}_{sp} \tag{6a}$$
$$\Psi_{sp} \triangleq \left\{\Delta\mathbf{h}_{sp} \in C^{N_s \times 1} : \left\|\Delta\mathbf{h}_{sp}\right\|^2 \leq \xi_{sp}\right\} \tag{6b}$$

where $\widehat{\mathbf{h}}_{pm}$ and $\widehat{\mathbf{h}}_{sp}$ are the estimates of $\mathbf{h}_{pm}$ and $\mathbf{h}_{sp}$. $\Delta\mathbf{h}_{pm}$ and $\Delta\mathbf{h}_{sp}$ represent the channel uncertainties of $\mathbf{h}_{pm}$ and $\mathbf{h}_{sp}$. Ψ_{pm} and Ψ_{sp} are uncertainty regions of $\mathbf{h}_{pm}$ and $\mathbf{h}_{sp}$. ξ_{pm} and ξ_{sp} are the radiuses of the uncertainty regions Ψ_{pm} and Ψ_{sp}.

The probabilistic CSI error models for $\mathbf{h}_{pm}$ and $\mathbf{h}_{sp}$ are given as

$$\mathbf{h}_{pm} = \widehat{\mathbf{h}}_{pm} + \Delta\mathbf{h}_{pm}, \Delta\mathbf{h}_{pm} \sim \mathcal{CN}\left(0, \mathbf{E}_{pm}\right) \tag{7a}$$
$$\mathbf{h}_{sp} = \widehat{\mathbf{h}}_{sp} + \Delta\mathbf{h}_{sp}, \Delta\mathbf{h}_{sp} \sim \mathcal{CN}\left(0, \mathbf{E}_{sp}\right) \tag{7b}$$

where $\mathbf{E}_{pm} \succ 0$ and $\mathbf{E}_{sp} \succ 0$ are the covariance matrices of the corresponding channel error vectors.

III. PROBLEM FORMULATION

In this section, we formulate the TTP of the SBS and the PT minimization problems in perfect CSI and imperfect CSI scenarios, respectively. The location and the identity of the SBS are always fixed and the SBS interacts with the PT frequently, hence, the SBS can be trusted. On the other hand, a SBS serves many different MDs, the locations and identities

of the MDs change frequently. Hence, the MD may not be friendly, i.e., it may be a potential eavesdropper to eavesdrop the PT's transmission. To avoid the PT's information leakage, we adopt physical layer security technique, which exploits the characteristics of wireless channels to guarantee the secure transmission of users [19]–[21]. The secrecy rate for the PT is given as

$$R_s = \left[B\log_2\left(1+\frac{\mathbf{w}_1^H\mathbf{h}_{pp}\mathbf{h}_{pp}^H\mathbf{w}_1}{\sigma_p^2+\mathbf{w}_2^H\mathbf{h}_{sp}\mathbf{h}_{sp}^H\mathbf{w}_2}\right) - B\log_2\left(1+\frac{\mathbf{w}_1^H\mathbf{h}_{pm}\mathbf{h}_{pm}^H\mathbf{w}_1}{\sigma_m^2+\mathbf{w}_2^H\mathbf{h}_{sm}\mathbf{h}_{sm}^H\mathbf{w}_2}\right)\right]^+ \tag{8}$$

For the convenience of analyzing, we consider the worst-case case similar to [22]: the MD may first decode its own information s_2 and eliminate $\mathbf{w}_2^H\mathbf{h}_{sm}\mathbf{h}_{sm}^H\mathbf{w}_2$ by using successive interference cancellation (SIC) technology. Hence, the secrecy rate is given as

$$R_s = \left[B\log_2\left(1+\frac{\mathbf{w}_1^H\mathbf{h}_{pp}\mathbf{h}_{pp}^H\mathbf{w}_1}{\sigma_p^2+\mathbf{w}_2^H\mathbf{h}_{sp}\mathbf{h}_{sp}^H\mathbf{w}_2}\right) - B\log_2\left(1+\frac{\mathbf{w}_1^H\mathbf{h}_{pm}\mathbf{h}_{pm}^H\mathbf{w}_1}{\sigma_m^2}\right)\right]^+. \tag{9}$$

A. OPTIMIZATION PROBLEM IN PERFECT CSI SCENARIO

We aim to minimize the TTP of the PT and the SBS while ensuring the performance requirements of the PUs, the SBS and the MD. Mathematically, the TTP of the PT and the SBS minimization problem under perfect CSI model is formulated as

$$\begin{aligned}
\mathbf{P}_1: \ & \min_{\mathbf{w}_1,\mathbf{w}_2,p_u,f} \mathbf{w}_1^H\mathbf{w}_1+\mathbf{w}_2^H\mathbf{w}_2 && (10a)\\
& \text{s.t. } \upsilon f^3\tau_2+p_u\tau_2 \le e_h, && (10b)\\
& R_s \ge r_s, && (10c)\\
& \tau_2 B\log_2\left(1+\frac{p_u\widetilde{h}_{ms}}{\|\mathbf{H}\mathbf{w}_1\|^2+\sigma_s^2}\right)+\tau_2\frac{f}{C} \ge \theta, && (10d)\\
& 0 \le f \le f_{\max}, && (10e)\\
& 0 \le p_u \le \min\left(p_{\max}^u, \frac{\Upsilon}{|h_{mp}|^2}\right) && (10f)
\end{aligned}$$

where r_s, Υ, $f_{\max}$ and $p_{\max}^u$ are the minimum secrecy rate of the PT and the maximum tolerable interference power of the PR, the maximum CPU frequency, the maximum transmit power of the MD, respectively. The objective function is to minimize the TTP of the PT and the SBS. (10b) is the energy causality of the MD. (10c) represents the secrecy rate constraint of the PT. (10d) denotes the task computation constraint. (10e) and (10f) are the CPU frequency and the transmit power constraints of the MD, respectively. (10f) guarantees the interference power at the PR can not exceed Υ. h_{mp} is always not perfect. To guarantee the interference power constraint of the PT, h_{mp} can be substituted by its worst estimate value.

Notice that, in the WPT phase, we don't consider the interference power constraint, which is included in the secrecy rate constraint. Due to the half-duplex operation mode assumption, in the MEC phase, we don't consider the secrecy rate constraint. It is worthing noting that $\tau_1+\tau_2 = T$. τ_1 and τ_2 can be optimized by one-dimension search. However, this will increase the complexity of our proposed algorithm. Hence, we fix τ_1 and τ_2 for simplicity.

B. OPTIMIZATION PROBLEMS IN IMPERFECT CSI SCENARIO

The TTP of the PT and the SBS minimization problem under bounded error model is formulated as

$$\begin{aligned}
\mathbf{P}_2: \ & \min_{\mathbf{w}_1,\mathbf{w}_2,p_u,f} \mathbf{w}_1^H\mathbf{w}_1+\mathbf{w}_2^H\mathbf{w}_2, && (11a)\\
& \text{s.t. } \upsilon f^3\tau_2+p_u\tau_2 \le e_h, \quad \forall\Delta\mathbf{h}_{pm}\in\Psi_{pm}, && (11b)\\
& R_s \ge r_s, \quad \forall\Delta\mathbf{h}_{pm}\in\Psi_{pm}, \forall\Delta\mathbf{h}_{sp}\in\Psi_{sp}, && (11c)\\
& (10d)-(10f) && (11d)
\end{aligned}$$

The TTP of the PT and the SBS minimization problem under probabilistic CSI error model is formulated as

$$\begin{aligned}
\mathbf{P}_3: \ & \min_{\mathbf{w}_1,\mathbf{w}_2,p_u,f} \mathbf{w}_1^H\mathbf{w}_1+\mathbf{w}_2^H\mathbf{w}_2,\\
& \text{s.t. } \Pr\left(\upsilon f^3\tau_2+p_u\tau_2 \le e_h\right) \ge p_e,\\
& \Delta\mathbf{h}_{pm} \sim \mathcal{CN}\left(0,\mathbf{E}_{pm}\right) && (12a)\\
& \Pr\left(R_s \le r_s\right) \le p_m,\\
& \Delta\mathbf{h}_{pm} \sim \mathcal{CN}\left(0,\mathbf{E}_{pm}\right), \Delta\mathbf{h}_{sp} \sim \mathcal{CN}\left(0,\mathbf{E}_{sp}\right) && (12b)\\
& (10d)-(10f) && (12c)
\end{aligned}$$

where $p_e \in (0, 1]$ and $1-p_m \in (0, 1]$ are the minimum probabilities that the energy causality of the MD and secrecy rate of the PT constraints should be satisfied.

IV. PROBLEM SOLVING VIA TWO-PHASE METHODS

In this section, the TTP of the PT and the SBS minimization problems $\mathbf{P}_1$, $\mathbf{P}_2$ and $\mathbf{P}_3$ are solved by two-phase iterative optimization algorithms.

A. PERFECT CSI CASE

Notice that, the problem $\mathbf{P}_1$ is nonconvex due to the coupled variables $\mathbf{w}_1$, $\mathbf{w}_2$, p_u and f in (10c)-(10d). The goal of $\mathbf{P}_1$ is to minimize the TTP of the PT and the SBS while ensuring the calculation of the task with θ bits. Obviously, the larger number of bits needed to be calculated the more energy the MD costs, which results in the increasing of the objective value of the problem $\mathbf{P}_1$. Motivated by this fact, we propose a two-phase iterative optimization algorithm. In the first phase, we **calculate the minimum amount of the energy that the MD needed to complete the calculation of the task**. Then, in the second phase, **the TTP of the PT and the SBS is minimized**.

1) THE OPTIMIZATION PROBLEM IN THE FIRST PHASE

In the first phase, we minimize the energy cost of the MD to calculate θ bits task with given $\mathbf{w}_1$ and $\mathbf{w}_2$. The optimization problem of this phase is given as

$$P_{1.1}: \min_{p_u, f} \upsilon f^3 + p_u \tag{13a}$$
$$\text{s.t. } (10d) - (10f). \tag{13b}$$

This problem is convex and can be solved by off-the-shelf convex optimization tools. To gain more engineering insights, we leverage the Lagrangian dual method to solve this problem [23]. The partial Lagrangian of the problem $\mathbf{P}_{1.1}$ is given as

$$\begin{aligned}\mathcal{L}(f, p_u, \lambda) &= \upsilon f^3 + p_u \\ &- \lambda\left(\tau_2 B\log_2\left(1+\frac{p_u \widetilde{h}_{ms}}{\|\mathbf{H}\mathbf{w}_1\|^2+\sigma_s^2}\right)+\frac{f}{C}\tau_2-\theta\right)\end{aligned} \tag{14}$$

where λ is the dual variable associated with constraint (10d). The corresponding dual function is given as

$$\Theta(\lambda) = \min_{f, p_u} \mathcal{L}(\lambda) \tag{15a}$$
$$\text{s.t. } (10e), (10f). \tag{15b}$$

Then, the dual problem is given as

$$\max_{\lambda} \{\Theta(\lambda) \,|\, \lambda \geq 0\} \tag{16}$$

According to the Karush-KuhnTucker (KKT) conditions [23], the optimal solutions f^* and p_u^* are obtained from the following lemma.

Lemma 1: For any given λ, the optimal solutions f^* and p_u^* are given as

$$f^* = \min\left(\sqrt{\frac{\lambda\tau_2}{3\upsilon C}}, f_{\max}\right) \tag{17}$$

$$p_u^* = \min\left(\left[B\frac{\lambda\tau_2}{\ln 2} - \frac{\|\mathbf{H}\mathbf{w}_1\|^2+\sigma_s^2}{\widetilde{h}_{ms}}\right]^+, p_{\max}\right) \tag{18}$$

Having obtained (f^*, p_u^*), we solve the dual problem (16) to calculate the minimum amount of the energy that the MD needed. We adopt subgradient based method is to obtain the optimal λ^{opt} for problem (16). One subgradient for problem (16) is given as

$$\Delta\lambda = -\left(\tau_2 B\log_2\left(1+\frac{p_u^* \widetilde{h}_{ms}}{\|\mathbf{H}\mathbf{w}_1\|^2+\sigma_s^2}\right)+\frac{f^*}{C}\tau_2-\theta\right) \tag{19}$$

Then, the dual variable λ is updated as

$$\lambda^{(n+1)} = \lambda^{(n)} + \alpha\Delta\lambda \tag{20}$$

where $\alpha > 0$ is the step size.

2) THE OPTIMIZATION PROBLEM OF THE SECOND PHASE

In the second phase, we optimize the variables $\mathbf{w}_1$ and $\mathbf{w}_2$ based on the solutions (f^*, p_u^*) obtained in the first phase. The optimization problem in this section is formulated as

$$\mathbf{P}_{1.2}: \min_{\mathbf{w}_1, \mathbf{w}_2} \mathbf{w}_1^H\mathbf{w}_1 + \mathbf{w}_2^H\mathbf{w}_2,$$
$$\text{s.t. } (10b) - (10d). \tag{21a}$$

The problem $\mathbf{P}_{1.2}$ is nonconvex due to the constraint (10c). In order to transform this noncovex problem into convex form, we introduce an auxiliary variable β and reformulate the problem $\mathbf{P}_{1.2}$ as

$$\mathbf{P}_{1.2.1}: \min_{\mathbf{w}_1, \mathbf{w}_2, \beta} \mathbf{w}_1^H\mathbf{w}_1 + \mathbf{w}_2^H\mathbf{w}_2, \tag{22a}$$
$$\text{s.t. } (10b), (10d) \tag{22b}$$
$$\begin{aligned}&B\log_2(1+\beta) \\ &- B\log_2\left(1+\frac{\mathbf{w}_1^H\mathbf{h}_{pm}\mathbf{h}_{pm}^H\mathbf{w}_1}{\sigma_p^2}\right) \geq r_s,\end{aligned} \tag{22c}$$
$$\frac{\mathbf{w}_1^H\mathbf{h}_{pp}\mathbf{h}_{pp}^H\mathbf{w}_1}{\sigma_p^2+\mathbf{w}_2^H\mathbf{h}_{sp}\mathbf{h}_{sp}^H\mathbf{w}_2} \geq \beta. \tag{22d}$$

The problem $\mathbf{P}_{1.2.1}$ is equivalent to the problem $\mathbf{P}_{1.2}$ [22]. The variable β can be optimized by one-dimension search. For any given β, after some mathematical manipulations, the problem $\mathbf{P}_{1.2.1}$ can be transformed as

$$\mathbf{P}_{1.2.2}: \min_{\mathbf{w}} \mathbf{w}^H\mathbf{w}, \tag{23a}$$
$$\text{s.t. } \mathbf{w}^H\mathbf{G}_1\mathbf{w} \geq \frac{\upsilon f^3\tau_2 + p_u\tau_2}{(T-\tau_2)\eta} - \sigma_m^2 \tag{23b}$$
$$\mathbf{w}^H\mathbf{G}_2\mathbf{w} \leq \frac{(1+\beta)\sigma_p^2}{2^{\frac{r_s}{B}}} - \sigma_p^2, \tag{23c}$$
$$\mathbf{w}^H\mathbf{G}_3\mathbf{w} \geq \beta\sigma_p^2, \tag{23d}$$
$$\mathbf{w}^H\mathbf{G}_4\mathbf{w} \leq \frac{p_u\widetilde{h}_{ms}}{2^{\frac{1}{\tau_2 B}\left(\theta-\frac{f}{C}\tau_2\right)}-1} - \sigma_s^2 \tag{23e}$$

where

$$\mathbf{w} = \begin{bmatrix}\mathbf{w}_1^H & \mathbf{w}_2^H\end{bmatrix}^H \tag{24}$$
$$\mathbf{G}_1 = \begin{bmatrix}\mathbf{h}_{pm}\mathbf{h}_{pm}^H & \mathbf{0} \\ \mathbf{0} & \mathbf{h}_{sm}\mathbf{h}_{sm}^H\end{bmatrix} \tag{25}$$
$$\mathbf{G}_2 = \begin{bmatrix}\mathbf{h}_{pm}\mathbf{h}_{pm}^H & \mathbf{0} \\ \mathbf{0} & \mathbf{0}\end{bmatrix} \tag{26}$$
$$\mathbf{G}_3 = \begin{bmatrix}\mathbf{h}_{pp}\mathbf{h}_{pp}^H & \mathbf{0} \\ \mathbf{0} & -\beta\mathbf{h}_{sp}\mathbf{h}_{sp}^H\end{bmatrix} \tag{27}$$
$$\mathbf{G}_4 = \begin{bmatrix}\mathbf{H}^H\mathbf{H} & \mathbf{0} \\ \mathbf{0} & \mathbf{0}\end{bmatrix} \tag{28}$$

By introducing $\mathbf{W} \triangleq \mathbf{w}\mathbf{w}^H$, problem $\mathbf{P}_{1.2.2}$ can be equivalently rewritten as

$$\mathbf{P}_{1.2.3}: \min_{\mathbf{W}} \mathrm{Tr}(\mathbf{W}), \tag{29a}$$
$$\text{s.t. } \mathrm{Tr}(\mathbf{G}_1\mathbf{W}) \geq \frac{\upsilon f^3\tau_2 + p_u\tau_2}{(T-\tau_2)\eta} - \sigma_m^2, \tag{29b}$$
$$\mathrm{Tr}(\mathbf{G}_2\mathbf{W}) \leq \frac{(1+\beta)\sigma_p^2}{2^{\frac{r_s}{B}}} - \sigma_p^2, \tag{29c}$$

$$\mathrm{Tr}\left(\mathbf{G}_3\mathbf{W}\right) \geq \beta\sigma_p^2, \tag{29d}$$

$$\mathrm{Tr}\left(\mathbf{G}_4\mathbf{W}\right) \leq \frac{p_u\widetilde{h}_{ms}}{2^{\frac{1}{\tau_2 B}\left(\theta-\frac{f}{C}\tau_2\right)}-1}-\sigma_s^2, \tag{29e}$$

$$\mathbf{W} \succeq 0, \tag{29f}$$

$$\mathrm{rank}\left(\mathbf{W}\right) = 1. \tag{29g}$$

Notice that, the problem is nonconvex due to the rank-one constraint (29g), which can be relaxed by semidefinite relaxation (SDR) technique [24]. Then, the problem $\mathbf{P}_{1.2.3}$ can be relaxed as

$$\mathbf{P}_{1.2.4}: \ \min_{\mathbf{W}} \mathrm{Tr}\left(\mathbf{W}\right), \tag{30a}$$

$$\text{s.t. } (29b) - (29f). \tag{30b}$$

This relaxed problem is convex and can be efficiently solved by using some off-the-shelf convex optimization tools. The optimal solution $\mathbf{W}^*$ may not be rank-one and can be approximated by principal component approximation or Gaussian randomization procedure [24].

It is worth noting that, if the secrecy rate of the PT constraint is not considered, the number of the constraints of the will be less than 4, then, the following rank-one decomposition theorem can be used, which has low complexity.

Lemma 2 ([25] Theorem 2.3): Let $\mathbf{A}_i \in \mathcal{H}^n, i = 1, 2, \ldots, 4$ and $\mathbf{X} \in \mathcal{H}_+^n$, if $n \geq 3$ and $\mathrm{rank}\left(\mathbf{X}\right) \geq 2$, then one can find a nonzero vector $\mathbf{y}$ such that $Re\left\{\mathrm{Tr}\left(\mathbf{A}_i\mathbf{y}\mathbf{y}^H\right)\right\} = Re\left\{\mathrm{Tr}\left(\mathbf{A}_i\mathbf{X}\right)\right\}, i = 1, 2, \ldots, 4.$

The algorithm can be implemented from the constructive proof of Theorem 2.3 [25].

The proposed two-phase iterative optimization algorithm to solve the problem $\mathbf{P}_1$ is summarized in Table 1.

TABLE 1. Proposed method to solve $\mathbf{P}_1$.

Initialization:
Set $\lambda = \lambda_{int}, \mathbf{w}_1^{(0)}, \mathbf{w}_2^{(0)}, n = 0$;
repeat:
  repeat:
    Obtain $\left(f^{(n)*}, p_u^{(n)*}\right)$ by Lemma1 with given $\mathbf{w}_1^{(n)}, \mathbf{w}_2^{(n)}$ and λ;
    Update λ by (20);
  until: λ converges within a prescribed accuracy or the maximum number of iterations achieved.
  Set $\beta^{(i)} = \frac{i\beta_{\max}}{M}, i = 1, 2, \ldots, M$;
  for Each $\beta^{(i)}$ **do**
    Obtain $\mathbf{W}^*$ by solving $\mathbf{P}_{1.2.4}$;
    if $\mathrm{rank}\left(\mathbf{W}^*\right) = 1$ **then**
      Use its principal eigenvector as $\mathbf{w}^*$ and obtain $\mathbf{w}_1^*$ and $\mathbf{w}_2^*$ by (24);
    else
      Obtain a rank-one solution $\mathbf{W}^*$ using principal component approximation or Gaussian randomization procedure;
      Use its principal eigenvector as $\mathbf{w}^*$ and obtain $\mathbf{w}_1^*$ and $\mathbf{w}_2^*$ by (24);
    end if
  end for
  Select the $\beta^{(i)}$ that has minimal $\mathrm{Tr}\left(\mathbf{W}^*\right)$ and its corresponding $\mathbf{w}_1^*$ and $\mathbf{w}_2^*$.
  Set $n = n + 1$;
until: The objective function of problem $\mathbf{P}_1$ converges.

B. BOUNDED CSI ERROR CASE

In this subsection, we solve the TTP of the PT and the SBS minimization problem with bounded CSI error model. Obviously, the problem $\mathbf{P}_2$ is nonconvex and includes infinite number of constraints. We still use the two-phase iterative optimization algorithm to solve this problem. The first phase is same with that in perfect CSI case, hence, we mainly focus on the second phase.

In the second phase, we also introduce the auxiliary variable β and the optimization problem is formulated as

$$\mathbf{P}_{2.1}: \ \min_{\mathbf{w}_1,\mathbf{w}_2,\beta} \ \mathbf{w}_1^H\mathbf{w}_1 + \mathbf{w}_2^H\mathbf{w}_2 \tag{31a}$$

$$\text{s.t. } \mathbf{w}_1^H\mathbf{h}_{pm}\mathbf{h}_{pm}^H\mathbf{w}_1 + \mathbf{w}_2^H\mathbf{h}_{sm}\mathbf{h}_{sm}^H\mathbf{w}_2 \geq \frac{\upsilon f^3\tau_2 + p_u\tau_2}{\left(T-\tau_2\right)\eta} - \sigma_m^2, \forall\Delta\mathbf{h}_{pm} \in \Psi_{pm}, \tag{31b}$$

$$\mathbf{w}_1^H\mathbf{h}_{pm}\mathbf{h}_{pm}^H\mathbf{w}_1 \leq \frac{\left(1+\beta\right)\sigma_p^2}{2^{\frac{r_s}{B}}} - \sigma_p^2, \forall \Delta\mathbf{h}_{pm} \in \Psi_{pm}. \tag{31c}$$

$$(22d), \Delta\mathbf{h}_{sp} \in \Psi_{sp}, \tag{31d}$$

$$\mathbf{w}_1^H\mathbf{H}^H\mathbf{H}\mathbf{w}_1 \leq \frac{p_u\widetilde{h}_{ms}}{2^{\frac{1}{\tau_2 B}\left(\theta-\frac{f}{C}\tau_2\right)}-1} - \sigma_s^2. \tag{31e}$$

To obtain the solution of the problem $\mathbf{P}_{2.1}$, we need to transform the infinite inequality constraints (31b)-(31d) into linear matrix inequalities (LMIs) using the following lemma.

Lemma 3 (S-Procedure [23]): Define $f_m\left(\mathbf{x}\right) = \mathbf{x}^H\mathbf{X}_m\mathbf{x} + 2Re\left\{\mathbf{y}_m^H\mathbf{x}\right\} + z_m, m \in \{1, 2\}$, where $\mathbf{x} \in \mathbb{C}^{N\times 1}$, $\mathbf{y}_m \in \mathbb{C}^{N\times 1}$, $\mathbf{X} \in \mathbb{H}^N$ and z_m is a real constant. Then, the expression $f_1\left(\mathbf{x}\right) \leq 0 \Rightarrow f_2\left(\mathbf{x}\right) \leq 0$ holds if and only if there exists $\delta \geq 0$ such that

$$\delta\begin{bmatrix}\mathbf{X}_1 & \mathbf{y}_1 \\ \mathbf{y}_1^H & z_1\end{bmatrix} - \begin{bmatrix}\mathbf{X}_2 & \mathbf{y}_2 \\ \mathbf{y}_2^H & z_2\end{bmatrix} \succeq \mathbf{0}, \tag{32}$$

provided that there exists a point $\widehat{\mathbf{x}}$ such that $f_1\left(\widehat{\mathbf{x}}\right) < 0$.

According to (5a) and introducing $\mathbf{W}_1 \triangleq \mathbf{w}_1\mathbf{w}_1^H$, and $\mathbf{W}_2 \triangleq \mathbf{w}_2\mathbf{w}_2^H$, (31b) can rewritten as

$$-\Delta\mathbf{h}_{pm}^H\mathbf{W}_1\Delta\mathbf{h}_{pm} - 2Re\left(\widehat{\mathbf{h}}_{pm}^H\mathbf{W}_1\Delta\mathbf{h}_{pm}\right) + \left(\frac{\upsilon f^3\tau_2 + p_u\tau_2}{\left(T-\tau_2\right)\eta} - \sigma_m^2 - \mathbf{h}_{sm}^H\mathbf{W}_2\mathbf{h}_{sm}\right) - \widehat{\mathbf{h}}_{pm}^H\mathbf{W}_1\widehat{\mathbf{h}}_{pm} \leq 0 \tag{33}$$

$\left\|\Delta\mathbf{h}_{pm}\right\|^2 \leq \xi_{pm}$ can be equivalently written as

$$\Delta\mathbf{h}_{pm}^H\Delta\mathbf{h}_{pm} - \xi_{pm} \leq 0. \tag{34}$$

Employing Lemma 3, the constraints (31b) can be converted to the following LMI constraint

$$\begin{bmatrix}\delta_1\mathbf{I}_{N_p} & \mathbf{0} \\ \mathbf{0} & -\delta_1\xi_{pm} - \frac{\upsilon f^3\tau_2 + p_u\tau_2}{\left(T-\tau_2\right)\eta} + \sigma_m^2\end{bmatrix} + \mathbf{U}_{\widehat{\mathbf{h}}_{pm}}^H\mathbf{W}_1\mathbf{U}_{\widehat{\mathbf{h}}_{pm}} + \mathbf{U}_{\mathbf{h}_{sm}}^H\mathbf{W}_2\mathbf{U}_{\mathbf{h}_{sm}} \succeq 0 \tag{35}$$

where $\delta_1 \geq 0$ and

$$\mathbf{U}_{\widehat{\mathbf{h}}_{pm}} = \left[\, \mathbf{I}_{N_p} \quad \widehat{\mathbf{h}}_{pm} \,\right] \tag{36}$$

$$\mathbf{U}_{\mathbf{h}_{sm}} = \left[\, \mathbf{0}_{N_s} \quad \mathbf{h}_{sm} \,\right] \mathbf{T}_1 \tag{37}$$

where $\mathbf{T}_1$ is $(N_s+1) \times \left(N_p+1\right)$ real matrices, which is defined as

$$\mathbf{T}_1(i,j) = \begin{cases} 0, & (i,j) \neq \left(N_s+1, N_p+1\right), \\ 1, & (i,j) = \left(N_s+1, N_p+1\right). \end{cases} \tag{38}$$

Following similar procedure, (31c) and (31d) can be converted as

$$\begin{bmatrix} \delta_2 \mathbf{I}_{N_p} & \mathbf{0} \\ \mathbf{0} & \left(\frac{(1+\beta)\sigma_p^2}{2^{\frac{r_s}{B}}} - \sigma_p^2\right) - \delta_2 \xi_{pm} \end{bmatrix} - \mathbf{U}_{\widehat{\mathbf{h}}_{pm}}^H \mathbf{W}_1 \mathbf{U}_{\widehat{\mathbf{h}}_{pm}} \succeq 0 \tag{39}$$

$$\begin{bmatrix} \delta_3 \mathbf{I}_{N_s} & \mathbf{0} \\ \mathbf{0} & -\delta_3 \xi_{sp} - \beta\sigma_p^2 \end{bmatrix} + \mathbf{U}_{\mathbf{h}_{pp}}^H \mathbf{W}_1 \mathbf{U}_{\mathbf{h}_{pp}} - \mathbf{U}_{\widehat{\mathbf{h}}_{sp}}^H \mathbf{W}_2 \mathbf{U}_{\widehat{\mathbf{h}}_{sp}} \succeq 0 \tag{40}$$

where $\delta_2 \geq 0$, $\delta_3 \geq 0$ and

$$\mathbf{U}_{\mathbf{h}_{pp}} = \left[\, \mathbf{0}_{N_p} \quad \mathbf{h}_{pp} \,\right] \mathbf{T}_2 \tag{41}$$

$$\mathbf{U}_{\widehat{\mathbf{h}}_{sp}} = \beta^{1/2} \left[\, \mathbf{I}_{N_s} \quad \widehat{\mathbf{h}}_{sp} \,\right] \tag{42}$$

where $\mathbf{T}_2$ is $\left(N_p+1\right) \times (N_s+1)$ real matrices, which is given as

$$\mathbf{T}_2(i,j) = \begin{cases} 0, & (i,j) \neq \left(N_p+1, N_s+1\right), \\ 1, & (i,j) = \left(N_p+1, N_s+1\right). \end{cases} \tag{43}$$

Then, with given β, the optimization problem $\mathbf{P}_{2.1}$ can be equivalently written as

$$\mathbf{P}_{2.1.2}: \min_{\mathbf{W}_1, \mathbf{W}_2, \delta_1, \delta_2, \delta_3} \operatorname{Tr}(\mathbf{W}_1) + \operatorname{Tr}(\mathbf{W}_2) \tag{44a}$$

$$\text{s.t. } (35), (39)-(40), \tag{44b}$$

$$\operatorname{Tr}\left(\mathbf{H}^H \mathbf{H} \mathbf{W}_1\right) \leq \frac{p_u \widetilde{h}_{ms}}{2^{\frac{1}{\tau_2 B}\left(\theta - \frac{f}{C}\tau_2\right)} - 1} - \sigma_s^2, \tag{44c}$$

$$\delta_1 \geq 0, \delta_2 \geq 0, \quad \delta_3 \geq 0, \tag{44d}$$

$$\mathbf{W}_1 \succeq 0, \mathbf{W}_2 \succeq 0, \tag{44e}$$

$$\operatorname{rank}(\mathbf{W}_1) = 1, \operatorname{rank}(\mathbf{W}_2) = 1 \tag{44f}$$

The problem $\mathbf{P}_{2.1.2}$ is nonconvex due to (44f), which can be relaxed by using SDR. Then, the problem can be relaxed as

$$\mathbf{P}_{2.1.3}: \min_{\mathbf{W}_1, \mathbf{W}_2, \delta_1, \delta_2, \delta_3} \operatorname{Tr}(\mathbf{W}_1) + \operatorname{Tr}(\mathbf{W}_2) \tag{45a}$$

$$\text{s.t. } (35), (39)-(40), (44c)-(44e). \tag{45b}$$

which is convex and can be solved using off-the-shelf convex optimization tools. If the solutions are not rank-one, principal component approximation or Gaussian randomization procedure can be adopted to give a suboptimal rank-one approximation. The problem $\mathbf{P}_2$ can be solved by the algorithm in Table 1 with slightly modification.

C. PROBABILISTIC CSI ERROR CASE

In this subsection, we deal with the TTP of the PT and the SBS minimization problem with probabilistic CSI error model. Notice that, the problem $\mathbf{P}_3$ is chance constrained, which is nonconvex. The two-phase iterative optimization algorithm still works on solving this problem. The first phase is same with the above two problems $\mathbf{P}_1$ and $\mathbf{P}_2$. In the second phase, we still introduce the auxiliary variable β and constraint (22d). Let $\mathbf{W}_1 \triangleq \mathbf{w}_1\mathbf{w}_1^H$, and $\mathbf{W}_2 \triangleq \mathbf{w}_2\mathbf{w}_2^H$. Then, we formulate the optimization problem with given β in the second phase as

$$\mathbf{P}_{3.1}: \min_{\mathbf{W}_1, \mathbf{W}_2} \operatorname{Tr}(\mathbf{W}_1) + \operatorname{Tr}(\mathbf{W}_2) \tag{46a}$$

$$\text{s.t. } \Pr\left\{\mathbf{h}_{pm}^H \mathbf{W}_1 \mathbf{h}_{pm} + \mathbf{h}_{sm}^H \mathbf{W}_2 \mathbf{h}_{sm} \geq \frac{\upsilon f^3 \tau_2 + p_u \tau_2}{(T-\tau_2)\eta} - \sigma_m^2\right\} \geq p_e, \tag{46b}$$

$$\Pr\left\{\mathbf{h}_{pm}^H \mathbf{W}_1 \mathbf{h}_{pm} \geq \frac{(1+\beta)\sigma_p^2}{2^{\frac{r_s}{B}}} - \sigma_p^2\right\} \leq p_m, \tag{46c}$$

$$\Pr\left\{\mathbf{h}_{pp}^H \mathbf{W}_1 \mathbf{h}_{pp} - \beta \mathbf{h}_{sp}^H \mathbf{W}_2 \mathbf{h}_{sp} \geq \beta\sigma_p^2\right\} \geq p_p, \tag{46d}$$

$$(44c), (44e), (44f). \tag{46e}$$

where p_p is the minimum probability of the constraint (22d) being satisfied. To solve the problem $\mathbf{P}_{3.1}$, we need to transform the chance constraints (46b)-(46d) into deterministic forms, which can be realized by Bernstein-type inequalities given as follows.

Lemma 4 (The Bernstein-Type Inequality I [17], [26]): Let $f(\mathbf{x}) = \mathbf{x}^H \mathbf{X} \mathbf{x} + 2Re\left\{\mathbf{x}^H \mathbf{y}\right\} + n$, where $\mathbf{X} \in \mathbb{H}^N$, $\mathbf{y} \in \mathbb{C}^{N \times 1}$, $\mathbf{x} \sim \mathcal{CN}(0, \mathbf{I})$. Then for any $\sigma \geq 0$, we have

$$\Pr\left\{f(\mathbf{x}) \geq \operatorname{Tr}(\mathbf{X}) + \sqrt{2\sigma}\sqrt{\|vec(\mathbf{X})\|^2 + 2\|\mathbf{y}\|^2} + \sigma s^+(\mathbf{X})\right\} \leq \exp(-\sigma) \tag{47}$$

where $s^+(\mathbf{X}) = [\phi(\mathbf{X})]^+$.

Lemma 5 (The Bernstein-type Inequality II [17], [27]): Let $f(\mathbf{x}) = \mathbf{x}^H \mathbf{X} \mathbf{x} + 2Re\left\{\mathbf{x}^H \mathbf{y}\right\} + n$, where $\mathbf{X} \in \mathbb{H}^N$, $\mathbf{y} \in \mathbb{C}^{N \times 1}$, $\mathbf{x} \sim \mathcal{CN}(0, \mathbf{I})$. Then for any $\sigma \geq 0$, we have

$$\Pr\left\{f(\mathbf{x}) \leq \operatorname{Tr}(\mathbf{X}) - \sqrt{2\sigma}\sqrt{\|vec(\mathbf{X})\|^2 + 2\|\mathbf{y}\|^2} - \sigma s^-(\mathbf{X})\right\} \leq \exp(-\sigma) \tag{48}$$

where $s^-(\mathbf{X}) = [\phi(-\mathbf{X})]^+$.

According to the two Bernstein-type inequalities, the chance constraints (46b)-(46d) can be converted to deterministic constraints. We take the constraint (46b) as an example. Substituting (7a) into (46b), after some mathematical manipulations, the constraint (46b) can be represented as

$$\Pr\left\{\mathbf{x}_{pm,0}^H \mathbf{A}_{pm,0} \mathbf{x}_{pm,0} + 2Re\left(\mathbf{x}_{pm,0}^H \mathbf{a}_{pm,0}\right) \leq c_{pm,0}\right\} \leq 1 - p_e \tag{49}$$

where $\mathbf{x}_{pm} \sim \mathcal{CN}(0, \mathbf{I})$ and

$$\mathbf{A}_{pm,0} = \mathbf{E}_{pm}^{1/2}\mathbf{W}_1\mathbf{E}_{pm}^{1/2} \tag{50}$$

$$\mathbf{a}_{pm,0} = \mathbf{E}_{pm}^{1/2}\mathbf{W}_1\widehat{\mathbf{h}}_{pm} \tag{51}$$

$$\begin{aligned} c_{pm,0} = & \frac{\upsilon f^3\tau_2 + p_u\tau_2}{(T-\tau_2)\eta} - \sigma_m^2 \\ & - \widehat{\mathbf{h}}_{pm}^H\mathbf{W}_1\widehat{\mathbf{h}}_{pm} - \mathbf{h}_{sm}^H\mathbf{W}_2\mathbf{h}_{sm} \end{aligned} \tag{52}$$

Applying Bernstein-type Inequality II, (49) can be converted to the following constraint

$$\begin{aligned} \mathrm{Tr}\left(\mathbf{A}_{pm,0}\right) - \sqrt{2\sigma_{pm,0}}\sqrt{\left\|vec\left(\mathbf{A}_{pm,0}\right)\right\|^2 + 2\left\|\mathbf{a}_{pm,0}\right\|^2} \\ - \sigma_{pm,0}s^-\left(\mathbf{A}_{pm,0}\right) - c_{pm,0} \geq 0 \end{aligned} \tag{53}$$

where $\sigma_{pm,0} = -\ln(1-p_e)$. (53) can be further transformed to three convex constraints, which are given as

$$\mathrm{Tr}\left(\mathbf{A}_{pm,0}\right) - \sqrt{2\sigma_{pm,0}}\rho_{pm,0} - \sigma_{pm,0}\upsilon_{pm,0} - c_{pm,0} \geq 0 \tag{54}$$

$$\left\|\begin{matrix} vec\left(\mathbf{A}_{pm,0}\right) \\ \sqrt{2}\mathbf{a}_{pm,0}\end{matrix}\right\| \leq \rho_{pm,0} \tag{55}$$

$$\upsilon_{pm,0}\mathbf{I} + \mathbf{A}_{pm,0} \succeq \mathbf{0},\ \upsilon_{pm,0} \geq 0 \tag{56}$$

Following similar procedure above, the problem $\mathbf{P}_{3.1}$ can be reformulated as

$$\begin{aligned} \mathbf{P}_{3.1.1}: \min_{\substack{\mathbf{W}_1,\mathbf{W}_2,\rho_{pm,0},\\ \rho_{pm,1},\rho_{sp},\upsilon_{pm,0},\\ \upsilon_{pm,1},\upsilon_{sp}}} \quad & \mathrm{Tr}(\mathbf{W}_1) + \mathrm{Tr}(\mathbf{W}_2) && (57a) \\ \text{s.t. } & \mathrm{Tr}\left(\mathbf{A}_{pm,1}\right) + \sqrt{2\sigma_{pm,1}}\rho_{pm,1} + \sigma_{pm,1}\upsilon_{pm,1} \\ & - c_{pm,1} \leq 0, && (57b) \\ & \left\|\begin{matrix} vec\left(\mathbf{A}_{pm,1}\right) \\ \sqrt{2}\mathbf{a}_{pm,1}\end{matrix}\right\| \leq \rho_{pm,1}, && (57c) \\ & \upsilon_{pm,1}\mathbf{I} - \mathbf{A}_{pm,1} \succeq \mathbf{0},\ \upsilon_{pm,1} \geq 0, && (57d) \\ & \mathrm{Tr}\left(\mathbf{A}_{sp}\right) + \sqrt{2\sigma_{sp}}\rho_{sp} + \sigma_{sp}\upsilon_{sp} - c_{sp} \leq 0, && (57e) \\ & \left\|\begin{matrix} vec\left(\mathbf{A}_{sp}\right) \\ \sqrt{2}\mathbf{a}_{sp}\end{matrix}\right\| \leq \rho_{sp}, && (57f) \\ & \upsilon_{sp}I - \mathbf{A}_{sp} \succeq \mathbf{0},\ \upsilon_{sp} \geq 0, && (57g) \\ & (44c), (44e), (44f), (54)-(56) && (57h) \end{aligned}$$

where

$$\mathbf{A}_{pm,1} = \mathbf{E}_{pm}^{1/2}\mathbf{W}_1\mathbf{E}_{pm}^{1/2} \tag{58}$$

$$\mathbf{a}_{pm,1} = \mathbf{E}_{pm}^{1/2}\mathbf{W}_1\widehat{\mathbf{h}}_{pm} \tag{59}$$

$$c_{pm,1} = \frac{(1+\beta)\sigma_p^2}{2^{\frac{r_s}{B}}} - \sigma_p^2 - \widehat{\mathbf{h}}_{pm}^H\mathbf{W}_1\widehat{\mathbf{h}}_{pm} \tag{60}$$

$$\sigma_{pm,1} = -\ln(p_m) \tag{61}$$

$$\mathbf{A}_{sp} = \beta^{1/2}\mathbf{E}_{sp}^{1/2}\mathbf{W}_2\beta^{1/2}\mathbf{E}_{sp}^{1/2} \tag{62}$$

$$\mathbf{a}_{sp} = \beta\mathbf{E}_{sp}^{1/2}\mathbf{W}_2\widehat{\mathbf{h}}_{sp} \tag{63}$$

$$c_{sp} = \mathbf{h}_{pp}^H\mathbf{W}_1\mathbf{h}_{pp} - \beta\sigma_p^2 - \widehat{\mathbf{h}}_{sp}^H\beta^{1/2}\mathbf{W}_2\beta^{1/2}\widehat{\mathbf{h}}_{sp} \tag{64}$$

$$\sigma_{sp} = -\ln\left(1-p_p\right). \tag{65}$$

The problem $\mathbf{P}_{3.1.1}$ is convex and can be solved using off-the-shelf convex optimization tools. If the solutions are not rank-one, principal component approximation or Gaussian randomization procedure can be adopted to give a sub-optimal rank-one approximation. The problem $\mathbf{P}_3$ can be solved by the algorithm summarized in Table 1 with slightly modification.

D. COMPLEXITY ANALYSIS

In this subsection, we analyze the complexities of our proposed algorithms. The complexity of solving the optimization problem in the first phase mainly concentrates on the subgradient method. Suppose the subgradient method needs Ω iterations to converge. Similar to [28], we use the computational complexity of the interior-point method to measure the complexity of the second phase. The computational complexity of interior point method is related to the number of LMIs and second order cone constraints. The complexities of our proposed algorithm are given in Table 2, where $n_1 = N_p + N_s$, $n_2 = n_3 = N_p^2 + N_s^2$, N, M and Λ are the number of iterations of the two-phase iterative optimization algorithms, the times for one-dimension search of β and the complexity order of the principal component approximation or Gaussian randomization procedure.

V. SIMULATION RESULTS

In this section, simulation results are provided to illustrate the performance of the two-phase iterative optimization algorithms. Similar to [17], [18], [26], $\mathbf{H}$, $\mathbf{h}_{pp}$, $\mathbf{h}_{sm}$, $\mathbf{h}_{pm}$, $\mathbf{h}_{sp}$ h_{mp} are modeled as Rayleigh distribution with each element being a complex Gaussian random variable with zero mean and variance $\Omega_{\mathbf{H}}$, Ω_{pp}, Ω_{sm}, Ω_{pm}, Ω_{sp}, Ω_{mp}, respectively. Without loss of generality, we consider $\mathbf{h}_{sm} = \mathbf{h}_{ms}^*$ [29]. Other simulation parameters are summarized in Table 3. Notice that, the influences of the path loss of all links are included in the noise power.

Fig. 3 shows the TTP of the PT and the SBS versus the number of the calculation bits of the MD θ. As shown

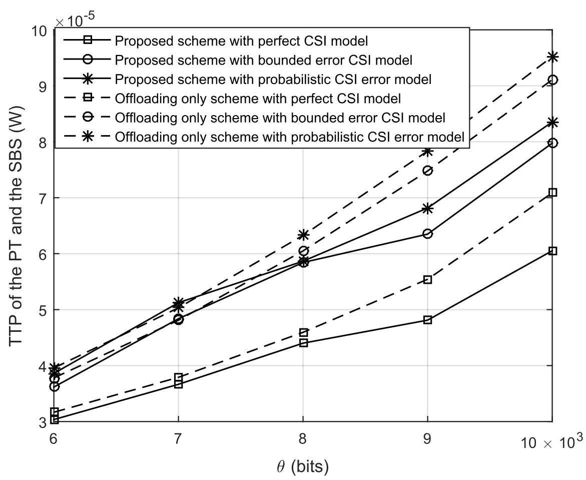

FIGURE 3. The TTP of the PT and the SBS versus θ.

TABLE 2. Complexity analysis.

Problem	Complexity Order
Perfect CSI model case	$N\left\{M\left[\Lambda+2n_1\left(4+4n_1+n_1^2\right)\right]+\Omega\right\}$
Bounded CSI error model case	$N\left\{M\left\{\Lambda+\sqrt{7+3N_p+2N_s}\,n_2\left\{\left[4+N_p^3+N_s^3+2(N_p+1)^3+(N_s+1)^3\right]+n_2\left[4+N_p^2+N_s^2+2(N_p+1)^2+(N_s+1)^2\right]+n_2^2\right\}\right\}+\Omega\right\}$
Probabilistic CSI error case	$N\left\{M\left\{\Lambda+\sqrt{7+3N_p+2N_s+6n_3}\left[7+3N_p^3+2N_s^3+n_3\left(7+3N_p^2+2N_s^2\right)+2\left(N_p^2+N_p+1\right)^2+\left(N_s^2+N_s+1\right)^2+n_3^2\right]\right\}+\Omega\right\}$

TABLE 3. Simulation parameters.

	Parameters	Values
Unchanged	$f_{\max}$	1.5 GHz
	$p^u_{\max}$	1 W
	$\Omega_{\mathbf{H}}$	10^{-2}
	τ_2	30 ms
	B	200 KHz
	υ	10^{-28}
	η	0.8
	T	100 ms
	p_e, p_m, p_p	0.95, 0.05, 0.95
	$\sigma_p^2, \sigma_m^2, \sigma_s^2$	-20 dBm
	$\Omega_i, i \in \{pp, pm, sm, sp, mp\}$	10^{-1}
Default	θ	10^4 bits
	ξ_{pm}	0.02
	ξ_{sp}	0.02
	r_s	10^5 bits/sec
	Υ	-10 dBm
	Ω_{sm}	5×10^{-2}
	$\mathbf{E}_{pm}$	$e_{pm}\mathbf{I}$
	$\mathbf{E}_{sp}$	$e_{sp}\mathbf{I}$
	e_{pm}	0.002
	e_{sp}	0.002
	C	1000
	N_p, N_s	3, 3

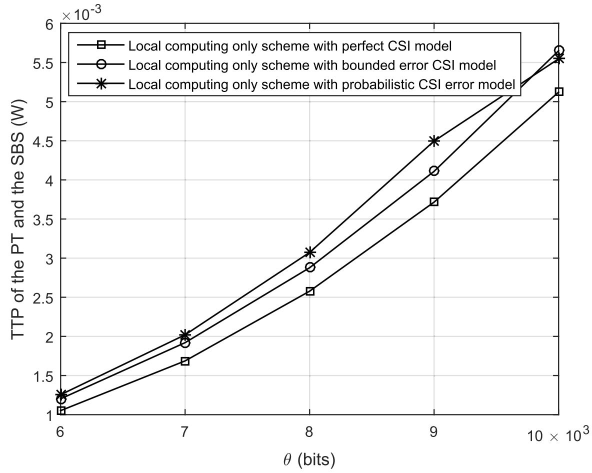

FIGURE 4. The TTP of the PT and the SBS versus θ with local computing only schemes.

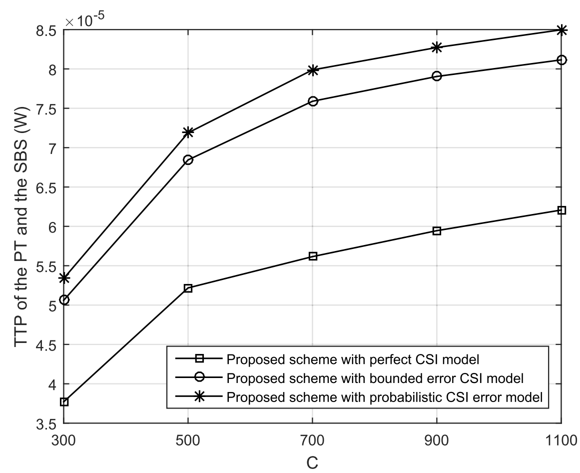

FIGURE 5. The TTP of the PT and the SBS versus C.

in Fig. 3, the TTP of the PT and the SBS increases with θ. The energy consumption of the MD increases with θ. Hence, the SBS and the PT must use larger power to charge the MD, which results in the increasing of the TTP of the PT and the SBS. It can be observed that the perfect CSI case has lower TTP of the PT and the SBS than the other two CSI cases, which matches our intuition that the CSI errors degrade the performance of the system. The second phenomenon is a common phenomenon in Fig. 4 - Fig. 7. We also compare the performance of our proposed method with two benchmark methods: local computing only method and offloading only method. As can be seen from Fig. 3 and Fig. 4, our proposed method has better performance than the two benchmark methods.

Fig. 5 and Fig. 6 show the TTP of the PT and the SBS and the task offloading ratio versus the number of CPU frequency for computing 1-bit data C, respectively. As shown in Fig. 5 and Fig. 6, the curves of the TTP of the PT and the SBS and the task offloading ratio increase with C. These two phenomena can be explained by the following reasons. Larger value of C means the weaker local computing ability of the MD, which results in the a decreasing of the energy efficiency of the MD and an increasing of the TTP of the PT and the SBS. With the decrease of the local computing ability of the MD, the MD needs to offload more task bits to the SBS to obtain the optimal TTP of the PT and the SBS.

Fig. 7 shows the TTP of the PT and the SBS versus the maximum tolerable interference power of the PR Υ. As shown in Fig. 7, the TTP of the PR and the SBS decreases with Υ. Larger Υ indicates the larger transmit power the MD can used, i.e., stronger offloading ability of the MD, which decreases the energy cost of the MD for calculating θ bits and the TTP of the PT and the SBS.

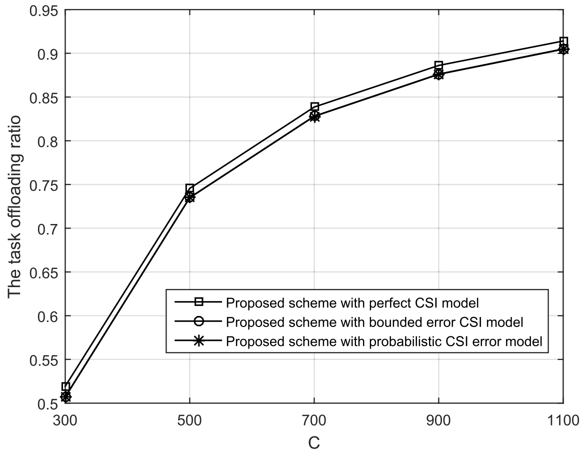

FIGURE 6. The task offloading ratio versus C.

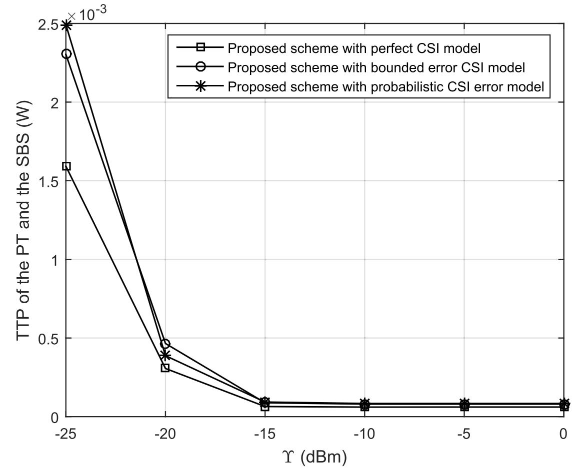

FIGURE 7. The TTP of the PT and the SBS versus Υ.

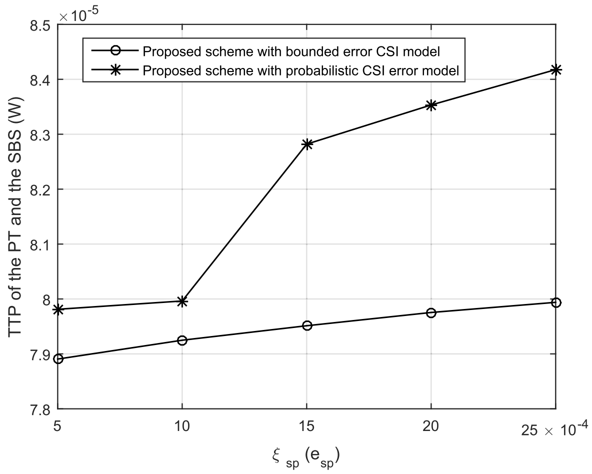

FIGURE 8. The TTP of the PT and the SBS versus ξ_{sp} and e_{sp}.

Fig. 8 shows the TTP of the PT and the SBS versus ξ_{sp} and e_{sp} in bounded and probabilistic CSI error cases. It can be observed that the curves of TTP of the PT and the SBS increase with e_{sp} and ξ_{sp}. This is because that the larger the ξ_{sp} is the more uncertain the estimated bounded error CSI is and the worse the performance of the system will be. We use $\mathbf{E}_{sp} = e_{sp}\mathbf{I}$, hence, larger e_{sp} mean larger variance of the CSI error, which results in larger uncertainties of the estimated CSI and the increasing of the TTP of the PT and the SBS.

VI. CONCLUSIONS

In this paper, WPT, CR, underlay spectrum sharing scheme, physical-layer security and MEC were combined to construct a robust secure wireless powered underlay MISO cognitive-based MEC system. The TTP of the PT and the SBS minimization problems were studied under perfect CSI, bounded CSI error and probabilistic CSI error models, respectively. The nonconvex optimization problems were solved through two-phase iterative optimization algorithms combined with Lagrangian dual, SDR, S-Procedure and Bernstein-type inequalities. Simulation results investigated the performance of the proposed MEC system versus different system parameters.

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