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Joint RRH Activation and Robust Coordinated Beamforming for Massive MIMO Heterogeneous Cloud Radio Access Networks

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ABSTRACT Heterogeneous cloud radio access networks (H-CRANs), proposed to boost both spectral and energy efficiency while reducing the signaling overhead, have been regarded as a promising paradigm for fifth-generation wireless communication systems. To reduce the network power consumption, in this paper, we propose a joint remote radio head (RRH) activation and outage constrained coordinated beamforming (CoBF) algorithm for massive multiple-input multiple-output H-CRANs. Considering the imperfect channel state information and power consumption of fronthaul links and individual transmission power limitations at the RRHs, the downlink network power minimization problem subject to the constraints of specified outage probabilities at each macro user equipment (MUE) and each RRH user equipment (RUE) is reformulated. For a given RRH activation set, we first derive a conservative convex approximation for the outage constraints of RUEs by using semidefinite relaxation and an extended Bernstein-type inequality, while a closed-form expression is obtained for the outage constraints of MUEs. Then, we reformulate the nonconvex problem into a semidefinite program. Moreover, we propose a low-complexity algorithm to perform the joint optimization of the RRH activation and robust CoBF by using the group sparse beamforming method through the weighted ℓ_1/ℓ_2 norm reformulation, where the group sparsity patterns of beamformers are used to guide the RRHs that can be switched off. Simulation results demonstrate that the proposed algorithm can significantly reduce the network power consumption by 28% in the low signal-to-interference-plus noise ratio scenario. In addition, the algorithm can approach the system performance of the exhaustive search algorithm while having a much lower computational complexity.

INDEX TERMS Heterogeneous cloud radio access network, massive MIMO, coordinated beamforming, semidefinite relaxation, outage probability, group sparse.

I. INTRODUCTION

With the proliferation of smart devices such as smartphones and tablets, cellular networks face an exponential growth of mobile data traffic. The fifth-generation (5G) wireless communication increasingly deploys advanced technologies that are expected to address the explosive growth of mobile traffic and power consumption [1]–[3]. Massive multiple-input multiple-output (MIMO) and heterogeneous cloud radio access networks (H-CRANs) are two promising approaches to provide high capacity and energy efficiency [4]–[6] while reducing the operating expenditures of a large scale deployed macrocell base stations (MBSs) and ultra-dense distributed remote radio heads (RRHs) [7], [8]. In massive MIMO H-CRANs, a high-power MBS with large-scale antenna array is used to serve the macro user equipments (MUEs) that are relatively close to the MBS.

And the abundant degrees of spatial freedom introduced by massive MIMO can be utilized to alleviate intra-cell and inter-cell interference. Additionally, the ultra-dense deployed low-power RRHs with a few antennas are used to serve RRH user equipments (RUEs) that are close to RRHs. Due to extensive reuse of limited spectrum resources, the throughput and reliability of each user can be greatly improved, particularly in hot spots and inside buildings [9], [10]. Meanwhile, mobile users can be adaptively or simultaneously served by the RRH and/or MBS, which aim to achieve high data rates and extensive connectivity with reduced control signaling for handover.

In view of H-CRANs' significant superiority in spectrum efficiency (SE) and energy efficiency (EE), a large number of studies explored the optimization of SE and EE in H-CRANs in recent years. Radio resource management plays a crucial role in achieving the benefits and arouses the primary concern in H-CRANs [11]. A sum-rate maximization involving power allocation and user association with quality of service (QoS) constraints has been investigated in [12], where it is modeled as a generalized Stackelberg equilibrium problem, and a distributed algorithm has been proposed. The benefits and challenges of utilizing resource sharing in H-CRANs have been investigated in [13]. There, potential technologies for achieving resource sharing are discussed. Additionally, potential techniques, performance trade-offs and challenges are considered in green H-CRANs [14]. Using the variational inequality theory, Wang *et al.* [15] propose a distributed power allocation algorithm that achieves the system's ergodic sum-rate maximization.

A massive MIMO H-CRAN is one of promising techniques in 5G networks due to its ability to further boost network performance [16], [17]. For instance, the study of [18] presents a novel joint optimization of user association and resource allocation in massive MIMO HetNets. The optimal user-specific base station clusters and resource allocation are formulated as a convex network utility function for maximizing the system EE, and a dual subgradient-based algorithm is proposed. The EE problem of ON-OFF switching, user association and power control is studied in an H-CRAN with massive MIMO [19]. Assuming that the channel state information (CSI) is limited, several formulations and schedules have been presented for various optimization targets in massive MIMO systems [20]–[22].

Recently, extensive beamforming designs have been studied in massive MIMO systems and H-CRANs. In [23], both EE and the queuing delay are considered jointly in multimedia H-CRANs, and an average weighted utility function is formulated to measure the EE performance. Moreover, the authors propose a real-time global beamforming algorithm based on the Lyapunov optimization framework to optimize an EE-delay tradeoff. In [24], considering the QoS constraints of users and the power constraints of RRHs for the downlink of C-RAN, the problem of joint optimization of the transmit beamforming, user grouping and virtual base station clustering is formulated as a general utility maximization problem. In addition, coordinated beamforming (CoBF) algorithms based on a successive convex approximation and block successive upper bound minimization are proposed in [25] and [26], respectively. Ma *et al.* [27] propose a two-stage cooperative precoding transmission scheme based on interference alignment and soft-space-reuse and then develop an optimal power allocation strategy to maximize the total network capacity. A sparse beamforming design with QoS requirements and power constraints is investigated in [28] and [29]. In [30], to minimize the network power consumption, a three-stage robust group sparse beamforming (GSB) algorithm is proposed for the multicast C-RAN with imperfect CSI. Hybrid beamforming for reducing power consumption and radio frequency (RF) component cost has attracted enormous attention in recent years [31]. Several joint RRH selection and beamforming designs have been developed to optimize the tradeoff between network power consumption and delay in a downlink slotted C-RAN in [32] and [33].

The aforementioned studies primarily focus on radio resource management and various beamforming designs to optimize SE and EE with QoS and hardware component constraints in H-CRANs. However, considering the high complexity of CoBF due to a large scale of antennas at MBS and a considerable number of RRHs, CoBF is costly in practical massive MIMO H-CRANs. Furthermore, the lack of existing studies of the joint RRH activation and outage constrained beamforming makes the system design much more challenging. Motivated by the above, we investigate a massive MIMO H-CRAN with the outage constraints of RUEs and MUEs. To this end, a joint RRH activation and robust CoBF (JRARCoBF) algorithm is proposed to minimize the total network power consumption. As illustrated in Fig. 1, an H-CRAN comprised of a large-scale antenna MBS and a considerable number of conventional multiple-antenna RRHs is investigated. The formulated total power minimization problem is intractable because of having no closed-form expressions for outage probability constraints. The major contributions of the paper are summarized as follows:

- We formulate the joint RRH activation and outage constrained CoBF for the massive MIMO H-CRAN to minimize the total power consumption of the network.
- We present conservative convex approximations for RUEs' outage constraints. Given a selected RRH set, the original problem is reformulated to a semidefinite program (SDP).
- A low-complexity JRARCoBF algorithm is proposed to address the power consumption minimization problem in which the GSB method is utilized to assist RRH selection. The simulation results verify the effectiveness of the proposed algorithm.

The rest of this paper is organized as follows. Section II describes the system model and the problem formulation. The CoBF design with a given RRH selection is proposed in Section III. A low-complexity JRARCoBF algorithm is proposed in Section IV. The simulation results are illustrated in Section V to verify the efficacy of the proposed algorithm. Finally, Section VI concludes the paper.

Notation: $\mathbb{C}^n$, $\mathbb{R}^n$ and $\mathbb{R}^n_{++}$ denote the sets of n-dimensional complex, real and positive real vectors, respectively. $\mathbb{C}^{m\times n}$ denotes the set of $m \times n$ complex matrices. $\mathbb{S}^n$, $\mathbb{S}^n_+$ and $\mathbb{H}^n$ denote the sets of n-dimensional real symmetric matrices, real symmetric positive semidefinite matrices and Hermitian matrices, respectively. $\mathbf{I}_n$ denotes an $n \times n$ identity matrix, while $\boldsymbol{e}(i)$ denotes the i-th unit column vector of an appropriate dimension. $(\cdot)^T$, $(\cdot)^H$, $(\cdot)^{1/2}$ and $\mathrm{Tr}(\cdot)$ denote the transposition, Hermitian, square root and trace operators of a matrix or vector, respectively. $\|\cdot\|_F$ and $\|\cdot\|$ denote the Frobenius and Euclidean norms of a matrix and a vector, respectively. $\lambda_{\max}(\mathbf{U})$ denotes the maximum eigenvalue of matrix $\mathbf{U}$; $\mathrm{vec}(\mathbf{U})$ denotes a vectorization of matrix $\mathbf{U}$; and $\mathbf{U} \succeq \mathbf{0}$ denotes that $\mathbf{U}$ is a positive semidefinite matrix. $\mathrm{Re}\{\cdot\}$ represents taking the real part of the argument; $\{\mathbf{W}_i\}$ denotes the set of all matrices $\mathbf{W}_i$ with the subscript i. $\mathcal{CN}(\mu, \sigma^2)$ denotes a complex Gaussian distribution with mean μ and variance σ^2. $\mathcal{CN}(\mathbf{u}, \boldsymbol{\Sigma})$ denotes the distribution of a circularly symmetric complex Gaussian random vector with mean vector $\mathbf{u}$ and covariance matrix $\boldsymbol{\Sigma}$, and $\sim$ stands for "distributed as". $\Pr\{\cdot\}$, $e^{(\cdot)}$, $\ln(\cdot)$ and $\mathbb{E}[\cdot]$ denote the probability function, the exponential function, the natural logarithmic function and the statistical expectation operator, respectively. $\lfloor\cdot\rceil$ represents rounding to the nearest integer.

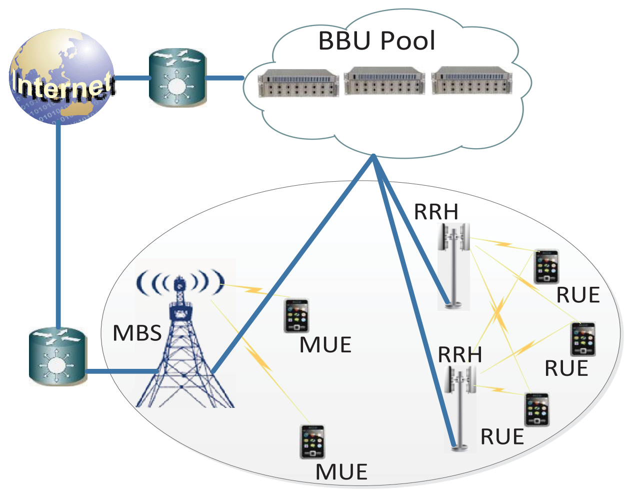

FIGURE 1. An illustration of a massive MIMO H-CRAN, where the MBS is equipped with a large number of antennas and the RRHs are equipped with a few antennas.

II. SYSTEM MODEL AND PROBLEM FORMULATION

We consider a time-division duplex (TDD) downlink full spectrum reuse massive MIMO H-CRAN system that consists of an MBS and L RRHs as illustrated in Fig. 1. We assume that the RRHs are deployed within the coverage area of the MBS. The MBS and RRHs are connected to the baseband unit (BBU) pool through the backhaul and fronthaul links, respectively. The MBS is equipped with N_{M} antennas, each RRH is equipped with N_{R} antennas, for a typical massive MIMO system we assume that N_M is much larger than N_R. Define the set of RRHs as $\mathcal{L} = \{1, \cdots, L\}$; they cooperatively serve a set of scheduled RUEs with user-centric clustering. Moreover, let $\mathcal{M} = \{1, \cdots, M\}$ be the set of MUEs that are scheduled by the MBS, and $\mathcal{I} = \{1, \cdots, I\}$ denote the set of RUEs scheduled by RRHs. Additionally, let $\mathcal{A}$ denote the set of active RRHs, and $\mathcal{A} \subseteq \mathcal{L}$, $\mathcal{S}$ denote the set of sleeping RRHs, $\mathcal{A} \cup \mathcal{S} = \mathcal{L}$. Assume that the BBU pool performs centralized processing of all RUE's signals and distributes the data of each RUE to the selected cluster of RRHs via the fronthaul links, with each RUE being collaboratively served by the selected cluster.

A. SIGNAL MODELS FOR MUEs AND RUEs

We consider the CoBF in RRHs the probabilistic outage constraints for RUEs and MUEs when fixed transmit beamforming is deployed at the MBS by utilizing zero-forcing (ZF) beamforming [34]. An opportunistic spatial-temporal and location-based user scheduling is adopted by steering the beam direction towards the scheduled users with a good spatial separation within a certain period of time [35]. Under the above assumption, the received signal z_m at the m-th MUE is given by

$$z_m = \mathbf{g}_{0m}^H \mathbf{v}_m s_{0m} + \sum_{j\neq m}^{M} \mathbf{g}_{0m}^H \mathbf{v}_j s_{0j} + \sum_{i=1}^{I} \sum_{l\in\mathcal{A}} \mathbf{h}_{1lm}^H \mathbf{w}_{li} s_{1i} + n_{0m}, \quad (1)$$

where $\mathbf{g}_{0m} \in \mathbb{C}^{N_{\mathrm{M}}}$ denotes the channel vector from the MBS to the m-th MUE, $\mathbf{v}_m \in \mathbb{C}^{N_{\mathrm{M}}}$ denotes the corresponding beamforming vector, $\mathbf{h}_{1lm} \in \mathbb{C}^{N_{\mathrm{R}}}$ denotes the channel vector from RRH l to the m-th MUE, and $\mathbf{w}_{li} \in \mathbb{C}^{N_{\mathrm{R}}}$ is the beamforming vector for RUE i at RRH l; $s_{0m} \in \mathbb{C}$ and $s_{1i} \in \mathbb{C}$ denote the transmit signals for the m-th MUE, $m \in \mathcal{M}$, and for the i-th RUE, $i \in \mathcal{I}$, respectively. Without loss of generality, we assume that $\mathbb{E}[|s_{0m}|^2] = 1$ and $\mathbb{E}[|s_{1i}|^2] = 1$. The term n_{0m} is the additive white Gaussian noise (AWGN) at MUE m with the distribution $\mathcal{CN}(0, \sigma_{0m}^2)$.

In downlink massive MIMO systems, ZF beamforming is able to completely alleviate the interference between MUEs, potentially performing almost as well as dirty paper coding (DPC). It is assumed that the channel at the powerful MBS is perfectly known. We concentrate on adopting the ZF beamforming, the beamforming matrix $\mathbf{V}$ is expressed as

$$\mathbf{V} = \mathbf{G}^H \left(\mathbf{G}\mathbf{G}^H\right)^{-1} = [\mathbf{v}_1, \mathbf{v}_2, \cdots, \mathbf{v}_M], \quad (2)$$

where $\mathbf{G} = [\mathbf{g}_{01}, \ \mathbf{g}_{02}, \ \cdots, \ \mathbf{g}_{0M}]$ denotes the channel matrix from the MBS to all MUEs, and $\mathbf{v}_m$ accounts for a column vector of $\mathbf{V}$. With ZF beamforming at the MBS, the interference across different MUEs is completely eliminated. Therefore we have

$$z_m = \mathbf{g}_{0m}^H \mathbf{v}_m s_{0m} + \sum_{i=1}^{I} \sum_{l\in\mathcal{A}} \mathbf{h}_{1lm}^H \mathbf{w}_{li} s_{1i} + n_{0m}. \quad (3)$$

Thus, the signal-to-interference-plus-noise ratio (SINR) of the m-th MUE can be expressed as

$$\mathrm{SINR}_m^{(\mathrm{MUE})} = \frac{\left|\mathbf{g}_{0m}^H \mathbf{v}_m\right|^2}{\sum_{i=1}^{I} \sum_{l\in\mathcal{A}} \left|\mathbf{h}_{1lm} \mathbf{w}_{li}^H\right|^2 + \sigma_{0m}^2}. \tag{4}$$

The signal observed by each RUE is the superposition of signals from all RRHs and the MBS; thus, the received signal $y_i \in \mathbb{C}$ at i-th RUE is given by

$$y_i = \sum_{l\in\mathcal{A}} \mathbf{h}_{0li}^H \mathbf{w}_{li} s_{1i} + \sum_{k\neq i} \sum_{l\in\mathcal{A}} \mathbf{h}_{0li}^H \mathbf{w}_{lk} s_{1k} + \sum_{m=1}^{M} \mathbf{g}_{1i}^H \mathbf{v}_m s_{0m} + n_{1i}, \tag{5}$$

where $\mathbf{h}_{0li} \in \mathbb{C}^{N_\mathrm{R}}$ denotes the channel vector from the l-th RRH to i-th RUE, $\mathbf{g}_{1i} \in \mathbb{C}^{N_\mathrm{M}}$ denotes the channel vector from the MBS to the i-th RUE, and n_{1i} is the AWGN at RUE i with the distribution $\mathcal{CN}(0, \sigma_{1i}^2)$. From (5), the SINR of the i-th RUE can be expressed as

$$\mathrm{SINR}_i^{(\mathrm{RUE})} = \frac{\sum_{l\in\mathcal{A}} \left|\mathbf{h}_{0li}^H \mathbf{w}_{li}\right|^2}{\sum_{k\neq i} \sum_{l\in\mathcal{A}} \left|\mathbf{h}_{0li}^H \mathbf{w}_{lk}\right|^2 + \sum_{m=1}^{M} \left|\mathbf{g}_{1i}^H \mathbf{v}_m\right|^2 + \sigma_{1i}^2}. \tag{6}$$

As each RRH has a maximum transmit power constraint, the beamforming vector satisfies the following constraint condition:

$$\sum_{i=1}^{I} \|\mathbf{w}_{li}\|^2 \leq P_l, \quad \forall l \in \mathcal{A}, \tag{7}$$

where P_l denotes the maximum transmission power of the l-th RRH. For simplicity, we assume that the transmit power is unconstrained at the powerful MBS.

B. POWER CONSUMPTION MODEL

In this section, we adopt the network power consumption model that includes transmit power consumption and circuit power consumption. Specifically, the total transmit power consumption can be written as

$$P_\mathrm{T} = \sum_{l\in\mathcal{A}} \sum_{i=1}^{I} \frac{1}{\eta_l} \|\mathbf{w}_{li}\|^2, \tag{8}$$

where η_l denotes the efficiency of the power amplifier (PA) of the l-th RRH. The circuit power consumption includes the transport link power consumption and the circuit power consumption of the antenna that depends on the mode of RRH. Therefore, the total circuit power consumption is given by [33]

$$P_\mathrm{C} = \sum_{l\in\mathcal{A}} P_l^\mathrm{a} + \sum_{l\in\mathcal{S}} P_l^\mathrm{s} + P_\mathrm{olt}, \tag{9}$$

where P_olt represents the optical line terminal (OLT) power consumption of fronthaul links, and P_l^s and P_l^a denote the circuit power of antenna in the sleep and active modes, respectively. Thus, the total power consumption of the network can be represented as

$$P(\mathcal{A}, \mathbf{w}) = \sum_{l\in\mathcal{A}} \sum_{i=1}^{I} \frac{1}{\eta_l} \|\mathbf{w}_{li}\|^2 + \sum_{l\in\mathcal{A}} P_l^\mathrm{c} + \sum_{l\in\mathcal{S}} P_l^s + P_\mathrm{olt}, \tag{10}$$

where $\mathbf{w} = \left[\mathbf{w}_{11}^T, \cdots, \mathbf{w}_{L1}^T, \cdots, \mathbf{w}_{1I}^T, \cdots, \mathbf{w}_{LI}^T\right]^T$. Let $\left(P_l^\mathrm{a} - P_l^\mathrm{s}\right)$ and $\sum_{l\in\mathcal{L}} P_l^\mathrm{s} + P_\mathrm{olt}$ be constants. Then, the total network power consumption can be written as

$$P(\mathcal{A}, \mathbf{w}) = \sum_{l\in\mathcal{A}} \left(\sum_{i=1}^{I} \frac{1}{\eta_l} \|\mathbf{w}_{li}\|^2 + P_l^\mathrm{c} \right) + c, \tag{11}$$

where c is a constant representing $\sum_{l\in\mathcal{L}} P_l^\mathrm{s} + P_\mathrm{olt}$, and $P_l^\mathrm{c} = P_l^\mathrm{a} - P_l^\mathrm{s}$ denotes the circuit power difference between the active and sleep modes of the l-th RRH.

C. PROBLEM FORMULATION

We assume that the perfect CSI about the channels among MBS and MUEs and the channels among MBS and RUEs is available at the powerful MBS, while the RRHs have imperfect CSI about the channels among RRHs and RUEs. Specifically, we assume that RRHs can obtain the partial CSI of RUEs through imperfect channel estimation and know only the channel statistical information of MUEs due to poor channel conditions from MUEs to RRHs. Therefore, the actual channels of RUEs and MUEs at RRHs can be modeled by [30]

$$\mathbf{h}_{0li} = \hat{\mathbf{h}}_{0li} + \mathbf{e}_{0li}, \tag{12}$$

$$\mathbf{h}_{1lm} \sim \mathcal{CN}\left(\mathbf{0}, \mathbf{C}_{1lm}\right), \tag{13}$$

where $\hat{\mathbf{h}}_{0li} \in \mathbb{C}^{N_\mathrm{R}}$ denotes the estimated channel vector and is known to RRH, while $\mathbf{e}_{0li} \in \mathbb{C}^{N_\mathrm{R}}$ denotes the estimated error. $\mathbf{e}_{0li}$ is modeled by

$$\mathbf{e}_{0li} \sim \mathcal{CN}\left(\mathbf{0}, \mathbf{C}_{0li}\right), \tag{14}$$

where the covariance matrix $\mathbf{C}_{0li}$ is positive definite. Thus, the joint RRH activation and CoBF with outage constraints is formulated as follows:

$$\min_{\mathcal{A},\mathbf{w}} \; P(\mathcal{A}, \mathbf{w}) \tag{15a}$$

$$\text{s.t.} \; \Pr\left(\mathrm{SINR}_m^{(\mathrm{MUE})} \geq \beta_m\right) \geq 1 - \theta_m, \quad \forall m \in \mathcal{M}, \tag{15b}$$

$$\Pr\left(\mathrm{SINR}_i^{(\mathrm{RUE})} \geq \gamma_i\right) \geq 1 - \rho_i, \quad \forall i \in \mathcal{I}, \tag{15c}$$

$$\sum_{i=1}^{I} \|\mathbf{w}_{li}\|^2 \leq P_l, \quad \forall l \in \mathcal{A}, \tag{15d}$$

where β_m and γ_i denote the target SINR of the m-th MUE and the i-th RUE, respectively, while θ_m and ρ_i denote the corresponding outage probabilities of the m-th MUE and the i-th RUE, respectively.

From the network power consumption model in (11), we know that there are two approaches that can reduce the total power consumption: one is to reduce the transmit power consumption, and the other is to shut down some RRHs and the associated transport links. Unfortunately, the two approaches are in conflict over the same time-frequency resource. Specifically, reducing the transmit power will result in the need to activate more RRHs to achieve a higher beamforming gain to meet the QoS requirements. However, activating more RRHs will increase the power consumption of circuit and transport links. Consequently, we need to explore the tradeoff between the two approaches; a joint design of RRH activation and coordinated transmit beamforming is an appropriate approach to solving the power consumption minimization problem of (15).

III. OUTAGE CONSTRAINED CoBF WITH A GIVEN ACTIVE RRH SET $\mathcal{A}$

In this section, we first reformulate problem (15) with a given active RRH by semidefinite relaxation (SDR). Then, we convert the outage probability constraints to second-order cones (SOCs) by applying the Bernstein-type inequality [37]. Finally, problem (15) is reformulated as an SDP and solved by adopting off-the-shelf convex solvers.

A. PROBLEM REFORMULATION WITH A GIVEN $\mathcal{A}$

Consider a given active RRH set $\mathcal{A}$ for problem (15), assuming that there are L_s selected RRHs to be shut down in $\mathcal{L}$. Let $\mathbf{h}_{1m} \in \mathbb{C}^{N_R(L-L_s)}$ denote the channel vector aggregate from the RRHs in $\mathcal{A}$ to the m-th MUE, $\mathbf{w}_i \in \mathbb{C}^{N_R(L-L_s)}$ denote the beamforming vector aggregate of the i-th RUE excluding the beamforming vectors of inactive RRHs, $\hat{\mathbf{h}}_{0i}$ denote the channel estimation vector aggregate from the RRHs in $\mathcal{A}$ to the i-th RUE, and $\mathbf{e}_{0i} \in \mathbb{C}^{N_R(L-L_s)}$ denote the corresponding channel estimation error vector aggregate from the RRHs in $\mathcal{A}$ to the i-th RUE. The problem with a given $\mathcal{A}$ can be expressed as

$$
\begin{aligned}
&\min_{\mathbf{w}} P(\mathcal{A}, \mathbf{w}) && (16a)\\
&\text{s.t. } \Pr\left(\mathrm{SINR}_m^{(\mathrm{MUE})} \geq \beta_m\right) \geq 1-\theta_m, \forall m \in \mathcal{M}, && (16b)\\
&\quad \Pr\left(\mathrm{SINR}_i^{(\mathrm{RUE})} \geq \gamma_i\right) \geq 1-\rho_i, \forall i \in \mathcal{I}, && (16c)\\
&\quad \sum_{i=1}^{I} \|\mathbf{w}_{li}\|^2 \leq P_l, \forall l \in \mathcal{A}. && (16d)
\end{aligned}
$$

The probability constraint of the m-th MUE in (16b) is a cumulative distribution function of an exponential random variable with parameter θ_m. (16b) can be rewritten as

$$
\sum_{i=1}^{I} \mathbf{w}_i^H \mathbf{C}_{1m} \mathbf{w}_i \leq \Big(\frac{1}{\beta_m}\left|\mathbf{g}_{0m}^H \mathbf{v}_m\right|^2 - \sigma_{0m}^2\Big) \ln(1/\theta_m), \quad \forall m \in \mathcal{M}, \quad (17)
$$

where $\mathbf{C}_{1m} \triangleq \mathbb{E}[\mathbf{h}_{1m}\mathbf{h}_{1m}^H]$. Define $\mathbf{A}_{ni} \in \mathbb{C}^{N_R(L-L_s)\times N_R(L-L_s)}$ as a block-diagonal matrix, where its n-th main diagonal block square matrix is $\mathbf{I}_{N_R}$ and the remaining entries are zeros, as such the beamforming vector from the n-th RRH in $\mathcal{A}$ to the i-th RUE can be expressed as $\mathbf{A}_{ni}\mathbf{w}_i$, where $\mathbf{w}_i \in \mathbb{C}^{N_R L}$ is the beamforming vector aggregate of the i-th RUE including the zero vectors of inactive RRHs. Applying SDR and substituting $\mathbf{W}_i = \mathbf{w}_i\mathbf{w}_i^H$ into (16) [36], we can rewrite problem (16) as

$$
\begin{aligned}
&\min_{\{\mathbf{W}_i\}} \sum_{n=1}^{L-L_s}\sum_{i=1}^{I}\left(\frac{1}{\bar{\eta}_n}\mathrm{Tr}\left(\mathbf{A}_{ni}\mathbf{W}_i\mathbf{A}_{ni}^H\right)+\bar{P}_n^{\mathrm{c}}\right)+c && (18a)\\
&\text{s.t. } \sum_{i=1}^{I}\mathrm{Tr}(\mathbf{C}_{1m}\mathbf{W}_i) \leq \Big(\frac{1}{\beta_m}\left|\mathbf{g}_{0m}^H\mathbf{v}_m\right|^2-\sigma_{0m}^2\Big) \times \ln(1/\theta_m), \forall m \in \mathcal{M}, && (18b)\\
&\quad \Pr\left\{\boldsymbol{\delta}_1^H\mathbf{Q}_i\boldsymbol{\delta}_1 + 2\mathrm{Re}\{\mathbf{r}_i^H\boldsymbol{\delta}_1\} + c_i \geq 0\right\} \geq 1-\rho_i, \quad \forall i \in \mathcal{I}, && (18c)\\
&\quad \sum_{i=1}^{I}\mathrm{Tr}\left(\mathbf{A}_{ni}\mathbf{W}_i\mathbf{A}_{ni}^H\right) \leq \bar{P}_n, \quad n=1,\cdots,L-L_s, && (18d)\\
&\quad \mathbf{W}_i \succeq \mathbf{0}, \quad \forall i \in \mathcal{I}, && (18e)
\end{aligned}
$$

where $\bar{\eta}_n$ and $\bar{P}_n^{\mathrm{c}}$ are the efficiency of the PA and the circuit power difference between the active and sleep modes of the n-th RRH in $\mathcal{A}$, respectively, and $\bar{P}_n$ is the transmit power constraint on the n-th RRH in $\mathcal{A}$, $\boldsymbol{\delta}_i \sim \mathcal{CN}(\mathbf{0}, \mathbf{I}_{(L-L_s)N_R})$. The remaining parameters in (18) are defined as follows:

$$
\begin{aligned}
&\mathbf{Q}_i \triangleq \mathbf{C}_{0i}^{1/2}\Big(\frac{1}{\gamma_i}\mathbf{W}_i - \sum_{k\neq i}\mathbf{W}_k\Big)\mathbf{C}_{0i}^{1/2}, && (19a)\\
&\mathbf{r}_i \triangleq \mathbf{C}_{0i}^{1/2}\Big(\frac{1}{\gamma_i}\mathbf{W}_i - \sum_{k\neq i}\mathbf{W}_k\Big)\hat{\mathbf{h}}_{0i}, && (19b)\\
&c_i \triangleq \hat{\mathbf{h}}_{0i}^H\Big(\frac{1}{\gamma_i}\mathbf{W}_i - \sum_{k\neq i}\mathbf{W}_k\Big)\hat{\mathbf{h}}_{0i} - \sum_{m=1}^{M}\left|\mathbf{g}_{1i}^H\mathbf{v}_m\right|^2 - \sigma_{1i}^2, && (19c)\\
&\mathbf{C}_{0i} \triangleq \mathbb{E}[\mathbf{e}_{0i}\mathbf{e}_{0i}^H]. && (19d)
\end{aligned}
$$

A good method for addressing (18c) is to obtain the appropriate convex approximations to probabilistic constraints. Such Bernstein-type inequality proposed in [37] and [38] can conservatively approximate the probability inequality to make the resulting problem computationally tractable. Specially, (18c) has the same form with the rate outage constrained formulation in [38] except for extra inter-cell interference. Therefore, we present a form of the Bernstein-type inequality, as described by lemma 1.

Lemma 1: Let $\boldsymbol{\delta}_1 \sim \mathcal{CN}(\mathbf{0}, \mathbf{I}_{(L-L_s)N_R})$, $\mathbf{Q}_i \in \mathbb{H}^{(L-L_s)N_R}$, $\mathbf{r}_i \in \mathbb{C}^{(L-L_s)N_R}$, and define

$$
f(\boldsymbol{\delta}_1, \mathbf{Q}_i, \mathbf{r}_i) \triangleq \boldsymbol{\delta}_1^H\mathbf{Q}_i\boldsymbol{\delta}_1 + 2\mathrm{Re}\{\mathbf{r}_i^H\boldsymbol{\delta}_1\}. \quad (20)
$$

Then, the following desirable inequality holds: $\forall i \in \mathcal{I}$,

$$
\Pr\Big\{f(\boldsymbol{\delta}_1, \mathbf{Q}_i, \mathbf{r}_i) \geq \Psi(\ln(1/\rho_i) \mid \mathbf{Q}_i, \mathbf{r}_i)\Big\} \geq 1-\rho_i, \quad (21)
$$

where $\Psi\colon \mathbb{R}_{++} \to \mathbb{R}$ is defined by

$$
\Psi\left(\ln\left(1/\rho_i\right) \mid \mathbf{Q}_i, \mathbf{r}_i\right) \triangleq \mathrm{Tr}\left(\mathbf{Q}_i\right) + \ln\ (\rho_i)\lambda^+\left(\mathbf{Q}_i\right) - \sqrt{2\ln\left(1/\rho_i\right)}\sqrt{\|\mathbf{Q}_i\|_F^2 + 2\left\|\mathbf{r}_i\right\|^2}, \quad (22)
$$

where $\lambda^{+}(\mathbf{Q}_i) \triangleq \max\{\lambda_{\max}(-\mathbf{Q}_i), 0\}$. The proof of Lemma 1 can refer to [38].

Applying the result in Lemma 1, the constraints in (18c) can be made equivalent to $2I$ linear matrix inequalities (LMIs) and I SOCs; the detailed derivation is provided in Appendix A. Thus, problem (18) can be approximately reformulated as the following SDP:

$$\min_{\substack{\{\mathbf{W}_i\}\\ \mathbf{t},\mathbf{a}}} \sum_{n=1}^{L-L_s} \sum_{i=1}^{I} \left(\frac{1}{\bar{\eta}_n} \mathrm{Tr}\left(\mathbf{A}_{ni}\mathbf{W}_i\mathbf{A}_{ni}^H\right) + \bar{P}_n^{c}\right) + c \tag{23a}$$

$$\text{s.t.} \sum_{i=1}^{I} \mathrm{Tr}(\mathbf{C}_{1m}\mathbf{W}_i) \le \left(\frac{1}{\beta_m}\left|\mathbf{g}_{0m}^H\mathbf{v}_m\right|^2 - \sigma_{0m}^2\right) \times \ln(1/\theta_m), \quad \forall m \in \mathcal{M}, \tag{23b}$$

$$\left(\{\mathbf{W}_i\}, \mathbf{t}, \mathbf{a}\right) \in \mathcal{C}_{\mathrm{R}}(\mathcal{A}), \tag{23c}$$

$$\sum_{i=1}^{I} \mathrm{Tr}\left(\mathbf{A}_{ni}\mathbf{W}_i\mathbf{A}_{ni}^H\right) \le \bar{P}_n, \quad n=1,\cdots,L-L_s, \tag{23d}$$

$$\mathbf{W}_i \succeq \mathbf{0}, \quad \forall i \in \mathcal{I}, \tag{23e}$$

where $\mathcal{C}_{\mathrm{R}}$ denotes conservative approximations to the constraint sets with respect to (23c) and is defined by (42) in Appendix. $\mathbf{t} \in \mathbb{R}^I$ and $\mathbf{a} \in \mathbb{R}^I$ are auxiliary variables. Thus, the centralized solution of problem (23) can be easily obtained by using off-the-shelf convex solvers (e.g., CVX). Note that solutions of problem (23) may not always be of rank one. If solutions $\mathbf{W}_i^\star$ of problem (23) are of rank one, i.e., $\mathbf{W}_i^\star = \mathbf{w}_i^\star(\mathbf{w}_i^\star)^H$, solutions of (18) can be obtained as $\mathbf{w}_i^\star$ by rank-one decomposition. Otherwise, a rank-one approximation can be obtained by Gaussian randomization [36].

According to the solution of problem (18), we know that the problem in (15) is solved by searching over all possible permutations of $\mathcal{A}$ that leads to an exponential increase in complexity as the RRH number increases. In order to reduce the computational complexity, we will develop an efficient algorithm to solve the problem (15) in Section IV.

IV. JOINT RRH ACTIVATION AND ROBUST CoBF ALGORITHM

In this section, we first propose a weighted group sparsity inducing norm with respect to the beamforming vector assemblage $\mathbf{w}$ to relax the objective function in (15) for the purpose of making the problem tractable. Then, we reformulate the problem (15) as an SDP, and apply the Bernstein-type inequality to solve the outage probability constraints. Finally, we present a RRH priority sorting scheme and proposed a binary search-based joint RRH activation and robust CoBF algorithm.

A. GSB REFORMULATION

Assuming that some RRHs are shut down, the corresponding beamforming vectors will be zeros, resulting in a group sparse structure of the aggregated beamforming vector. First, we rewrite the sparse beamforming vector as

$$\tilde{\mathbf{w}}_l = \left[\mathbf{w}_{l1}^T, \cdots, \mathbf{w}_{lI}^T\right]^T \in \mathbb{C}^{N_{\mathrm{R}}I}, \tag{24}$$

$$\mathbf{w} = \left[\tilde{\mathbf{w}}_1^T, \cdots, \tilde{\mathbf{w}}_L^T\right]^T \in \mathbb{C}^{N_{\mathrm{R}}IL}. \tag{25}$$

The RRH l will be shut down if $\left\|\tilde{\mathbf{w}}_l\right\|_2 = 0$. Therefore, we can adopt the mixed ℓ_1/ℓ_2-norm to induce group-sparsity for $\mathbf{w}$ by utilizing the group sparse structure of the optimal aggregated beamforming vector. Accordingly, by introducing convex relaxation of (11) [33], the approximate sparse beamforming vector can be obtained by solving the minimization problem of the weighted group-sparsity inducing norm given by

$$\min_{\mathbf{w}} \left(2\sum_{l=1}^{L}\sqrt{\frac{P_l^c}{\eta_l}}\left\|\tilde{\mathbf{w}}_l\right\|_2 + c\right) \tag{26a}$$

$$\text{s.t. } \Pr\left(\mathrm{SINR}_m^{(\mathrm{MUE})} \ge \beta_m\right) \ge 1-\theta_m, \quad \forall m \in \mathcal{M}, \tag{26b}$$

$$\Pr\left(\mathrm{SINR}_i^{(\mathrm{RUE})} \ge \gamma_i\right) \ge 1-\rho_i, \quad \forall i \in \mathcal{I}, \tag{26c}$$

$$\sum_{i=1}^{I}\left\|\tilde{\mathbf{w}}_l\right\|^2 \le P_l, \quad \forall l \in \mathcal{L}, \tag{26d}$$

Problem (26) has the same constraint expressions as problem (16), other than the active RRH set. In view of this, we will follow the same approach to solve the problem. Define $\mathbf{A}_{li} \in \mathbb{C}^{N_{\mathrm{R}}L\times N_{\mathrm{R}}L}$ as a block-diagonal matrix, and its l-th main diagonal block square matrix is $\mathbf{I}_{N_{\mathrm{R}}}$ and the remaining entries are zeros, so that the beamforming vector from the l-th RRH in $\mathcal{L}$ to the i-th RUE can be expressed as $\mathbf{A}_{li}\mathbf{w}_i$. In addition, all the channel vector aggregates of MUEs and RUEs and the corresponding channel estimation vector aggregates include zero vectors of inactive RRHs. Applying SDR by substituting $\mathbf{W}_i = \mathbf{w}_i\mathbf{w}_i^H$ [36] into problem (26) yields

$$\min_{\{\mathbf{W}_i\}} \left(2\sum_{l=1}^{L}\sqrt{\frac{P_l^c}{\eta_l}\sum_{i=1}^{I}\mathrm{Tr}\left(\mathbf{A}_{li}\mathbf{W}_i\mathbf{A}_{li}^H\right)} + c\right) \tag{27a}$$

$$\text{s.t.} \sum_{i=1}^{I} \mathrm{Tr}(\mathbf{C}_{1m}\mathbf{W}_i) \le \left(\frac{1}{\beta_m}\left|\mathbf{g}_{0m}^H\mathbf{v}_m\right|^2 - \sigma_{0m}^2\right) \times \ln(1/\theta_m), \quad \forall m \in \mathcal{M}, \tag{27b}$$

$$\Pr\left\{\boldsymbol{\delta}_1^H\mathbf{Q}_i\boldsymbol{\delta}_1 + 2\mathrm{Re}\{\mathbf{r}_i^H\boldsymbol{\delta}_1\} + c_i \ge 0\right\} \ge 1-\rho_i, \quad \forall i \in \mathcal{I}, \tag{27c}$$

$$\sum_{i=1}^{I} \mathrm{Tr}\left(\mathbf{A}_{li}\mathbf{W}_i\mathbf{A}_{li}^H\right) \le P_l, \quad \forall l \in \mathcal{L}, \tag{27d}$$

$$\mathbf{W}_i \succeq \mathbf{0}, \quad \forall i \in \mathcal{I}, \tag{27e}$$

where $\boldsymbol{\delta}_1 \sim \mathcal{CN}(\mathbf{0}, \mathbf{I}_{LN_{\mathrm{R}}})$ and $\mathbf{Q}_i \in \mathbb{H}^{LN_{\mathrm{R}}}$. Similarly, the extended form of the Bernstein-type inequality is applied to handle (27c). Using the result in Lemma 1, the problem in

(27) is approximated as

$$\min_{\substack{\{\mathbf{W}_i\}\\ \mathbf{t},\mathbf{a}}} \left(2\sum_{l=1}^{L}\sqrt{\frac{P_l^c}{\eta_l}\sum_{i=1}^{I}\mathrm{Tr}\left(\mathbf{A}_{li}\mathbf{W}_i\mathbf{A}_{li}^H\right)+c}\right) \tag{28a}$$

$$\text{s.t.} \sum_{i=1}^{I}\mathrm{Tr}(\mathbf{C}_{1m}\mathbf{W}_i) \leq \left(\frac{1}{\beta_m}\left|\mathbf{g}_{0m}^H\mathbf{v}_m\right|^2-\sigma_{0m}^2\right) \times \ln(1/\theta_m), \quad \forall m\in\mathcal{M}, \tag{28b}$$

$$\left(\{\mathbf{W}_i\},\mathbf{t},\mathbf{a}\right)\in\mathcal{C}_{\mathrm{R}}(\mathcal{L}), \tag{28c}$$

$$\sum_{i=1}^{I}\mathrm{Tr}\left(\mathbf{A}_{li}\mathbf{W}_i\mathbf{A}_{li}^H\right)\leq P_l, \quad \forall l\in\mathcal{L}, \tag{28d}$$

$$\mathbf{W}_i\succeq\mathbf{0}, \quad \forall i\in\mathcal{I}, \tag{28e}$$

where $\mathcal{C}_{\mathrm{R}}$ is defined by (42) in Appendix A denotes conservative approximations to the constraint sets with respect to (27c). $\mathbf{t}\in\mathbb{R}^I$ and $\mathbf{a}\in\mathbb{R}^I$ are auxiliary variables. Similarly, we can use off-the-shelf convex solvers (e.g., CVX) to obtain the centralized solution of problem (28).

B. JOINT RRH ACTIVATION AND OUTAGE-CONSTRAINED CoBF

1) RRH PRIORITY

After obtaining the approximately optimal sparse beamformer $\mathbf{w}_i^\star$ in problem (28), the next step is to select the active RRHs. Clearly, (26a) implies that the RRHs with larger P_l^c and lower PA efficiency should be shut down preferentially. Additionally, most existing studies propose that the transmit antennas with smaller coefficients should have a higher priority to be shut down by applying the ideal case of group sparsity inducing norm minimization [39]. However, a smaller transmit coefficient priority would result in shutting down RRHs with good channel conditions inappropriately, and a greater transmit power would be consumed by the rest of active RRHs in order to ensure the QoS. Therefore, it is reasonable to consider the channel gain of RRHs; the summed channel gain of RRH l is defined by $\kappa_l = \sum_{i=1}^{I}\|\mathbf{h}_{li}\|^2$. Intuitively, from the perspective of the broadcast channel capacity, an RRH with lower κ_l will have a higher priority for being shut down to avoid inefficient power consumption. Consequently, considering the above factors comprehensively, a mixed priority function is defined as following

$$\omega_l=\sqrt{\frac{\kappa_l\eta_l}{P_l^c}}\left(\sum_{i}^{I}\left\|\mathbf{A}_{li}\mathbf{w}_i^\star\right\|_2\right), \tag{29}$$

where ω_l denotes the priority parameter of RRH l; the smaller ω_l is, the higher the priority of the corresponding RRH to be shut down. To describe the selection strategy clearly, we sort RRHs in the ascending order of $\bar{\omega}_l$: $\bar{\omega}_1\leq\bar{\omega}_2\leq\cdots\leq\bar{\omega}_L$. After RRHs sorting, we define $\bar{\mathbf{w}}_{\ell i}\in\mathbb{C}^{N_{\mathrm{R}}}$ as the beamforming vector for RUE i at the ℓ-th priority RRH, define $\bar{\mathbf{h}}_{1\ell m}$ as the channel vector from the ℓ-th priority RRH to the m-th MUE, and define $\hat{\bar{\mathbf{h}}}_{0\ell i}$ and $\bar{\mathbf{e}}_{0\ell i}$ as the channel estimation vector and the corresponding channel estimation error vector from the ℓ-th priority RRH to the i-th RUE, respectively.

2) RECONSTITUTION OF VECTORS

Assume that there are the first ℓ highest priority RRHs to be shut down, and the corresponding active RRH set is denoted by $\mathcal{A}_\ell$; then, we have $\mathcal{A}\in\{\mathcal{A}_0,\cdots,\mathcal{A}_\ell,\cdots,\mathcal{A}_L\}$ and $\mathcal{A}_0=\mathcal{L}$. Additionally, $\mathcal{A}_L=\emptyset$. If $\mathcal{A}=\mathcal{A}_\ell$, we restructure the aggregated beamforming vector, the aggregated channel estimation vector, and the channel estimation error vector for the RRHs to the i-th RUE as

$$\mathbf{w}_i=\left[\bar{\mathbf{w}}_{(\ell+1)i}^T,\cdots,\bar{\mathbf{w}}_{Li}^T\right]^T\in\mathbb{C}^{N_{\mathrm{R}}(L-\ell)}, \tag{30a}$$

$$\mathbf{h}_{1m}=[\bar{\mathbf{h}}_{1(\ell+1)m}^T,\cdots,\bar{\mathbf{h}}_{1Lm}^T]\in\mathbb{C}^{N_{\mathrm{R}}(L-\ell)I}, \tag{30b}$$

$$\hat{\mathbf{h}}_{0i}=[\hat{\bar{\mathbf{h}}}_{0(\ell+1)i}^T,\cdots,\hat{\bar{\mathbf{h}}}_{0Li}^T]^T\in\mathbb{C}^{N_{\mathrm{R}}(L-\ell)}, \tag{30c}$$

$$\mathbf{e}_{0i}=[\bar{\mathbf{e}}_{0(\ell+1)i}^T,\cdots,\bar{\mathbf{e}}_{0Li}^T]^T\in\mathbb{C}^{N_{\mathrm{R}}(L-\ell)}. \tag{30d}$$

Then, we can obtain the approximate minimum total network power consumption by solving the problem (23).

3) BINARY SEARCH-BASED SCHEME

Based on the ascending order $\bar{\omega}_1\leq\bar{\omega}_2\leq\cdots\leq\bar{\omega}_L$, we adopt a binary search-based JRARCoBF algorithm to minimize the power consumption and obtain the associated active RRH set and beamforming vectors. Specifically, the proposed JRARCoBF algorithm is summarized in Algorithm 1.

Algorithm 1 Proposed JRARCoBF Algorithm

1: Solve the problem (28):
  1) **If** it is feasible, output $\mathbf{W}_i^\star$, $\forall i\in\mathcal{I}$ and the associated beamforming vector $\mathbf{w}_i^\star$, calculating the priority parameter ω_l for each RRH according to (29), and sort them in ascending order $\bar{\omega}_1\leq\bar{\omega}_2\leq\cdots\leq\bar{\omega}_L$;
  2) **Else**, go to End;
2: Set $\ell=0$, $\ell_{\mathrm{low}}=0$, $\ell_{\mathrm{up}}=L$;
3: **Repeat**; Set $\ell\leftarrow\lfloor(\ell_{\mathrm{low}}+\ell_{\mathrm{up}})/2\rfloor$; Solve the problem (23) with $\mathcal{A}=\mathcal{A}_\ell$:;
  1) **If** it is feasible, set $\ell_{\mathrm{up}}=\ell$;
  2) **Else**, set $\ell_{\mathrm{low}}=\ell$;
4: **Until** $\ell_{\mathrm{up}}-\ell_{\mathrm{low}}=1$, obtain $\ell^\star=\ell_{\mathrm{low}}$ and the optimal active RRH set $\mathcal{A}_{\ell^\star}$;
5: Let $\mathcal{A}=\mathcal{A}_{\ell^\star}$, solve the problem (23), output $\mathbf{W}_i^\star$, $\forall i\in\mathcal{I}$ and the associated beamformers $\mathbf{w}_i^\star$
6: **End**

C. COMPLEXITY ANALYSIS

The computation cost of Algorithm 1 is primarily due to solving problem (23) and problem (28), which are the same convex problem with different dimensionality of variables. The convex problems with only SOC constraints and LMI can be solved by using the interior-point method (IPM) [40], [41]. To analyze the computational complexity of the proposed algorithm, a review of the basic elements of complexity analysis of IPMs is summarized in the sequel. Consider the following conic optimization problem:

$$\min_{\mathbf{x}\in\mathbb{R}^n} \boldsymbol{\nu}^T\mathbf{x} \tag{31a}$$

$$\text{s.t.} \sum_{i=1}^{n} x_i\mathbf{A}_i^j + \mathbf{B}^j \in \mathbb{S}_+^{k_j} \text{ for } j=1,\cdots,\iota, \tag{31b}$$

$$\mathbf{T}^j\mathbf{x} - \mathbf{b}^j \in \mathbb{K}^{k_j} \text{ for } j=\iota+1,\cdots,\tau. \tag{31c}$$

where $\boldsymbol{\nu} \in \mathbb{R}^n$, $\mathbf{A}_i^j$, $\mathbf{B}^j \in \mathbb{S}^{k_j}$ for $i = 1,\cdots,n$ and $j = 1,\cdots,\iota$, $\mathbf{T}^j \in \mathbb{R}^{k_j\times n}$ and $\mathbf{b}^j \in \mathbb{R}^{k_j}$ for $j = \iota+1,\cdots,\tau$, and $\mathbb{K}^{k_j}$ is an SOC of dimension k_j, i.e., $\mathbb{K}^k = \left\{\mathbf{x}\in\mathbb{R}^k \mid x_k \geq \sqrt{x_1^2+\cdots+x_{k-1}^2}\right\}$. We note that the linear constraint $\mathbf{a}^T\mathbf{x} - \mathbf{b} \geq 0$ is equivalent to the LMI constraint $\mathbf{a}^T\mathbf{x} - \mathbf{b} \in \mathbb{R}_+ = \mathbb{S}_+^1$, and thus can be transformed into the form (31b). As noted in [38], the complexity of a generic IPM for solving (31) consists of two parts:

1) OUTER ITERATION COMPLEXITY

For a given $\epsilon > 0$, the required number of iterations to reach an ϵ-optimal solution of (31) is on the order of

$$\sqrt{\Omega(\mathcal{K})}\cdot\ln(1/\epsilon), \tag{32}$$

where $\Omega(\mathcal{K}) = \sum_{j=1}^{\iota} k_j + 2(\tau-\iota)$ is a barrier parameter related to the cone $\mathcal{K}$. $\mathcal{K} = \prod_{j=1}^{\iota}\mathbb{S}_+^{k_j} \times \prod_{j=\iota+1}^{\tau}\mathbb{K}^{k_j}$ denotes the geometric complexity of the conic constraints in (31c).

2) INNER ITERATION COMPLEXITY

The search direction is found by solving $\bar{n}$ linear equations for $\bar{n}$ unknown variables in each inner iteration. The computational cost is primarily composed of the formation of the corresponding $\bar{n}\times\bar{n}$ coefficient matrix $\bar{\mathbf{H}}$ of $\bar{n}$ linear equations and the factorization of the coefficient matrix $\bar{\mathbf{H}}$. The order of the computational cost of forming the coefficient matrix $\bar{\mathbf{H}}$ for (31) is given by

$$C_{\text{form}} = \underbrace{\bar{n}\sum_{j=1}^{\iota}k_j^3 + \bar{n}^2\sum_{j=1}^{\iota}k_j^2}_{\text{due to (31b)}} + \underbrace{\bar{n}\sum_{j=\iota+1}^{\tau}k_j^2}_{\text{due to (31c)}}, \tag{33a}$$

and the order of the computational cost of factorizing the coefficient matrix $\bar{\mathbf{H}}$ for (31) is given by

$$C_{\text{fact}} = \bar{n}^3. \tag{34a}$$

Therefore, the order of the computational cost for each inner iteration is $C_{\text{form}} + C_{\text{fact}}$. By combining the computational costs of the outer and inner iterations, the order of the computational cost of a generic IPM for solving (31) can be expressed as

$$\sqrt{\Omega(\mathcal{K})}\cdot(C_{\text{form}} + C_{\text{fact}})\cdot\ln(1/\epsilon). \tag{35}$$

Note that the variables are complex-valued in (23) and (28); thus, the complex-valued SDPs need to be converted into the corresponding real-valued SDPs, which are the same problem as the former except for the doubled problem size. For simplicity, the variables in (28) and (23) are assumed to be real-valued. Assuming that there are L_s RRHs to be shut down, define $N = (L-L_s)N_R$. Then, the formula in (23) has $2I$ LMIs constraints of size N, $2I+M+L$ constraints of size 1, and I SOCs constraints of size N^2+N+1. Additionally, let $\bar{n}$ denote the number of decision variables in problem (23); $\bar{n}$ is on the order of IN^2. Consequently, the complexity of the IPM for solving (23) is on the order of

$$C_{(23)} = \sqrt{\Omega(\mathcal{K})}\cdot(C_{\text{form}} + C_{\text{fact}})\cdot\ln(1/\epsilon), \text{ (by (35))} \tag{36}$$

where ϵ denotes the predefined accuracy of the solution, and

$$\begin{aligned}
\Omega(\mathcal{K}) &= 2I(N+2)+M+L, \text{ (by (32))}\\
C_{\text{form}} &= \bar{n}(2I(N^3+1)+M+L)\\
&\quad+\bar{n}^2(2I(N^2+1)+M+L)\\
&\quad+\bar{n}(N^2+N+1)^2, \text{ (by (33a))}\\
C_{\text{fact}} &= \bar{n}^3. \text{ (by (34a))}
\end{aligned}$$

Using the same method, $C_{(28)}$ denotes the complexity order of the IPM of problem (28) with $\bar{n} = I(LN_R)^2$ and $N = LN_R$.

It is demonstrated that the dominant complexity of the proposed algorithm consists of two parts; the first is denoted by $C_{(28)}$; the second consists of an inner iteration and an outer iteration. The complexity order of an inner iteration is denoted by $C_{(23)}$, while the maximum number of outer iterations is logarithmic with L.

V. SIMULATION RESULTS

In this section, we use Monte Carlo simulations to demonstrate the effectiveness of the proposed JRARCoBF algorithm. Assume that the network coverage area is a sector centered at an MBS with the inner angle of 120°. MUEs are independently and uniformly distributed within the sector with a radius of 300 meters. RUEs are independently and uniformly distributed within the sector of a radius between 300 meters and 500 meters. RRHs are uniformly distributed along the arc of the radius of 400 meters. In addition, we assume that all MUEs and RUEs have the same target SINR, i.e., $\beta_m = \gamma_i = \gamma, \forall m \in \mathcal{M}, \forall i \in \mathcal{I}$; the SINR outage probabilities for all MUEs and RUEs are also identical, and are set to $\theta_m = \rho_i = 0.1, \forall m \in \mathcal{M}, \forall i \in \mathcal{I}$; the SINR satisfaction probabilities are higher than 90%.

In the simulations, we adopt the following channel model:

$$\mathbf{g}_{0m} = 10^{-\Gamma(d_{0m})/20}\sqrt{\varphi_{0m}\tau_{0m}}\mathbf{f}_{0m}, \tag{38a}$$

$$\mathbf{g}_{1i} = 10^{-\Gamma(d_{1i})/20}\sqrt{\varphi_{1i}\tau_{1m}}\mathbf{f}_{1i}, \tag{38b}$$

$$\mathbf{h}_{0li} = 10^{-\Gamma(d_{0li})/20}\sqrt{\varphi_{0li}\tau_{0li}}\mathbf{f}_{0li}, \tag{38c}$$

$$\mathbf{h}_{1lm} = 10^{-\Gamma(d_{1lm})/20}\sqrt{\varphi_{1lm}\tau_{1lm}}\mathbf{f}_{1lm}, \tag{38d}$$

where d_{0m} and d_{1i} denote the distances from the MBS to the m-th MUE and the i-th RUE, respectively; d_{1lm} and d_{0li} denote the distances from the l-th RRH to the m-th MUE and the i-th RUE, respectively. $\Gamma(d_{0m})$, $\Gamma(d_{1m})$, $\Gamma(d_{0li})$ and $\Gamma(d_{1lm})$ denote the path loss at distances d_{0m}, d_{1i}, d_{0li} and

TABLE 1. Simulation parameters.

Parameters	Values
γ (dB)	(1, 3, 5, 7, 9, 11, 13, 15)
Path loss at distance d (km)	148+37.6 $\log_2(d)$ dB
Standard deviation of shadowing	8 dB
Small-scale fading distribution	$\mathcal{CN}(\mathbf{0}, \mathbf{I})$
Bandwidth	10 MHz
Maximum transmit power of MBS	20 W
Maximum transmit power of RRH	1 W
PA efficiency η_l	30%
OLT power consumption of fronthaul links	20 W [1]
circuit power of antenna in sleep mode	10.65 W [1]
circuit power of antenna in active mode	5.05 W [1]
Number of antennas at MBS	32
Height of MBS	50 m
Height of RRH	30 m
Number of antennas at RRH	4
Number of MUEs	2
Number of RUEs	(5,10)
Number of RRHs	(5,10)

d_{1lm}, respectively. φ_{0m}, φ_{1i}, φ_{0il} and φ_{1ml} represent the shadowing coefficients; τ_{0m}, τ_{1i}, τ_{0li} and τ_{1lm} denote the antenna gains; $\mathbf{f}_{0m}$, $\mathbf{f}_{1i}$, $\mathbf{f}_{0li}$ and $\mathbf{f}_{1lm}$ represent the small-scale fading coefficients. Moreover, we assume that the MBS can obtain an accurate CSI, that RRHs can capture the large-scale fading, and that the CSI errors of the small-scale fading follow a complex Gaussian distribution with zero mean and the identical covariance matrix $\mathbf{C}_{0i} = \varepsilon^2 \mathbf{I}_{N_R}$, where ε^2 denotes the variance of CSI errors for the i-th RUE. The small-scale fading coefficients are generated randomly according to independent random variables following a complex Gaussian distribution. Moreover, the remaining parameters related to the simulation are provided in Table I. The simulation results are based on the statistical average of 500 channel realizations, where all the algorithms being tested yield feasible solutions. We compare the proposed algorithm to a conventional robust CoBF (RCoBF) algorithm, i.e., the RCoBF algorithm in which all RRHs are active [42]. Furthermore, we present the performance of the beamforming design with SINR constrained in the case of the perfect CSI and use it as a benchmark [43], while the respective algorithm is called the perfect CSI algorithm in the remainder of the paper.

Fig. 2 shows the feasibility rates of the JRARCoBF algorithm under various channel errors vs. the target SINR γ with

[1]These parameters are obtained from a practical energy consumption model, as shown in [33].

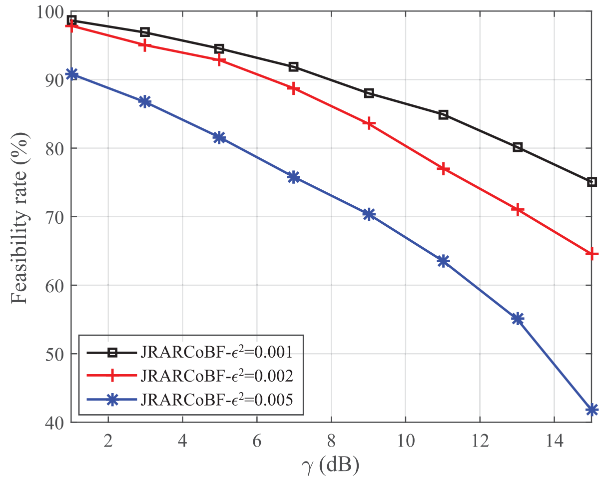

FIGURE 2. The feasibility rates at various channel errors with $L = 5$ and $I = 5$ for the JRARCoBF algorithm.

$L = 5$ and $I = 5$. It shows that the feasibility rate decreases with an increase of the target SINR γ and the channel error. Furthermore, the results show that the feasibility rates improve by approximately 70% at the $\gamma \le 9$ dB regime. In addition, we count the proportion of rank-one solutions among the feasible solutions related to the results shown in Fig. 2. Statistically, $\mathbf{W}_i^\star$ is considered a rank-one solution if the following conditions hold:

$$\frac{\lambda_{\max}\left(\mathbf{W}_i^\star\right)}{\mathrm{Tr}\left(\mathbf{W}_k^\star\right)} \ge 0.9999, i \in \mathcal{I}. \tag{39}$$

Fortunately, all the feasible solutions of 500 channel realizations are of rank one, indicating that the occurrence of high-rank solutions is very infrequent for the proposed algorithm; hence, the algorithm is feasible in practical systems.

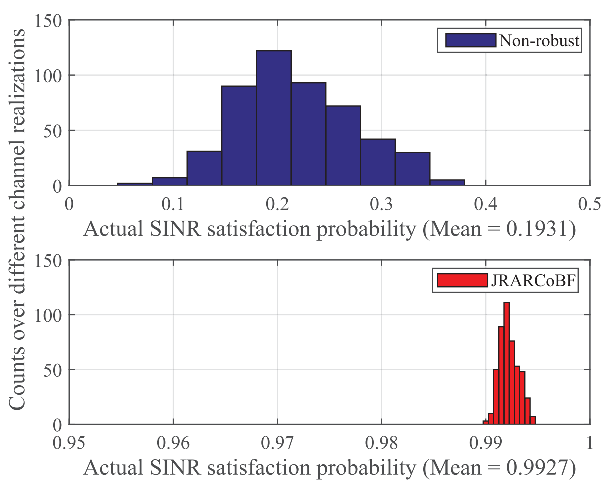

FIGURE 3. The actual SINR satisfaction probability at target SINR $\gamma = 9$ dB with $L = 5$, $I = 5$ and $\varepsilon^2 = 0.002$.

Fig. 3 shows the actual SINR satisfaction probability as a histogram, where the target SINR γ is 9 dB and $L = 5$, $I = 5$ and $\varepsilon^2 = 0.002$. In this figure, the non-robust algorithm is defined as the case of the channel estimation being regarded as perfect while channel estimation error still exists. The actual SINR satisfaction probability is defined as the probability that the minimum actual SINR for all MUEs and RUEs is higher than the target SINR by using the proposed algorithm. The conservatism with respect to the actual SINR satisfaction probability for the non-robust algorithm and the proposed algorithm is illustrated by histograms and the statistical results based on all feasible channel realizations associated with the results shown in Fig. 2. Fig. 3 shows that the actual SINR satisfaction probability of the non-robust algorithm is less than 38%, and the average satisfaction probability is only about 19% for all the channel realizations, which is far from the requirement of the target SINR satisfaction probability. This means that the non-robust algorithm cannot satisfy the outage probability constraints if CSI is imperfect. Additionally, we observe that the target SINR satisfaction probability of the JRARCoBF algorithm is indeed higher than 90% over all feasible channel realizations.

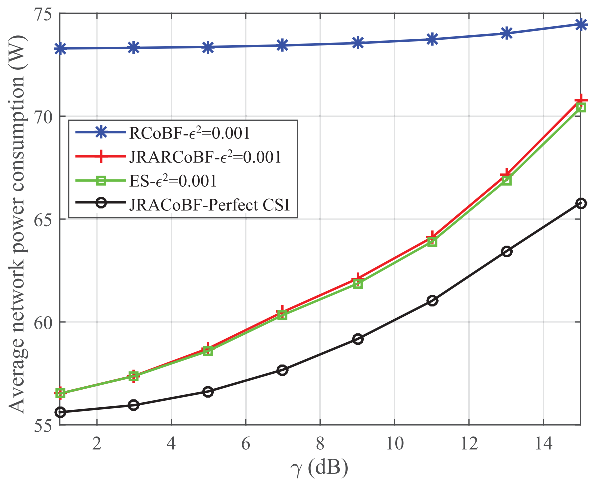

FIGURE 4. **Network power consumption of various algorithms with $L = 5$ and $I = 5$.**

Fig. 4 shows the network power consumption of various algorithms vs. the target SINR γ with $L = 5$, $I = 5$ and $\varepsilon^2 = 0.001$. Here, exhaustive search (ES) algorithm refers to the JRARCoBF based on exhaustive search. The figure shows that the performance of the proposed algorithm is very close to that of the ES algorithm while having a significantly reduced computational complexity [30]. In addition, compared with the RCoBF algorithm, the results show that the proposed algorithm has the potential to reduce the network power consumption by 26% in the low target SINR requirement and by 5% in the high target SINR requirement; this is because more RRHs need to be activated to meet the higher QoS requirement. Furthermore, the perfect CSI algorithm has the minimum power consumption due to extra power needed to compensate for the performance degradation caused by channel errors.

Fig. 5 shows the network power consumption of various algorithms and values of channel errors vs. the target SINR

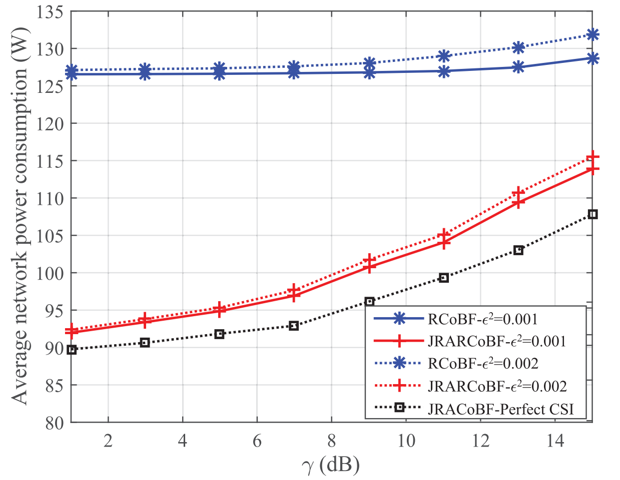

FIGURE 5. **Network power consumption of various algorithms with $L = 10$ and $I = 10$.**

γ with $L = 10$ and $I = 10$. Compared to the CoBF algorithm, the proposed algorithm has the potential to reduce the network power consumption by 28% in the low target SINR requirement and 9% in the high target SINR requirement for $\varepsilon^2 = 0.001$ and by 26% in the low target SINR requirement and 8% in the high target SINR requirement for $\varepsilon^2 = 0.002$. Moreover, additional power consumption would be needed for the proposed robust algorithm to accommodate the outage specification; the extra power increases gradually with the target SINRs for MUEs and RUEs. Furthermore, the results of Fig. 4 and Fig. 5 indicate that the proposed algorithm can further reduce the power consumption with the increase in the number of RRHs. Additionally, compared to $\varepsilon^2 = 0.001$, a slightly greater total network power consumption is needed at $\varepsilon^2 = 0.002$, just as expected.

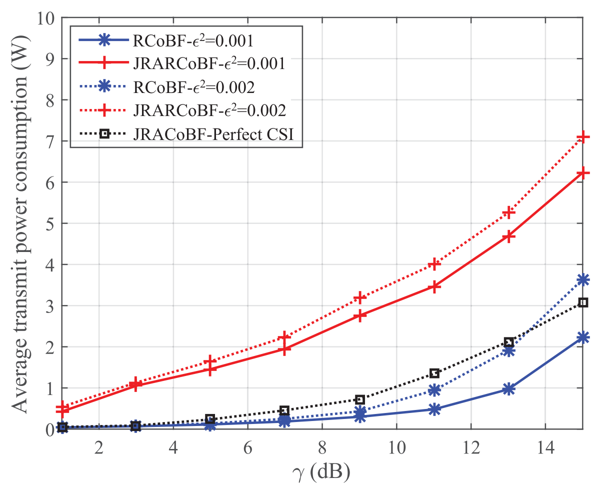

FIGURE 6. **The transmit power consumption of various algorithms vs. γ with $L = 10$ and $I = 10$.**

Fig. 6 and Fig. 7 depict the transmit power consumption and the circuit power consumption of the network, respectively. The figures show that the RCoBF algorithm has the

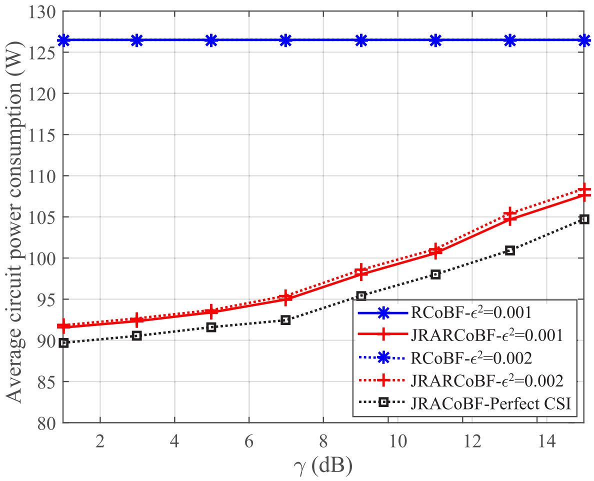

FIGURE 7. The circuit power consumption of various algorithms with $L = 10$ and $I = 10$.

lowest total transmit power consumption and yet the highest circuit power consumption. This is because the RCoBF algorithm only tries to minimize the transmit power consumption and neglects the considerable circuit power consumption including the transport link and RF circuit power consumption, so that all RRHs are activated for the maximum beamforming gain, while resulting in the highest total circuit power consumption.

TABLE 2. The average number of active RRHs at various target SINR γ and channel errors.

ε^2 \ γ	1	3	5	7	9	11	13	15
0.001	3.76	3.90	4.12	4.41	4.95	5.47	6.10	6.68
0.002	3.87	3.99	4.19	4.55	5.07	5.64	6.31	6.84

Table 2 lists the average number of active RRHs for various channel errors and target SINRs. The table shows that the proposed algorithm will shut down a larger number of RRHs with the increase in channel errors, indicating that a higher transmit power consumption and a larger number of active RRHs are needed to satisfy the QoS requirements and the outage specification. The result of Table 2 is in accordance with Fig. 6 and Fig. 7.

VI. CONCLUSION

In this paper, we present a joint RRH activation and outage-constrained CoBF algorithm for massive MIMO H-CRANs that aims to minimize the power consumption of the downlink in the presence of Gaussian CSI errors. The objective function and rate outage constraints under the RRH activation become complex, making it difficult to offer an intuitive solution. To overcome these difficulties, we first reformulated the objective function with a given active RRH set $\mathcal{A}$ and used an extended Bernstein-type inequality to rate outage constraints; then, we derived the beamforming vector by solving an SDP and presented a low-complexity JRARCoBF algorithm. Finally, the simulation results showed that the proposed algorithm effectively reduced the downlink network power consumption for various values $\varepsilon^2 = 0.001$ and 0.002, e.g., up to 28% and 26% in a low QoS requirement and 9% and 8% in a high QoS requirement, respectively. Compared to the ES algorithm, the proposed algorithm performs almost identically while accommodating certain error bounds and having a lower complexity.

APPENDIX
CONVEX APPROXIMATION FOR OUTAGE CONSTRAINTS

In view of the fact that Ψ (cf. (22)) is a monotonically decreasing function, and its inverse mapping is well defined as $\Psi^{-1} : \mathbb{R} \rightarrow \mathbb{R}_{++}$. By utilizing the characteristic that $e^{-\Psi^{-1}(-c_i)} > 0$ (where c_i is defined in (19c)) and Lemma 1, we have

$$\Pr\Big\{f(\boldsymbol{\delta}_1, \mathbf{Q}_i, \mathbf{r}_i) + c_i \geq 0\Big\} \geq 1 - e^{-\Psi^{-1}(-c_i)}, \quad (40)$$

which implies that $e^{-\Psi^{-1}(-c_i)} > 0$ is a conservative approximation over (18c), which can be rewritten as

$$\begin{aligned} &\mathrm{Tr}(\mathbf{Q}_i) + \ln(\rho_i) \cdot \lambda^+(\mathbf{Q}_i) \\ &\quad -\sqrt{2\ln\left(1/\rho_i\right)}\sqrt{\|\mathbf{Q}_i\|_F^2 + 2\|\mathbf{r}_i\|^2} + c_i \geq 0. \end{aligned} \quad (41)$$

According to the approach described in [38] and [44], the convex relaxation of (41) can be expressed by

$$\begin{aligned} \mathcal{C}_{\mathrm{R}}(\mathcal{A}) \triangleq \Big\{ &(\{\mathbf{W}_i\}, \mathbf{t}, \mathbf{a}) \Big| \mathrm{Tr}(\mathbf{Q}_i) + \ln\ (\rho_i)t_i + c_i \\ &- \sqrt{2\ln\left(1/\rho_i\right)} \left\| [a_i]^T \right\| \geq 0, \forall i \in \mathcal{I} \\ &\left\| \begin{bmatrix} \mathrm{vec}(\mathbf{Q}_i) \\ \sqrt{2}\mathbf{r}_i \end{bmatrix} \right\| \leq a_i, \forall i \in \mathcal{I} \\ &t_i \mathbf{I}_{LN_R} + \mathbf{Q}_i \succeq \mathbf{0}, t_i \geq 0, \forall i \in \mathcal{I} \Big\}, \end{aligned} \quad (42)$$

where $\mathbf{t} \triangleq [t_1, \cdots, t_I]^T \in \mathbb{R}^I$ and $\mathbf{a} \triangleq [a_1, \cdots, a_I]^T \in \mathbb{R}^I$, which are auxiliary variables. ∎

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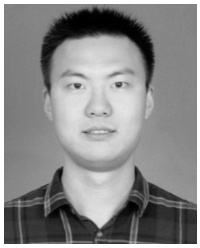

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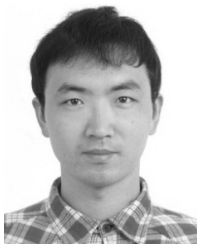

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