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A New Leakage-Based Precoding Scheme in IoT Oriented Cognitive MIMO-OFDM Systems

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ABSTRACT This paper considers physical layer interference management and network capacity improvement in Internet of Things (IoT)-oriented cognitive MIMO-OFDM systems, where the IoT devices access to the licensed spectrum by cognitive radio in spectrum underlay. Aiming to fully eliminate the interference to primary user as well as ensuring optimal QoS for all the cognitive IoT devices, in this paper, we propose a leakage-based precoding scheme with dimensionality reduction and SLNR criterion. More specifically, we first introduce a new channel estimation method using the multi-channel ratio algorithm that requires no feedback from the primary network. Second, with the estimated interference channel, we eliminate the interference to the primary user by a low complexity subspace projection with dimensionality reduction. Finally, by fully exploiting the generalized Rayleigh quotient, we propose the leakage-based precoding scheme that aims to optimize both the leakage power and noise power of the IoT devices. Theoretical and numerical results demonstrate that the proposed leakage-based precoding scheme can satisfy the low-cost and self-organized features of IoT networks, and achieves significant improvements on bit error rate performance and network capacity while causing no interference to the primary user.

INDEX TERMS Internet of Things (IoT), MIMO-OFDM, cognitive radio, signal-to-leakage-and-noise ratio (SLNR).

I. INTRODUCTION

Our society now is moving forward to an ''everything, everywhere and always connected'' future in which the users of the wireless system shift from individuals to things. To accommodate these challenges, researchers propose the concept of Internet of Things (IoT), which is expected to cater for a massive number of low-power plug and play devices with limited computational capabilities. Deployed by end users, IoT networks usually lack a predefined network infrastructure and utilize the internet backhaul, most of the time by wireless communication [1], [2]. With such a huge volume of IoT devices anticipated to be connected into the remaining wireless network, the IoT paradigm places an overwhelming demand on the spectrum resources [3]. Therefore, it is preferred for IoT network to share the licensed frequency band with the pre-existing primary network by cognitive radio [4].

Cognitive radio (CR) is proposed to enhance the efficient utilization of the radio spectrum, which enables cognitive users to opportunistically access to the licensed spectrum. Khan *et al.* [1] indicated that the things-oriented, Internet-oriented IoT are meaningless if IoT objects are not equipped with cognitive radio capability. The concept of cognitive radio is introduced into the IoT network, leading to an emerging research dimension of CR-based IoT [5]. It becomes an enabling technology that can meet future IoT spectrum demands by dynamically utilizing the vacant channels while ensuring uninterrupted primary network communications. Embedding CR into IoT networks is being viewed as a complement to existing efforts [6]–[8].

Traditional CR networks usually operate in spectrum overlay paradigm, where the cognitive users can utilize the licensed band only when primary user is non-active, and have to vacate the band once primary user arrives. In such paradigm, cognitive users need to perform spectrum sensing which is rather sophisticated for low cost IoT devices, and the network accessibility largely depends on the primary user activity [9]. Cooperative spectrum sensing methods with decision fusion center was proposed to enable simple devices jointly sense the licensed bands [10], [11]. However, due to the unplanned deployment of the plug and play devices, it would be costly for IoT networks to provide wireless cooperative links among these devices, which may introduce severe co-channel interference [12]. To overcome these challenges, with the help of interference management, the CR network can operate in the spectrum underlay paradigm. It allows simultaneous primary and cognitive communications, and achieves better spectral efficiency [13], [14]. As such underlay access is achieved mainly through the primary and cognitive network cooperation [15], and introduces multiuser interference, it is sort of overlooking the principle that CR cannot compromise on the performance of primary user [9]. Therefore, to design the efficient low-cost and self-organized cognitive precoding scheme becomes one of the key enablers for CR-based IoT network.

As CR-based IoT frameworks are still in their infancy, insufficient work has been done to identify efficient methodologies for low-cost plug and play IoT devices to utilize license spectrum while managing the interference to the license holder. Otermat *et al.* [5] indicated that the available spectrum becomes a limiting factor that is prevalent in all IoT applications. Moreover, the challenge of the interference amongst IoT devices can be alleviated by employing cognitive radio technology with proper precoding method [6]. Dai *et al.* [16] proposed cognitive MISO precoding algorithm based on the signal-to-leakage-and-noise ratio (SLNR) criterion. The authors just considered the scenario with a single secondary user, which can hardly be used in IoT network. Guler and Yener [17] focus on cognitive IoT network, and designed an interference alignment based iterative precoding method. With SDP approximation, the proposed algorithm minimizes the interference leakage by iterations between base station and cognitive users, and only achieves a fraction of the optimal capacity. Miridakis and Vergados [18] designed an MMSE based procoding scheme for MISO system to eliminate the co-channel interference by channel inversion. Nevertheless, when generalized to cognitive MIMO networks, the procoding causes interference to primary user and the computation complexity becomes unacceptable. Maso *et al.* [19] proposed an orthogonal precoding scheme named MU-VFDM. By exploiting the cooperation with primary user, the precoder is designed in cascaded linear structure and achieves better performance than the parallel precoding algorithms. Maso *et al.* [20] proposed a distributed cognitive interference alignment (DCIA) iterative precoding algorithm in absence of the cooperation. This DCIA algorithm only requires the local cognitive users to perform the spectrum sensing, reducing the overhead of channel estimation in cognitive M2M network. Studer and Durisi [21] developed a new quantized data detection algorithm for MIMO-OFDM networks to achieve trade-off between performance and complexity. Rossi *et al.* [22] considered the multiuser MIMO-OFDM system with iterative single-antenna receivers, and proposed a novel diagonal precoding (i.e. power allocation) scheme. By fully exploiting gain design at the receivers, the proposed scheme can hold more users, and makes network overloading feasible. Furthermore, for inter-carrier interference (ICI) in MIMO-OFDM system, Jin and Xia [23] indicated that ICI can be simply eliminated by a one-tap equalizer with the help of cyclic prefix (CP), and proposed an interference nulling based precoding scheme to cancel the ICI with insufficient CP. Sun *et al.* [24] proved that MIMO is helpful in mitigating the ICI, and proposed a new ICI/ISI-aware beamforming scheme in MIMO-OFDM system. Jin and Xia [25] proposed a robust precoder design based on channel statistics which can cancel the ICI with shortened CP, and minimize the average MMSE of the transmitted symbols.

As can be seen, for CR-based IoT, the existing physical layer precoding schemes usually manage the interference in a cooperative way which may degrade the performance of primary user, and most of the transceiver or iterative precoding methods are too complicated for low-cost IoT devices. Furthermore, due to the unplanned deployment and self-organizing features of IoT networks, it would be impractical to provide bidirectional links that meet the delay and latency requirements to ensure the cooperation [26].

Motivated by these observations, in this paper, we propose a leakage-based cognitive precoding scheme with low complexity that can satisfy the low-cost plug and play IoT networks. The main contributions of this paper can be summarized as follows.

- To estimate the interference channel without any cooperation or feedbacks from the primary user, a Multi-Channel Ratio decoding (MCR) based channel direction estimation approach is proposed to obtain the channel state information of the interference channel.
- With the estimated interference channel, a novel precoding method using subspace projection is proposed. Based on matrix dimensionality reduction, the proposed precoding method can fully eliminate the interference to the primary user with only a linear complexity to the number of cognitive users.
- Instead of zero-force the interference, we joint optimize the leakage interference and noise power among the cognitive users. By exploiting the generalized Rayleigh quotient, it can avoid the complicated optimization and further improves the degree of freedom in such system.
- Note that the entire coding process is performed at the cognitive base station without any coordination from the users. The proposed leakage-based precoding scheme can satisfy the low-cost and self-organized features of features of IoT networks, and achieves a considerably high network capacity while causing no interference to the primary user.

The rest of the paper is organized as follows. In Section II, system model is introduced with the interference elimination problem being formulated. In Section III, an improved leakage-based precoding scheme is proposed as a solution for the optimization problem. Simulation results are presented in Section IV, followed by the conclusions and future work given in Section V.

For the notation throughout this paper, we let we let a lower case italic symbol (e.g. x) denote a scalar value, a lower case bold italic symbol (e.g. $\boldsymbol{x}$) denote a vector, an upper case bold symbol (e.g. $\mathbf{X}$) denote a matrix. $\mathbf{I}_N$ denote the $N \times N$ identity matrix. $\mathrm{tr}\{\mathbf{A}\}$, $\mathrm{rank}\{\mathbf{A}\}$, $\mathbf{A}^T$ and $\mathbf{A}^H$ are the trace, rank, transpose and conjugate transpose of matrix $\mathbf{A}$, respectively. Moreover, $\mathbb{C}^{M\times N}$ denotes the space spanned by complex $M \times N$ matrices. $\|\boldsymbol{a}\|$ stands for the Euclidean 2-norm of the vector $\boldsymbol{a}$, $\mathbb{E}[\cdot]$ denotes the statistical expectation. All vectors are defined to be columns, and in vector and matrix definitions, subscript "p" refers to the primary tier.

II. SYSTEM MODEL AND PROBLEM FORMULATION

Without loss of generality, in this section, we consider the downlink of a centralized IoT oriented cognitive MIMO-OFDM system with N OFDM subcarriers, formed by a cognitive base station and K multi-antenna IoT devices (secondary users). In order to access to the licensed spectrum, the IoT oriented cognitive system coexists with a TDD-FDMA communication system which is formed by a primary base station and a primary user in each licensed band. Let N_T and $N_{r,k}$ denote the number of antenna at the cognitive base station and the k-th IoT device, respectively. The licensed base station is equipped with N_T transmitting antennas. Note that the transmit antennas can have different geometric structures, e.g., being placed along a line to form an uniform linear array (ULA), or along a circle to form a uniform circular array (UCA). Assuming that the multiple-antenna channels are subject to uncorrelated Rayleigh flat fading, the channel state information (CSI) of the IoT devices can be obtained at the cognitive base station by channel estimation with feedback [27].

Figure. 1 shows the IoT oriented cognitive system model. Note that, different with the traditional MIMO-OFDM underlay paradigm, we focus on the IoT oriented network with random deployed plug and play IoT devices, which lacks a predefined infrastructure and utilizes the wireless backhaul. It means that the cooperation among IoT nodes or between the primary and cognitive networks is not considered, and fully self-organized cognitive precoding scheme is needed. Furthermore, since IoT networks are expected to cater to a large number of low cost users, the coding process to manage the cognitive interference should be performed at the base station with low complexity, especially when the number of users becomes huge. Hence, interference alignment or iterative algorithms are not eligible for the proposed model. More specifically, in such model a cognitive base station communicates with several cognitive IoT users by MIMO-OFDM, and coexists with a primary network. As the primary network is assumed to run in TDD-FDMA, when accessing to a certain licensed band, the cognitive users are supposed to consider just the primary user in this band and the interference channel is denoted as $\boldsymbol{g}$ in the figure. Let the vector $\boldsymbol{s}_p$ denote the transmitted data intended for the primary user, and the data vector $\boldsymbol{s}_k \in \mathbb{C}^{N\times 1}, \boldsymbol{s}_k = [s_k(0), s_k(1), \cdots, s_k(N-1)]^T$

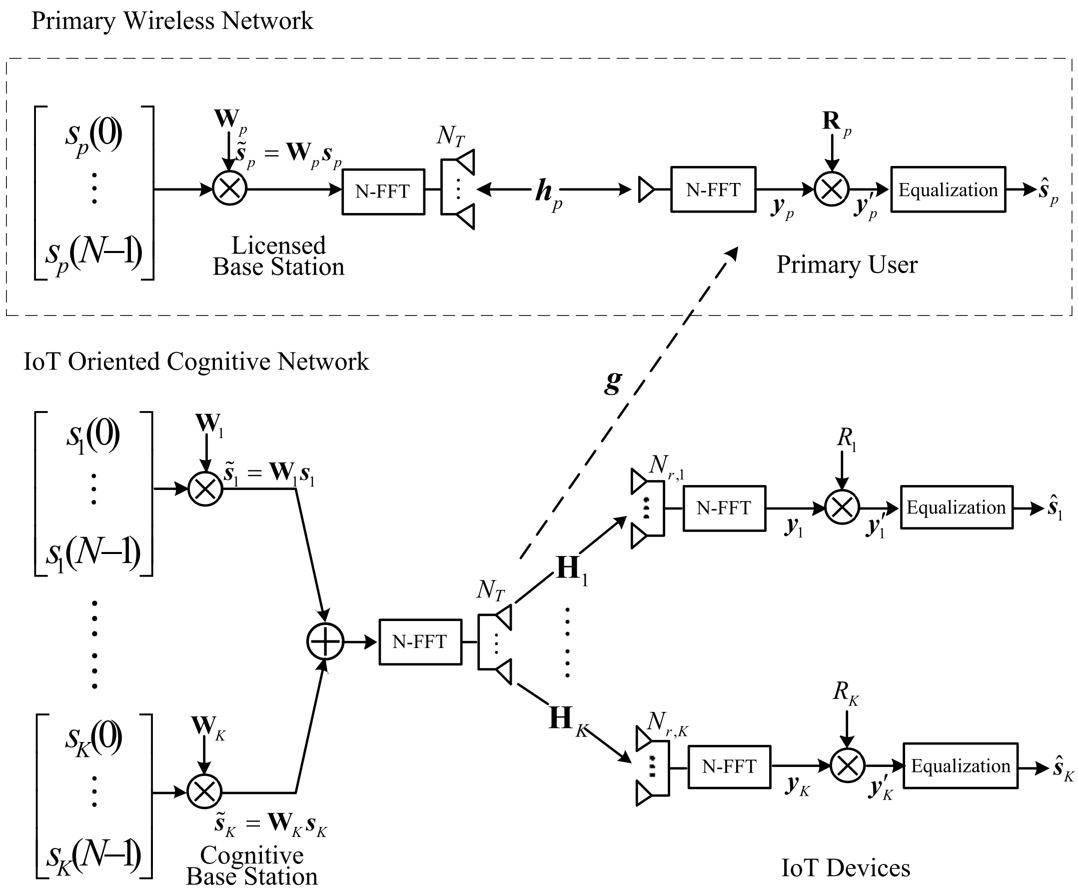

FIGURE 1. The model of IoT oriented cognitive MIMO-OFDM system downlink.

denotes the data for the k-th IoT device, where $s_k(i)$ is the symbol transmitted to device k on subcarrier i. For the k-th IoT device, the data $\boldsymbol{s}_k$ is multiplied by the $N_T N \times N$ precoding matrix $\mathbf{W}_k$, which results in the precoded vector $\tilde{\boldsymbol{s}}_k = \mathbf{W}_k \boldsymbol{s}_k$. The $N_T N \times 1$ elements of the vector $\tilde{\boldsymbol{s}}_k$ represent all the symbols for N_T transmitting antennas at N subcarriers. Both the data $\boldsymbol{s}_k$ and the precoding matrix $\mathbf{W}_k$ are assumed to be normalized as

$$\mathrm{E}\left\{\boldsymbol{s}_k \boldsymbol{s}_k^H\right\} = \mathbf{I}_N, \mathbf{tr}\left\{\mathbf{W}_k^H \mathbf{W}_k\right\} = 1, \quad \text{for } k = \{1, 2, \cdots, K\}. \tag{1}$$

After precoding, the N-point IFFT operation is applied to the precoded data. In order to generate the OFDM symbols, we first get the sum of the precoded vectors and then perform multiplication operation with the Fourier transform matrix $\mathbf{F}_{N_T}^H \in \mathbb{C}^{N_T N \times N_T N}$. Such that, we can get the Fourier transformed data vector $\boldsymbol{x}$ which is transmitted via the MIMO channels as

$$\boldsymbol{x} = \mathbf{F}_{N_T}^H \sum_{k=1}^{K} \tilde{\boldsymbol{s}}_k = \mathbf{F}_{N_T}^H \sum_{k=1}^{K} \mathbf{W}_k \boldsymbol{s}_k, \tag{2}$$

where the matrix $\mathbf{F}_{N_T}^H = \mathbf{F} \otimes \mathbf{I}_{N_T}$, here $\mathbf{F}$ is the regular N-point FFT matrix and operator $\otimes$ denotes the Kronecker product operator.

Consider the wide-band multipath channels in such system. Let vector $\boldsymbol{g} \in \mathbb{C}^{N \times 1}$ and $\boldsymbol{h}_p \in \mathbb{C}^{N \times 1}$ are the channel vectors of the interference link and primary link, respectively, and matrix $\mathbf{H}_k \in \mathbb{C}^{N_{r,k} \times N_T}$, for $k = \{1, 2, \cdots, K\}$ denote the channel matrix of the cognitive links. Note that the channels of primary and cognitive links are both standard independent identically distributed (i.i.d) Rayleigh fading channels that $\mathbf{g}$, $\boldsymbol{h}_p \sim \mathbb{C}N(0, \sigma^2 I_{N_T})$. For the channel matrix $\mathbf{H}_k$, we consider the Rayleigh channel with NeSH model [28] and one-ring MIMO channel model in [29], which can be represented as

$$\mathbf{H} = \mathbf{R}_{RX}^{1/2} \mathbf{H}_{iid} \mathbf{R}_{TX}^{1/2}, \tag{3}$$

where the $\mathbf{H}_{iid}$ is an ideal Rayleigh channel matrix, $\mathbf{R}_{RX}^{1/2}$ and $\mathbf{R}_{TX}^{1/2}$ are the compensator matrices at the receiver and the transmitter, respectively. The details of the MIMO channel model are shown in Appendix A. Without loss of generality, we assume that the multipath channels are slow-fading. Such that, in an entire transmitting packet length, the channel's parameters can be seen as quasi-static, and the cognitive base station can obtain the channel state information (CSI) of the IoT devices by channel estimation.

With the proposed system model, the signals received by the primary user and IoT devices can be given by

$$\boldsymbol{r}_p = \boldsymbol{h}_p \mathbf{W}_p s_p + \boldsymbol{g} \sum_{k=1}^{K} \mathbf{W}_k \boldsymbol{s}_k + \boldsymbol{v}_p, \tag{4}$$

$$\begin{aligned} \boldsymbol{r}_k &= \mathbf{H}_k \mathbf{F}_{N_T}^H \sum_{i=1}^{K} \mathbf{W}_i \boldsymbol{s}_i + \boldsymbol{v}_k \\ &= \mathbf{H}_k \mathbf{F}_{N_T}^H \mathbf{W}_k \boldsymbol{s}_k + \mathbf{H}_k \mathbf{F}_{N_T}^H \sum_{i=1, i\neq k}^{K} \mathbf{W}_i \boldsymbol{s}_i + \boldsymbol{v}_k, \end{aligned} \tag{5}$$

where the vectors $\boldsymbol{v}_p$ and $\boldsymbol{v}_k$, for $k = \{1, 2, \cdots, K\}$, are the additive complex white Gaussian noise vectors received at the primary user and IoT devices, respectively. The elements of these vectors are independent complex Gaussian random variables with variance σ_p^2 and σ_k^2.

With the received data, IoT devices perform the N-point FFT operation to demodulate the OFDM symbols as follows

$$\begin{aligned} \boldsymbol{y}_k &= \mathbf{F}_{N_{r,k}} \boldsymbol{r}_k, \quad \text{for } k = 1, 2, \cdots, K \\ &= \mathbf{F}_{N_{r,k}} \mathbf{H}_k \mathbf{F}_{N_T}^H \sum_{i=1}^{K} \mathbf{W}_i \boldsymbol{s}_i + \mathbf{F}_{N_{r,k}} \boldsymbol{v}_k \\ &= \mathbf{F}_{N_{r,k}} \mathbf{H}_k \mathbf{F}_{N_T}^H \mathbf{W}_k \boldsymbol{s}_k + \mathbf{F}_{N_{r,k}} \mathbf{H}_k \mathbf{F}_{N_T}^H \sum_{i=1, i\neq k}^{K} \mathbf{W}_i \boldsymbol{s}_i + \mathbf{F}_{N_{r,k}} \boldsymbol{v}_k \\ &= \mathbf{G}_k \mathbf{W}_k \boldsymbol{s}_k + \mathbf{G}_k \sum_{i\neq k}^{K} \mathbf{W}_i \boldsymbol{s}_i + \boldsymbol{n}_k, \end{aligned} \tag{6}$$

where $\mathbf{G}_k = \mathbf{F}_{N_r} \mathbf{H}_k \mathbf{F}_{N_T}^H$ is the equivalent frequency domain channel, which can be represented as

$$\mathbf{G}_k = \begin{bmatrix} G_k^{(1,1)} & G_k^{(1,2)} & \cdots & G_k^{(1,N)} \\ G_k^{(2,1)} & G_k^{(2,2)} & \cdots & G_k^{(2,N)} \\ \vdots & \vdots & \ddots & \vdots \\ G_k^{(N,1)} & G_k^{(N,2)} & \cdots & G_k^{(N,N)} \end{bmatrix}, \tag{7}$$

and $\boldsymbol{n}_k = \mathbf{F}_{N_{r,k}} \boldsymbol{v}_k$ is the equivalent frequency domain additive Gaussian noise. It can be drawn from equation (5) and (6) that the OFDM process, that is, the IFFT and FFT operation at the transmitter and the receiver side can be simplified to a frequency-domain model with the equivalent channel matrix $\mathbf{G}_k$. Note that as mentioned in [21], the ICI caused by the OFDM in this paper can be simply eliminated by a one-tap equalizer with the help of cyclic prefix. Since the Fourier transform matrix $\mathbf{F}$ is a unitary matrix, the encoding and decoding of the signals won't be affected by the equivalence.

As can be seen from equation (6), the second term $\mathbf{G}_k \sum_{i\neq k}^{K} \mathbf{W}_i \boldsymbol{s}_i$ is the co-channel interference among the IoT devices and proper precoding scheme is needed to suppress the interference. One possible way to design the precoding scheme would be to optimize the received data using the signal-to-interference-plus-noise ratio (SINR) criterion. However, the SINR based precoding scheme is prohibitively computational complex and will not lead to a closed-form solution [30]. In [31], the signal-to-leakage-plus-noise ratio (SLNR) criterion was proposed to decouple the SINR optimization problem into K separated sub-problems. However, without cooperative communication, the signal intended for one IoT device can be seen as interference to other devices. The interference power, which is known as the leakage power [32], [33], can be written as

$$P_{Leak,k} = \sum_{i=1, i\neq k}^{K} \|\mathbf{G}_i \mathbf{W}_k \boldsymbol{s}_k\|^2 = \left\|\overline{\mathbf{G}}_i \mathbf{W}_k \boldsymbol{s}_k\right\|^2, \tag{8}$$

where the matrix $\bar{\mathbf{G}}_k = [\mathbf{G}_1 \cdots \mathbf{G}_{k-1}\mathbf{G}_{k+1} \cdots \mathbf{G}_K]^T$ is an extended channel matrix that excludes $\mathbf{G}_k$ only. The interference power caused by device k to user i's received signal can be written as $\|\mathbf{G}_i\mathbf{W}_k\boldsymbol{s}_k\|^2$. Then the SLNR expression of device k is given by

$$\begin{aligned} SLNR_k &= \frac{\|\mathbf{G}_k\mathbf{W}_k\boldsymbol{s}_k\|^2}{N_{r,k}\sigma_k^2 + \sum\limits_{i=1,i\neq k}^{K} \|\mathbf{G}_i\mathbf{W}_k\boldsymbol{s}_k\|^2} \\ &= \frac{E\left[\boldsymbol{s}_k^H\mathbf{W}_k^H\mathbf{G}_k^H\mathbf{G}_k\mathbf{W}_k\boldsymbol{s}_k\right]}{N_{r,k}\sigma_k^2 + E\left[\sum_{i\neq k}\sum_{j\neq k}\boldsymbol{s}_k^H\mathbf{W}_k^H\mathbf{G}_i^H\mathbf{G}_j\mathbf{W}_k\boldsymbol{s}_k\right]} \\ &= \frac{\mathrm{tr}\left(\mathbf{W}_k^H\mathbf{G}_k^H\mathbf{G}_k\mathbf{W}_k\right)}{\mathrm{tr}\left(\mathbf{W}_k^H\left(N_{r,k}\sigma_k^2\mathbf{I} + \bar{\mathbf{G}}_k^H\bar{\mathbf{G}}_k\right)\mathbf{W}_k\right)}. \end{aligned} \tag{9}$$

With the proposed SLNR criterion, here we aim to design the optimal precoding matrix $\mathbf{W}_k$ at the cognitive base station, so as to maximize the IoT devices' leakage power ratio, as well as to eliminate the co-channel interference to the primary user. With the power constraint, the transmit power threshold is given and the precoding matrix $\mathbf{W}_k$, for $k = \{1, \cdots, K\}$, can be obtained by solving the following optimization problem (**P1**)

$$\begin{aligned} \mathbf{W}_k^{opt} &= \arg\max_{W_k}\{SLNR_k\} \\ &= \arg\max_{W_k}\left\{\frac{\mathrm{tr}\left(\mathbf{W}_k^H\mathbf{G}_k^H\mathbf{G}_k\mathbf{W}_k\right)}{\mathrm{tr}\left(\mathbf{W}_k^H\left(N_{r,k}\sigma_k^2\mathbf{I} + \bar{\mathbf{G}}_k^H\bar{\mathbf{G}}_k\right)\mathbf{W}_k\right)}\right\} \end{aligned} \tag{10}$$

Subject to

$$\boldsymbol{g}\mathbf{W}_k = 0 \tag{11}$$

$$\mathrm{tr}\left(\mathbf{W}_k^H\mathbf{W}_k\right) = 1, \quad for\ k = 1, 2, \cdots, K, \tag{12}$$

where the equation (10) is the objective function, and the equations (11) and (12) are the interference constraint and the power constraint, respectively. We see that **P1** is a quasi-convex optimization problem that has the global optimal, its objective function can be converted to a constrained convex minimization problem [34], and the interference constraint and power constraint also define a convex set over $\mathbf{W}_k$. Based on the proposed optimization problem, we design a leakage-based precoding scheme as a solution to the optimization problem above. Details of the proposed scheme will be given in the next section.

III. LEAKAGE-BASED PRECODING SCHEME DESIGN

With the leakage based problem formulated in section II, we next focus on the optimization problem **P1** and aim to propose an effective precoding scheme for cognitive IoT networks.

We first consider the problem **P1** with just the interference constraint (11). To fully eliminate the co-channel interference to the primary user, the cognitive base station needs to obtain the CSI of the interference channel. Since it is not guaranteed that the licensed system has cooperation with the cognitive system, the cognitive base station can hardly rely on the feedback from primary user to estimate the interference channel. Here, we propose to use the Multi-Channel Ratio decoding (MCR) algorithm in anti-jamming communication system to obtain the CSI of the interference channel.

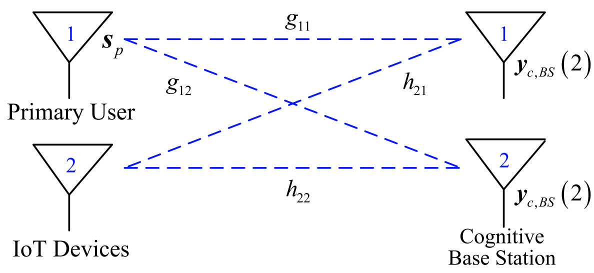

FIGURE 2. The Multi-Channel Ratio detection, $h_{i,j}/g_{i,j}$ is the channel coefficient for transmitter antenna i and receiver antenna j, include channel attenuation and phase shift.

The basic idea of MCR decoding is to fully exploit the ratio of the signal power detected on different antennas (i.e., the ratio of channel coefficients) in MIMO communications, so as to detect and estimate the interference channel [35]. Figure. 2 shows a simplified illustration of MCR with two pairs of antennas, note that it can easily be generalized to the case of multiple antennas. At first, the cognitive base station does not know the interference channel $\boldsymbol{g}_{11}$ and $\boldsymbol{g}_{12}$. As the primary users operate in Time Division Duplex (TDD), in the uplink timeslot, the cognitive base station remains silent while the primary user is transmitting. Such that, the cognitive base station can detect the signal $\boldsymbol{s}_p$ emitted by the primary user, and get the multi-path ratios of the received signals transmitted via diverse paths. The ratios represent the channel direction in Euclidean space, and we can project the cognitive interference to the orthogonal subspace of it. More specifically, the signals received by the cognitive base station's two antennas can be written as $\boldsymbol{y}_{c,BS}(1)$ and $\boldsymbol{y}_{c,BS}(2)$, respectively. As the signal to noise ratio (SNR) is high enough, ignoring the white noise, we have

$$\begin{cases} \boldsymbol{y}_{c,BS}(1) = \boldsymbol{g}'_{11}e^{j2\pi\Delta f_s t_i}\cdot\boldsymbol{s}_p \\ \boldsymbol{y}_{c,BS}(2) = \boldsymbol{g}'_{12}e^{j2\pi\Delta f_s t_i}\cdot\boldsymbol{s}_p, \end{cases} \tag{13}$$

where Δf_s is the frequency offset between the cognitive base station and the primary user, and t_i is the sampling time. Note that $e^{j2\pi\Delta f_s t_i}$ is the phase shift of the interference channel in its polar form and it can be compensated using phase-locked loop. We use φ to represent the MCR of the two channels as

$$\varphi = \frac{\boldsymbol{g}'_{11}}{\boldsymbol{g}'_{12}} = \frac{\boldsymbol{y}_{c,BS}(1)}{\boldsymbol{y}_{c,BS}(2)}. \tag{14}$$

Here, φ is the ratio of the channel coefficients. It is worth noting that φ does not rely on the primary signals. In other words, if the primary user does not move, φ should remain the same over a short period time (e.g., several ms). While in the next several downlink timeslots, due to the uplink-downlink duality, we can get the interference channel represented as $\boldsymbol{g} = \gamma(1, \varphi)$, where γ is the scale factor. When generalized to the case of multi-antenna, we can also estimate the interference channel in the same way as $\boldsymbol{g} = \gamma\left(1, \varphi_2, \varphi_3, \cdots, \varphi_{N_T}\right)$, and φ_i is the ratio of the received signal at antenna i to the signal at antenna 1.

Since the interference channel to the primary user is a MISO channel, the rank of the interference channel vector $\boldsymbol{g}$ equals to 1. There exists a matrix $\mathbf{P} \in \mathbb{C}^{N_T}$ that satisfies the equation

$$\begin{aligned} \boldsymbol{g}\mathbf{P} &= \gamma\left(1, \varphi_2, \varphi_3, \cdots, \varphi_{N_T}\right)\mathbf{P} \\ &= \gamma\left(\frac{\|\boldsymbol{g}\|}{\gamma}, 0, \cdots, 0\right), \end{aligned} \tag{15}$$

where the matrix $\mathbf{P}$ is an unitary one and has the unitarily invariant norm property that $\mathbf{P}\mathbf{P}^H = \mathbf{I}$ and $\|\mathbf{P}\mathbf{X}\|_2 = \|\mathbf{X}\|_2$ for $\forall \mathbf{X} \in \mathbb{C}^{N_T}$. Substitute equation (15) into the interference constraint (11), the constraint can be rewritten as

$$\begin{aligned} \boldsymbol{g}\mathbf{W}_k &= \boldsymbol{g}\mathbf{P}\mathbf{P}^H\mathbf{W}_k \\ &= \left(\|\boldsymbol{g}\|, 0, \cdots, 0\right)\mathbf{P}^H\mathbf{W}_k \\ &= 0. \end{aligned} \tag{16}$$

As the rank of $\boldsymbol{g}$ equals to 1, the Euclid norm of the interference channel vector has a nonzero value, i.e., $\|\boldsymbol{g}\| \neq 0$. In order to satisfy the constraint (11), all the elements in the first row of the matrix $\mathbf{P}^H\mathbf{W}_k$ should be zero. Assuming that $\tilde{\mathbf{W}}_k = \mathbf{P}^H\mathbf{W}_k$, pre-multiply the unitary matrix $\mathbf{P}$ on both sides of the equation, we get $\mathbf{W}_k = \mathbf{P}\tilde{\mathbf{W}}_k$. Substitute it into optimization problem **P1**, and the constraint (11) becomes inactive.

With the cognitive interference fully eliminated by the precoder $\tilde{\mathbf{W}}_k$, we next optimize the simplified problem **P2** with only the transmitting power constraint (12) as:

$$\tilde{\mathbf{W}}_k^{opt} = \arg\max_{\tilde{W}_k}\left\{\frac{\operatorname{tr}\left(\tilde{\mathbf{W}}_k^H\tilde{\mathbf{G}}_k^H\tilde{\mathbf{G}}_k\tilde{\mathbf{W}}_k\right)}{\operatorname{tr}\left(\tilde{\mathbf{W}}_k^H\left(N_{r,k}\sigma_k^2\mathbf{I} + \tilde{\bar{\mathbf{G}}}_k^H\tilde{\bar{\mathbf{G}}}_k\right)\tilde{\mathbf{W}}_k\right)}\right\} \tag{17}$$

Subject to

$$\operatorname{tr}\left(\mathbf{W}_k^H\mathbf{W}_k\right) = 1, \quad for\ k = 1, 2, \cdots, K, \tag{18}$$

where $\tilde{\mathbf{G}}_k = \mathbf{P}^H\mathbf{G}_k$ and $\tilde{\bar{\mathbf{G}}}_k = \mathbf{P}^H\bar{\mathbf{G}}_k$, for $k = 1, 2, \cdots, K$.

Since all the elements in the first row of matrix $\tilde{\mathbf{W}}_k$ equal to zero, we can reduce the dimension by just removing the first row of $\tilde{\mathbf{W}}_k$. In the objective function (17), the first column of the equivalent channel matrix $\tilde{\mathbf{G}}_k$ is multiplied by the first row of $\tilde{\mathbf{W}}_k$, the first column of $\tilde{\mathbf{G}}_k$ also can be removed. Note that the operation of dimensionality reduction will not affect the final result as the removed elements are all zeros. Let superscript $(\cdot)^-$ denote the transformed matrix that already gets its first row or column removed. The Problem **P2** can be transformed into an equivalent problem and the final precoding matrix $\tilde{\mathbf{W}}_k^{-opt}$ can be obtained by solving the problem **P3**,

$$\tilde{\mathbf{W}}_k^{-opt} = \arg\max_{\tilde{\mathbf{W}}_k^-}\left\{\frac{\operatorname{tr}\left(\tilde{\mathbf{W}}_k^{-H}\tilde{\mathbf{G}}_k^{-H}\tilde{\mathbf{G}}_k^-\tilde{\mathbf{W}}_k^-\right)}{\operatorname{tr}\left(\tilde{\mathbf{W}}_k^{-H}\left(N_{r,k}\sigma_k^2\mathbf{I} + \tilde{\bar{\mathbf{G}}}_k^{-H}\tilde{\bar{\mathbf{G}}}_k^-\right)\tilde{\mathbf{W}}_k^-\right)}\right\} \tag{19}$$

Subject to

$$\operatorname{tr}\left(\tilde{\mathbf{W}}_k^{-H}\tilde{\mathbf{W}}_k^-\right) = 1, \quad for\ k = 1, 2, \cdots, K. \tag{20}$$

Although this optimization problem involves the process of OFDM, a similar mathematical optimization problem can be found in the generalized Rayleigh quotient as shown in Appendix B. Instead of using the Lagrange multiplier, we can derive the solution to the optimization problem **P3** by exploiting the generalized Rayleigh quotient and design the transformed precoding matrix $\tilde{\mathbf{W}}_k^{-opt}$ as

$$\tilde{\mathbf{W}}_k^{-opt} = \mathbf{V}_k\mathbf{U}_k, \tag{21}$$

where $\mathbf{U}_k$ is an N-dimension unitary matrix with arbitrary value, and the column vectors of $\mathbf{V}_k = \left\{\boldsymbol{v}_{k,1}, \boldsymbol{v}_{k,2}, \cdots, \boldsymbol{v}_{k,N}\right\}$ are the N bases of the generalized eigen-space which is formed by the generalized eigenvectors of matrices $\tilde{\mathbf{G}}_k^{-*}\tilde{\mathbf{G}}_k^-$ and $N_{r,k}\sigma_k^2\mathbf{I} + \tilde{\bar{\mathbf{G}}}_k^{-H}\tilde{\bar{\mathbf{G}}}_k^-$. The generalized eigen-space satisfies that

$$\tilde{\mathbf{G}}_k^{-H}\tilde{\mathbf{G}}_k^-\mathbf{V}_k = \left(N_{r,k}\sigma_k^2\mathbf{I} + \tilde{\bar{\mathbf{G}}}_k^{-H}\tilde{\bar{\mathbf{G}}}_k^-\right)\mathbf{V}_k\boldsymbol{\Lambda}_k. \tag{22}$$

With elementary matrix operations, from equation (22), we can get

$$\begin{aligned} \mathbf{V}_k^H\tilde{\mathbf{G}}_k^{-H}\tilde{\mathbf{G}}_k^-\mathbf{V}_k &= \boldsymbol{\Lambda}_k \\ \mathbf{V}_k^H\left(N_{r,k}\sigma_k^2\mathbf{I} + \tilde{\bar{\mathbf{G}}}_k^{-H}\tilde{\bar{\mathbf{G}}}_k^-\right)\mathbf{V}_k &= \mathbf{I}, \end{aligned} \tag{23}$$

in which $\boldsymbol{\Lambda}_k = diag\left\{\lambda_{k,1}, \lambda_{k,2}, \cdots, \lambda_{k,N}\right\}$ is the generalized eigenvalues corresponding to the largest N generalized eigenvectors in $\mathbf{V}_k = \left\{\boldsymbol{v}_{k,1}, \boldsymbol{v}_{k,2}, \cdots, \boldsymbol{v}_{k,N}\right\}$. Substitute the equation (21), (22) and (23) to the objective function (19), we obtain that

$$\begin{aligned} &\frac{\operatorname{tr}\left(\tilde{\mathbf{W}}_k^{-H}\tilde{\mathbf{G}}_k^{-H}\tilde{\mathbf{G}}_k^-\tilde{\mathbf{W}}_k^-\right)}{\operatorname{tr}\left(\tilde{\mathbf{W}}_k^H\left(N_{r,k}\sigma_k^2\mathbf{I} + \tilde{\bar{\mathbf{G}}}_k^{-H}\tilde{\bar{\mathbf{G}}}_k^-\right)\tilde{\mathbf{W}}_k\right)} \\ &= \frac{\operatorname{tr}\left(\mathbf{U}_k^H\mathbf{V}_k^H\tilde{\mathbf{G}}_k^{-H}\tilde{\mathbf{G}}_k^-\mathbf{V}_k\mathbf{U}_k\right)}{\operatorname{tr}\left(\mathbf{U}_k^H\mathbf{V}_k^H\left(N_{r,k}\sigma_k^2\mathbf{I} + \tilde{\bar{\mathbf{G}}}_k^{-H}\tilde{\bar{\mathbf{G}}}_k^-\right)\mathbf{V}_k\mathbf{U}_k\right)} \\ &= \frac{\operatorname{tr}\left(\mathbf{V}_k^H\tilde{\mathbf{G}}_k^{-H}\tilde{\mathbf{G}}_k^-\mathbf{V}_k\right)}{\operatorname{tr}\left(\mathbf{V}_k^H\left(N_{r,k}\sigma_k^2\mathbf{I} + \tilde{\bar{\mathbf{G}}}_k^{-H}\tilde{\bar{\mathbf{G}}}_k^-\right)\mathbf{V}_k\right)} \\ &= \frac{\operatorname{tr}\left(\boldsymbol{\Lambda}_k\right)}{\operatorname{tr}\left(\mathbf{I}\right)} = \frac{1}{N}\sum_{n=1}^{N}\lambda_{k,n}. \end{aligned} \tag{24}$$

In order to maximize the transformed objective function (24), we choose the largest N generalized eigenvectors as the columns of matrix $\mathbf{V}_k$ to get the optimal precoding matrix $\tilde{\mathbf{W}}_k^{-opt} = \mathbf{V}_k \mathbf{U}_k$, thus leading to the property that the value range of (25) can be given as

$$\lambda_{k,N} \leq \frac{\mathrm{tr}\left(\tilde{\mathbf{W}}_k^{-H} \tilde{\mathbf{G}}_k^{-H} \tilde{\mathbf{G}}_k^{-} \tilde{\mathbf{W}}_k^{-}\right)}{\mathrm{tr}\left(\tilde{\mathbf{W}}_k^{H}\left(N_{r,k}\sigma_k^2 \mathbf{I} + \tilde{\tilde{\mathbf{G}}}_k^{-H} \tilde{\tilde{\mathbf{G}}}_k^{-}\right)\tilde{\mathbf{W}}_k\right)} \leq \lambda_{k,1}. \quad (25)$$

We can see that, instead of using the Lagrange multiplier and KKT conditions, the SLNR based design exploits the generalized Rayleigh quotient and avoids the complicated joint optimization of the precoding matrix.

Based on the aforementioned analysis, for the k-th IoT device, the optimal precoding scheme of the original Problem **P1** can be finally obtained as

$$\mathbf{W}_k^{opt} = \mathbf{P}\begin{pmatrix} \mathbf{0} \\ \beta_k \left\{ \boldsymbol{v}_{k,1}, \boldsymbol{v}_{k,2}, \cdots, \boldsymbol{v}_{k,N} \right\} \end{pmatrix}. \quad (26)$$

Here we let $\mathbf{U} = diag\{\beta_1, \cdots, \beta_k\}$ as the power allocation factor which can be obtained by the water-filling algorithm. Since the matrix $\mathbf{P} \in \mathbb{C}^{N_T}$ is an unitary matrix, the optimal precoding matrix in (10) has the unitarily invariant norms that

$$\begin{aligned} \left\|\mathbf{W}_k^{opt}\right\|_2 &= \mathrm{Tr}\left(\begin{pmatrix} \mathbf{0} \\ \beta_k \mathbf{V}_k \end{pmatrix}^H \mathbf{P}^H \mathbf{P} \begin{pmatrix} \mathbf{0} \\ \beta_k \mathbf{V}_k \end{pmatrix}\right) \\ &= \mathrm{Tr}\left(\begin{pmatrix} \mathbf{0} \\ \beta_k \mathbf{V}_k \end{pmatrix}^H \begin{pmatrix} \mathbf{0} \\ \beta_k \mathbf{V}_k \end{pmatrix}\right) \\ &= \beta_k^2 \mathrm{Tr}\left(\begin{pmatrix} \mathbf{0} \\ \mathbf{V}_k \end{pmatrix}^H \begin{pmatrix} \mathbf{0} \\ \mathbf{V}_k \end{pmatrix}\right). \end{aligned} \quad (27)$$

Consequently, we get the solution to the leakage-based precoding problem as

$$\mathbf{W}_k^{opt} = \beta_k \mathbf{P}\begin{pmatrix} \mathbf{0} \\ \mathbf{V}_k \end{pmatrix}. \quad (28)$$

The proposed optimal precoding matrix $\mathbf{W}_k^{opt}$ at the base station can eliminate the interference to the primary user as well as ensuring an optimal QoS for all IoT devices in the IoT oriented cognitive MIMO-OFDM system.

IV. COMPLEXITY ANALYSIS

Computational complexity is also a primary concern in CR-based IoT networks due to the very limited energy budget of IoT devices. In this section, we will analyze the complexity of the proposed precoding scheme.

Here the complexity is counted as the number of flops, and a flop is defined to be a real floating point operation such as the addition, multiplication or division [36]. For the proposed precoding scheme, it requires totally $2K$ times of SVD operations to get the generalized eigenvector and also $2K$ times of matrix multiplication. As the number of users becomes larger, it usually has $N_T \gg N_r$ for $K \gg 1$. Hence, the complexity is on the order of $\mathcal{O}(K^3 N_T + K^2 N_T^2)$ flop counts. Similarly, the BD precoding algorithm has the complexity on the order of $\mathcal{O}(K^3 N_T + K^2 N_T^2 + K^4)$, the complexity of the ZF precoding algorithm with the Moore-Pseudo operation is $\mathcal{O}(K^2 N_T^2)$ and the count of the MMSE algorithm is $\mathcal{O}(K^3 N_T^3 + K^2 N_T)$. Note that, to eliminate the cognitive interference, these methods also need the cooperation from the primary users or operate in an iterative way by SDP approximation. In general, an SDP problem requires $\mathcal{O}\left[\sqrt{KN_T}\log(1/\varepsilon)\right]$ iterations to converge with ε as the solution accuracy [32].

From the analysis above, we can see that the proposed precoding scheme is closed-form without iteration. Its computational complexity is much lower than that of the BD and MMSE algorithm, and is of the same order as the low complexity ZF algorithm with only a linear increase.

V. SIMULATION RESULTS

In this section, numerical results are presented. To evaluate the effectiveness of the proposed precoding scheme, we compare the bit error rate (BER) and the sum capacity of the leakage-based precoding scheme with several existing precoding algorithms. The detailed simulation parameters are listed in Table 1.

TABLE 1. Simulation parameters.

Item	Parameter
Transmission Radius	1000m
Simulation Channel	One-ring Rayleigh Channel
Bandwidth	1.92MHz
Multipath	6
Transmit Power	200mW (P) and 150mW (C)
Minimum Received Power	-90dBm
Number of Primary Users	Totally 3 (1 for Each Channel)
Number of IoT users	12
Receive Antenna $N_{r,k}$	2 and 3
Transmit Antenna N_T	24
OFDM Subcarrier N	64
Cyclic Prefix	16
Modulation	QPSK

According to the 3GPP TR 36.814 specification [37], a circular area with the radius of 1000m is considered as the coverage of the primary base station with primary users operating in TDD-FDMA. A cognitive MIMO-OFDM network with a cognitive base station and K cognitive IoT users ($K = 12$ in the simulation) are located in this area. The locations of the users are generated using the stochastic geometry model, for which the basic idea is to model the nodes as Poisson Point Processes (PPPs) and calculate the network performance characteristics by averaging over various network topologies [38]. We assume that the cognitive base station has 24 omni-directional antennas and the users have 2 or 3 antennas. In simulation, the desired received signal strength of both the cognitive and primary users are set to -90dBm. The transmission power constraints for primary and cognitive base station are 200mW (23dBm) and 150mW (21.7dBm), respectively. We evaluate the leakage-based precoding scheme in the scenario of rich-scattering Rayleigh environment with 6 multipath and the simulation of each precoding algorithm is performed by averaging over 3000 random channel realizations generated with the Monte-Carlo method.

Figure. 3 and Figure. 4 show the BER performance and the sum capacity comparison of the proposed leakage-based precoding scheme with the existing Zero Forcing (ZF), Block Diagonalization (BD) and Minimum Mean Square Error (MMSE) precoding algorithms. It can be seen that in terms of both the BER and sum capacity, our leakage-based precoding scheme outperforms the other three

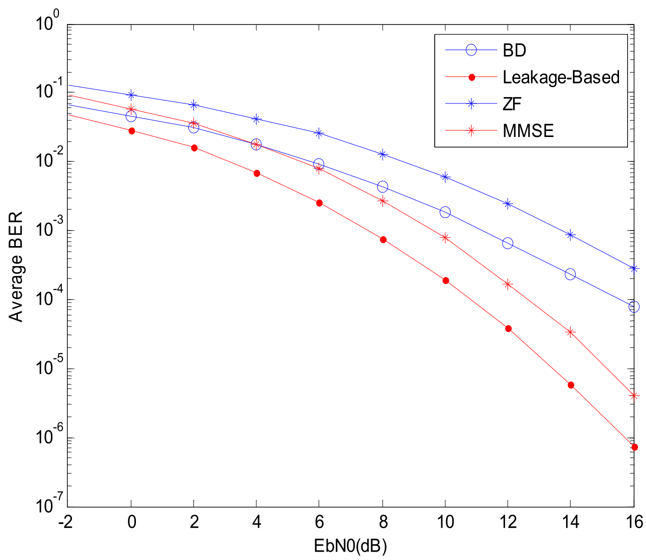

FIGURE 3. BER performance comparison in IoT oriented cognitive MIMO-OFDM system.

precoding algorithm with a lower computational complexity. This is because that unlike the existing precoding algorithms which just focus on suppressing the co-channel interference and may amplify the white noise, the proposed precoding scheme achieves the optimization of both the IoT devices' leakage power and the noise power. This leads to a result that both the noise and the power loss from other IoT devices are reduced to the minimum level. Moreover, with the same BER condition, the transmit power of IoT devices with the proposed leakage-based precoding scheme will be reduced by approximately 5dB compared with the BD and ZF precoding algorithms.

Figure. 5 shows the sum capacity of primary users with the proposed leakage-based precoding scheme and the cooperative precoding method in [17], we also consider the scenario that the cognitive network does not perform precoding and the scenario with only primary users as the benchmarks. As can be seen, when there are only primary users in the network, the primary users can achieve the best performance and the primary network actually becomes a non-cognitive one without cognitive interference. On the other hand, when the cognitive network does not perform precoding, the cognitive interference is considered as noise at the primary users and it would significantly degrade the network capacity. It also shows that the proposed leakage-based precoding scheme outperforms the cooperative method and achieves almost the same sum capacity as the scenario with only primary users. This is because that the proposed scheme is self-organized and can fully eliminate the interference to the primary user, while in cooperative precoding, the primary network need to sacrifice the transmit power and degree of freedom to cooperate with cognitive users, with may lower the network capacity.

Furthermore, in consideration of the prior research [26] on interference suppression precoding design, the precoding

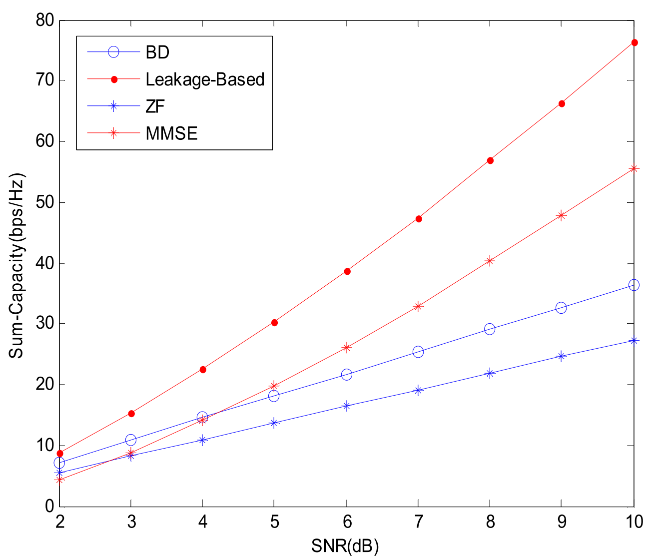

FIGURE 4. Sum capacity comparison in IoT oriented cognitive MIMO-OFDM system.

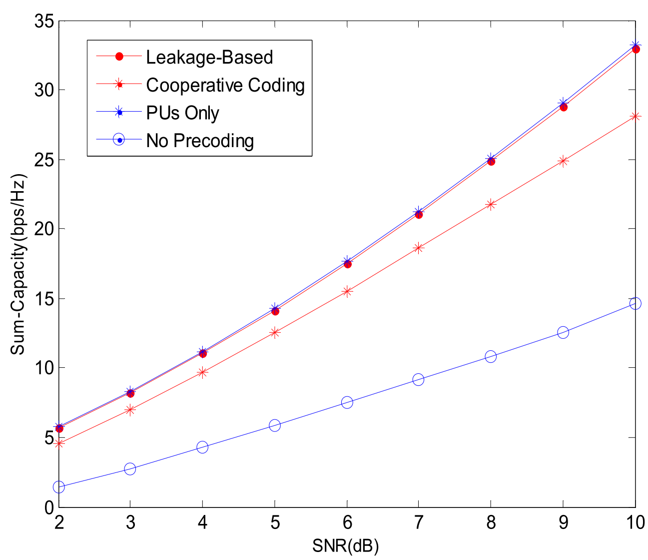

FIGURE 5. Sum capacity of primary users with different interference management methods.

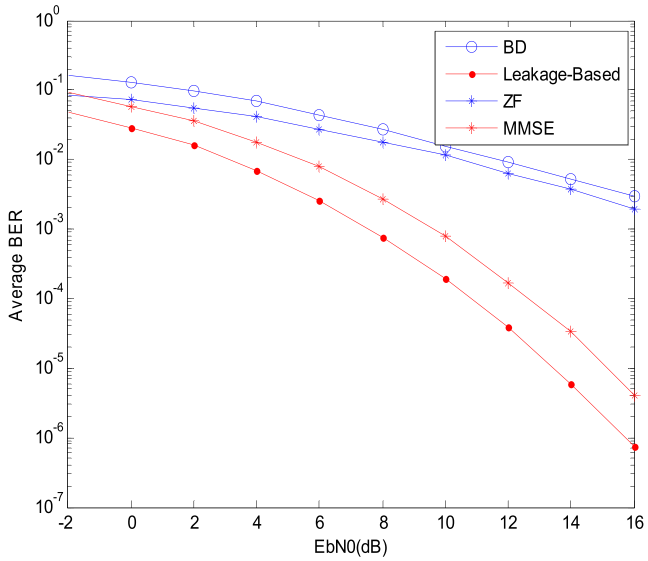

FIGURE 6. BER performance comparison whth more receive antennas than transmit antennas.

methods which nullify the co-channel interference in multi-user cognitive MIMO system impose a strong restriction on the antenna configuration. According to the restriction, the number of the antennas should meet the constraint

$$N_T \geq \sum_{i=1, i\neq k}^{K} N_{r,i}, \quad for\ k = 1, 2, \cdots, K. \tag{29}$$

It means that in order to provide more degrees of freedom to eliminate the co-channel interference to the primary user, the multi-user MIMO network requires more transmit antennas than the sum of receive antennas.

Next, we consider the scenario with more receiving antennas than transmitting antennas. In this scenario, the restriction on the antenna configuration (29) is not satisfied by the IoT oriented cognitive MIMO-OFDM system and we evaluate the BER performance of the proposed precoding scheme. The simulation result is shown in Figure. 6. When the number of receive antennas exceeds that of transmitting antennas, it can be seen from Figure. 6 that compared with the classical precoding algorithms, the proposed precoding scheme provides superior BER performance. This is because that instead of eliminating the interference completely, the leakage-based precoding scheme just performs partial interference suppression. It requires less degrees of freedom to manage the co-channel interference, such that, it does not impose such strong restriction on the antenna configuration. The simulation results indicate that our proposed leakage-based precoding scheme is robust to the constraint on the antenna configuration, and can retain desirable system performance in IoT oriented cognitive MIMO-OFDM system.

VI. CONCLUSION

In this paper, we propose a leakage-based precoding scheme in IoT oriented cognitive network with the help of dimensionality reduction and SLNR criterion. In order to satisfy the low-cost and self-organized features of IoT, we first introduce a new channel estimation method using the MCR decoding algorithm that requires no cooperation with the primary network. Second, we fully eliminate the interference to the licensed user by a low complexity subspace projection with dimensionality reduction. Finally, instead of zero-force the interference, the proposed precoding scheme optimizes both the leakage power and noise power, which further improves the degree of freedom in such network. The entire coding process is performed at the cognitive base station without any coordination from the users, which makes it an efficient self-organized precoding scheme for IoT networks with low complexity. As a result, it allows for more effective utilization of the multi-channel resource in spatial dimension as well as eliminating the interference to the primary users. Numerical results demonstrate that, with the proposed leakage-based precoding scheme, both the sum capacity and the BER performance of IoT oriented cognitive MIMO-OFDM system can be greatly enhanced, even when the constraint on the antenna configuration is violated.

In addition, in this paper, we mainly focus on the physical layer interference management with stochastic geometry model. Extending the results of this paper to network layer can be interesting future work. One possible approach is to exploit the multi-hop relay and explore the routing algorithm to further improve the network performance. Moreover, stochastic geometry is widely used to model wireless networks with random topologies. When extended to network layer, the routing algorithms largely depend on the spatial location of the network nodes. Investigating various topologies of cognitive IoT networks in more specific scenarios and propose corresponding protocols can be further avenues for our work.

APPENDIX A

Consider the Karhunen-Loeve representation of the Rayleigh channel as

$$\mathbf{H} = \mathbf{R}_{RX}^{1/2}\mathbf{H}_{iid}\mathbf{R}_{TX}^{1/2}, \tag{30}$$

where $\mathbf{H}_{iid}$ is an i.i.d complex Gaussian matrix with zero-mean and unit-variance. Let θ be the azimuth angle of the user location, s be the distance between the base station and the far field scatterer ring with the radius of r.Δ represents the angle spread of the transmit signal, which can be approximated as $\Delta \approx \arctan(r/s)$. According to the one-ring model, the elements of $\mathbf{R}_{RX}^{1/2}$ can be given as

$$[\mathbf{R}_{TX}]_{p,q} = \frac{1}{2\Delta}\int_{-\Delta}^{\Delta} e^{j\mathbf{g}^{\mathrm{T}}(\alpha+\theta)(\boldsymbol{u}_p-\boldsymbol{u}_q)}d\alpha. \tag{31}$$

Here $\mathbf{g}(\alpha+\theta) = -(2\pi/\lambda)\,(\cos(\alpha), \sin(\alpha))^{\mathrm{T}}$ is the vector for the planar wave with the angle of arrival α and the carrier wavelength $\lambda \cdot \mathbf{u}_p$ and $\mathbf{u}_q$ are the position of the transmit antennas p and q, respectively. As the NeSH model, the compensation matrix $\mathbf{R}_{TX}^{1/2}$ is presented as

$$[\mathbf{R}_{RX}]_{i,j} = \frac{\sigma_s^2}{d_{cor}} e^{-\frac{|d_{i,j}|}{d_{cor}}}, \tag{32}$$

where $d_{i,j}$ represents the distance between the two antennas i and j, σ_s is the standard deviation of shadow fading and d_{cor} is defined as the correlation distance corresponding to the distance at which the correlation drops to 0.5.

APPENDIX B

The generalized Rayleigh quotient is represented as

$$R(\boldsymbol{x}) = \frac{\boldsymbol{x}^T \mathbf{A} \boldsymbol{x}}{\boldsymbol{x}^T \mathbf{B} \boldsymbol{x}} \quad \left(\boldsymbol{x} \in \mathbb{R},\ \boldsymbol{x} \neq \vec{0}\right), \tag{33}$$

where the matrices $\mathbf{A}$ and $\mathbf{B}$ should be symmetric positive definite. Let λ_i denote the i-th generalized eigenvalue of the equation $\mathbf{A}\boldsymbol{x} = \lambda \mathbf{B}\boldsymbol{x}$, for $i = 1, 2, \cdots, n$, which is sorted in descending order as $\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_n$. The value of the generalized Rayleigh quotient can be limited by

$$\lambda_1 \leq R(x) = \frac{x^T \mathbf{A} x}{x^T \mathbf{B} x} \leq \lambda_n \quad (x \in \mathbb{R},\ x \neq \mathbf{0}). \tag{34}$$

The equality in (34) occurs only when x is equal to the eigenvector corresponding to the smallest eigenvalue, i.e., $\boldsymbol{x} = \boldsymbol{x}_1 \sim \lambda_1$ for the left equality, and the largest one, i.e., $\boldsymbol{x} = \boldsymbol{x}_n \sim \lambda_n$ for the right equality, in the Rayleigh quotient. Therefore, the optimization problem that follows the form of the Rayleigh quotient can be solved by exploiting the eigenvector which avoids the complicated joint optimization.

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