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The Optimal MMSE Transceiver Design for IoT-oriented Cognitive Radio Systems[1]

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Abstract: *This paper studies interference alignment scheme and minimum mean square error (MMSE) improvement in Internet of Things (IoT)-oriented cognitive systems, where IoT devices share the licensed spectrum by cognitive radio in spectrum underlay. Target to manage the inter-tier interference caused by cognitive spectrum sharing as well as ensure an MMSE at receivers, the interference alignment algorithms is proposed. In particular, we focus on the problem of designing the optimal linear pre-coding to minimize the total mean square error while satisfying transmit power constraints. Firstly, we introduce a system model of the downlink IoT-oriented cognitive multi-input multi-output (MIMO) system. Secondly, we propose an interference nulling based cognitive interference alignment scheme, and then, the pre-coding and post-coding matrix designs for the primary transceivers to minimum mean square error (MSE), as well as to eliminate the co-channel interference to the primary receivers. We also apply these interference alignment scheme and matrix designs for the secondary links. Finally, the numerical results are used to evaluate performance of the proposed algorithm.*

Keywords: *Internet of Things, Cognitive Radio, MMSE, Precoding, Interference Alignment.*

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INTRODUCTION

Recently, Internet of Things (IoT) have been received a great deal of attention for their potentials to provide an everything, everywhere connectivity. IoT is a set of technologies that can interconnect anything, from daily life objects to more sophisticated networked devices [1]. Billions of devices will be connected to the Internet and those connections could facilitate data to analyze, preplan, manage, and make intelligent decisions autonomously. To solve the growing demand for wireless traffic, the IoT oriented cognitive approach, where IoT devices access to the licensed spectrum by cognitive radio (CR) in spectrum underlay, is proposed [2], [3].

Cognitive Radio is a promising communication technology for IoT, since its opportunistic communication paradigm is suitable to communicating objects which can generate bursty traffic [4]. Cognitive Radio can help to overcome the problem of collision and excessive contention in the wireless access network, which arises from deploying multiple objects connected to the infrastructure over

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radio links. However, the spectrum sharing will cause cross-tier interference, which limits the reusability of frequency resources. This becomes a key challenge in developing the IoT technology [4], [5].

In order to guarantee the desired signal can be recovered free of cross-tier interference, the cognitive interference caused by IoT oriented devices should be aligned into the subspace orthogonal to the primary link [6]. Authors in [7] and [8] proposed self-organized cognitive interference alignment schemes to manage the interference and improve the network capacity. Unlike [6]-[8], this paper proposes a minimum mean square error (MMSE)-based precoding scheme that can satisfy the transmit power constraint.

1. Related works

A number of state-of-the-art cognitive radio transceiver design algorithms have been proposed in the literature, which also aim to eliminate the co-channel interference to the primary receivers, and to improve the utilization of the licensed spectrum. The authors in [6] used the maximum eigenmode beamforming algorithm for the transmission between the transmitter and receivers, in which the primary receiver releases some of its eigenmodes for the secondary transmitters. The proposed algorithm allows the opportunistic transmitters to send data for the secondary receivers and to use the same frequency band of a preexisting primary network to guarantee that none of the interference is imposed on the performance of the primary network. The scheme is proposed in [9] for a single secondary link and then extended to multiple secondary links in [10] under the assumption of the perfect CSI at all nodes. However, the methods in [9, 10] employ independent optimization. In [11], authors proposed a fast algorithm to perform interference alignment (IA) in a cognitive radio network. In this work, the interferences at the primary receivers are aligned away from the desired subspaces of the primary receivers. Author in [12] proposed a selective interference alignment with user selection. The proposed algorithm judiciously chooses a set of cognitive transmitters to be aligned to each primary receiver as a subset of the cross-tier interferers. The selective algorithm considers a trade-off between complexity and sum rate.

Multiple previous works considered the use of beamforming for IoT network. Authors in [7] proposed leakage-based precoding algorithm with dimensionality reduction and signal-to-leakage-and-noise ratio (SLNR) maximization. In [8], an interference nulling based cognitive IA scheme is proposed where both co-tier and cross-tier interferences are aligned into the orthogonal subspace at each IoT receiver. However, the algorithm is only optimal when signal-to-noise ratio (SNR) is high. Therefore, the authors proposed a partial cognitive interference alignment scheme that further improves the network performance under a low and intermediate SNR. In [13], a beamforming approach for IoT simultaneous wireless information and power transfer systems is proposed, which minimizes the mean square error (MSE) of the information decode device while satisfying the energy constraint of the energy harvesting device. In [14], authors proposed a robust artificial noise aided beamforming approach under the bounded channel state information error model. However, a multi-cast scenario or a non-orthogonal multiple access is not considered in that work.

2. Contributions of the paper

In this paper, in order to improve performance of both the primary network and the secondary network, we propose a minimum mean square error (MMSE)-based precoding scheme that satisfy the transmit power constraint. The main contributions of the paper are summarized as follows:

- A IoT cooperative scheme is proposed to improve the performance of both the primary network and the IoT cognitive network. In this scheme, the primary network allows the IoT cognitive network to access its spectrum band.

- And vice verse, the cognitive IoT transmitters transmits a signal into the orthogonal subspace at the primary network. To fully eliminate the interference, we propose an interference nulling based cognitive interference alignment scheme. In addition, we also introduce the pre-coding and post-coding matrix designs for the primary transceivers to minimum mean square error, as well as to eliminate the co-channel interference to the primary receivers. These interference alignment scheme and matrix designs are also applied to the secondary links.

- Simulation results show that our proposed beamforming scheme obtains a performance gain in comparison to the channel inversion beamforming in both the primary network and the IoT cognitive network

3. Organization of the paper

The rest of the paper is organized as follows. Section II introduces a system model, while Section III proposes an interference alignment scheme. Simulation results are presented in Section IV, followed by conclusions in Section V.

SYSTEM MODEL

For the notations, we use the upper-case boldface letters for matrices and lower-case boldface letters for vectors, i.e., $\mathbb{C}^{N\times M}$ represents the space of $N\times M$ complex matrices and I_M indicates an $M\times M$ identity matrix. X^H, $|X|$, and $\mathrm{tr}\{X\}$ stand for conjugate transpose, determinant and trace of a matrix A, respectively. A complex Gaussian random vector variable $\mathbf{z}$ with the mean μ and the variance σ^2 is represented as $\mathbf{z} \sim \mathcal{CN}(\mu, \sigma^2)$.

In this section, we consider a downlink of a centralized IoT-oriented cognitive MIMO system as shown in Fig. 1, which consists of K+1 transmitters and K+1 receivers. The primary devices (transmitter and receiver) are denoted by the index 0 and the secondary devices are denoted by the index i (i = 1,….,K). The i^{th} transmitter equips $N_{t,i}$ antennas and the i^{th} receiver equips $N_{r,t}$ antennas.

In this network, the i^{th} transmitter (i = 0,...,K) conveys d_i independent data streams (denotes as $\mathbf{x}_i \in \mathbb{C}^{d_i\times 1}$), which are pre-processed by the precoding matrix $\mathbf{V}_i \in \mathbb{C}^{N_{t,i}\times d_i}$. Assuming that the data stream x_i and the precoding matrix V_i is denoted by:

$$\mathrm{E}\{\mathbf{x}_i\mathbf{x}_i^H\} = \mathbf{I}_{d_i},\ i = 0,\dots,K, \quad (1)$$

$$tr\{\mathbf{V}_i\mathbf{V}_i^H\} = P_i,\ i = 0,\dots,K, \quad (2)$$

where P_i is the transmission power constraint.

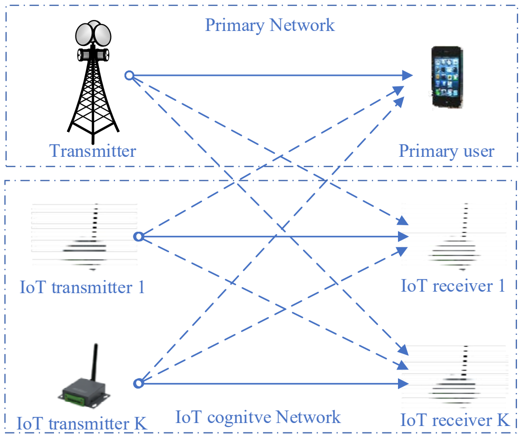

Fig.1. A model of the IoT cognitive system downlink.

The received signal at the primary device and the i^{th} IoT receiver is given by

$$\mathbf{y}_0 = \mathbf{H}_{0,0}\mathbf{V}_0\mathbf{x}_0 + \sum_{j=1}^{K}\mathbf{H}_{j,0}\mathbf{V}_j\mathbf{x}_j + \mathbf{n}_0 \quad (3)$$

and

$$\mathbf{y}_i = \mathbf{H}_{i,i}\mathbf{V}_i\mathbf{x}_i + \textstyle\sum_{j=0,j\neq i}^{K}\mathbf{H}_{j,i}\mathbf{V}_j\mathbf{x}_j + \mathbf{n}_i,\ i = 1,\dots,K, \quad (4)$$

where the matrix $\mathbf{H}_{j,t}$ denotes the channel matrix between the j^{th} transmitter and the i^{th} receiver (i,j = 0,...,K), the vector $\boldsymbol{n}_i$ represents the additive white Gaussian noise (AWGN) with zero mean and covariance matrix $\sigma_i^2 IN_{r,t}$ (i = 0,...,K). It is assumed that entries of the Rayleigh channel matrix are standard independent identically distributed (i.i.d.) with zero-mean and unit-variance, and all channel status information (CSI) are known in the secondary network.

From (3) and (4), the Signal-to-Interference-Plus-Noise Ratio (SINR) at the primary receiver and the i[th] IoT receiver can be defined as

$$\begin{aligned} SINR_0 &= \frac{\left|\mathbf{H}_{0,0}\mathbf{V}_0\mathbf{x}_0\right|^2}{\sum_{j=1}^{K}\left|\mathbf{H}_{j,0}\mathbf{V}_j\mathbf{x}_j\right|^2 + \sigma_0^2} \\ &= \frac{\mathrm{E}\{\mathbf{H}_{0,0}\mathbf{V}_0\mathbf{x}_0\mathbf{x}_0^H\mathbf{V}_0^H\mathbf{H}_{0,0}^H\}}{\sum_{j=1}^{K}\mathrm{E}\{\mathbf{H}_{j,0}\mathbf{V}_j\mathbf{x}_j\mathbf{x}_j^H\mathbf{V}_j^H\mathbf{H}_{j,0}^H\} + \sigma_0^2} \\ &= \frac{\mathrm{tr}\{\mathbf{H}_{0,0}\mathbf{V}_0\mathbf{V}_0^H\mathbf{H}_{0,0}^H\}}{\sum_{j=1}^{K}\mathrm{tr}\{\mathbf{H}_{j,0}\mathbf{V}_j\mathbf{V}_j^H\mathbf{H}_{j,0}^H\} + \sigma_0^2} \end{aligned} \tag{5}$$

And

$$\begin{aligned} SINR_i &= \frac{\left|\mathbf{H}_{i,i}\mathbf{V}_i\mathbf{x}_i\right|^2}{\sum_{j=0,j\neq i}^{K}\left|\mathbf{H}_{j,i}\mathbf{V}_j\mathbf{x}_j\right|^2 + \sigma_i^2} \\ &= \frac{\mathrm{E}\{\mathbf{H}_{i,i}\mathbf{V}_i\mathbf{x}_i\mathbf{x}_i^H\mathbf{V}_i^H\mathbf{H}_{i,i}^H\}}{\sum_{j=0,j\neq i}^{K}\mathrm{E}\{\mathbf{H}_{j,i}\mathbf{V}_j\mathbf{x}_j\mathbf{x}_j^H\mathbf{V}_j^H\mathbf{H}_{j,i}^H\} + \sigma_i^2} \\ &= \frac{\mathrm{tr}\{\mathbf{H}_{0,0}\mathbf{V}_0\mathbf{V}_0^H\mathbf{H}_{0,0}^H\}}{\sum_{j=1}^{K}\mathrm{tr}\{\mathbf{H}_{j,i}\mathbf{V}_j\mathbf{V}_j^H\mathbf{H}_{j,i}^H\} + \sigma_i^2} \end{aligned} \tag{6}$$

$i = 1,\ldots,K$

Let $\mathbf{U}_i$ denote the post-coding matrix at the i[th] receiver to suppress the interference. Since, the receiver gets d_i input data streams, the output signal of this receiver filter is given by

$$\begin{aligned} \mathbf{r}_0 &= \mathbf{U}_0\mathbf{y}_0 \\ &= \mathbf{U}_0\mathbf{H}_{0,0}\mathbf{V}_0\mathbf{x}_0 + \mathbf{U}_0\sum_{j=1}^{K}\mathbf{H}_{j,0}\mathbf{V}_j\mathbf{x}_j + \mathbf{U}_0\mathbf{n}_0, \end{aligned} \tag{7}$$

and

$$\begin{aligned} \mathbf{r}_i &= \mathbf{U}_i\mathbf{y}_i \\ &= \mathbf{U}_i\mathbf{H}_{i,i}\mathbf{V}_i\mathbf{x}_i + \mathbf{U}_i\sum_{j=0,j\neq i}^{K}\mathbf{H}_{j,i}\mathbf{V}_j\mathbf{x}_j + \mathbf{U}_i\mathbf{n}_i, \end{aligned}$$

$i = 1,\ldots,K$ (8)

INTERFERENCE ALIGNMENT SCHEMES DESIGN

In this section, we propose an interference alignment scheme for the IoT cognitive system downlink. Firstly, we introduce the pre-coding and post-coding matrix designs for the primary transceivers to minimum MSE, as well as to eliminate the co-channel interference to the primary receivers. Besides, we also apply this interference alignment scheme to the secondary links and design the pre-coding and post-coding matrices such that the interference between devices are suppressed.

In the full interference alignment design, a receiver must receive its intended information without any distortion caused by transmitters. Therefore, the pre-coding matrix must satisfy the following condition:

$$\widetilde{\mathbf{H}}_j\mathbf{V}_j = 0, j = 1,\ldots,K \tag{9}$$

where $\widetilde{\mathbf{H}}_j = [\mathbf{H}_{j,0}^T, \mathbf{H}_{j,1}^T,\ldots,\mathbf{H}_{j,j-1}^T,\mathbf{H}_{j,j+1}^T,\ldots,\mathbf{H}_{j,K}^T]^T$.

To satisfy (9), the pre-coding matrix $\mathbf{V}_j$ can be obtained by implement the null space of $\widetilde{\mathbf{H}}_j$ [15].

Denote the singular value decomposition of the matrix $\widetilde{\mathbf{H}}_j$ as

$$\widetilde{\mathbf{H}}_j = \widetilde{\mathbf{U}}_j\boldsymbol{\Lambda}_j[\widetilde{\mathbf{V}}_j^{(1)}\ \widetilde{\mathbf{V}}_j^{(o)}]^H, \tag{10}$$

where $\widetilde{\mathbf{V}}_j^{(1)}$ holds the first right singular vectors, and $\widetilde{\mathbf{V}}_j^{(0)}$ holds the last ($N_{t,j}$- L_j) right singular vectors, with $L_j = rank(\widetilde{\mathbf{H}}_j)$. Thus, $\widetilde{\mathbf{V}}_j^{(0)}$ is a null space of the matrix $\widetilde{\mathbf{H}}_j$.

Let define the matrix

$$\begin{aligned} \mathbf{V} &= [\mathbf{V}_1\ \ \mathbf{V}_2\ \ \ldots\ \ \mathbf{V}_K] \\ &= \left[\widetilde{\mathbf{V}}_1^{(0)}\widetilde{\mathbf{V}}_1^{(0)H}\ \ \widetilde{\mathbf{V}}_2^{(0)}\widetilde{\mathbf{V}}_2^{(0)H}\ \ \ldots\ \ \widetilde{\mathbf{V}}_K^{(0)}\widetilde{\mathbf{V}}_K^{(0)H}\right]\mathbf{W} \end{aligned} \tag{11}$$

Where

$$\mathbf{W} = \begin{bmatrix} \mathbf{W}_1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \mathbf{W}_K \end{bmatrix}, \tag{12}$$

with $\mathbf{W}_i$ is chosen to meet the transmission power constraint.

From (3), (5) and (9), the transmission data rates of the primary and secondary receiver are given as,

$$R_0 = \log\left|\mathrm{I} + \frac{\mathbf{H}_{0,0}\mathbf{V}_0\mathbf{V}_0^H\mathbf{H}_{0,0}^H}{\sigma_0^2}\right| \tag{13}$$

And

$$R_i = \log\left|\mathrm{I} + \frac{\mathbf{H}_{i,i}\mathbf{V}_i\mathbf{V}_i^H\mathbf{H}_{i,i}^H}{\sum_{j=0,j\neq i}^{K}\mathbf{H}_{j,i}\mathbf{V}_j\mathbf{V}_j^H\mathbf{H}_j,i^H + \sigma_i^2}\right| \tag{14}$$

Minimum MSE for Downlink Primary Network

The mean square error of the primary receivers can be defined as,

$$\begin{aligned} MSE_0 &= \mathrm{E}[|\mathbf{r}_0 - \mathbf{x}_0|^2] \\ &= \mathrm{tr}\{\mathbf{U}_0\mathbf{H}_{0,0}\mathbf{V}_0\mathbf{V}_0^H\mathbf{H}_{0,0}^H\mathbf{U}_0^H\} - \mathrm{tr}\{\mathbf{U}_0\mathbf{H}_{0,0}\mathbf{V}_0\}, \\ &\quad - \mathrm{tr}\{\mathbf{V}_0^H\mathbf{H}_{0,0}^H\mathbf{U}_0^H\} + \mathrm{tr}\{\mathbf{I}\} + \sigma_0^2\mathrm{tr}\{\mathbf{U}_0\mathbf{U}_0^H\} \end{aligned} \tag{15}$$

The beamforming matrices are required to minimize the MSE under the constraint of BS power:

$$\begin{aligned} \min_{\mathbf{U}_0,\mathbf{V}_0} \quad & MSE \\ s.t \quad & tr\{\mathbf{V}_0\mathbf{V}_0^H\} - P_0 \end{aligned} , \tag{16}$$

The Lagrange dual function could be constructed as

$$\begin{aligned} L = \; & \mathrm{tr}\{\mathbf{U}_0\mathbf{H}_{0,0}\mathbf{V}_0\mathbf{V}_0^H\mathbf{H}_{0,0}^H\mathbf{U}_0^H - \mathbf{U}_0\mathbf{H}_{0,0}\mathbf{V}_0 - \mathbf{V}_0^H\mathbf{H}_{0,0}^H\mathbf{U}_0^H + \mathbf{I}\} \\ & + \sigma_0^2\mathrm{tr}\{\mathbf{U}_0\mathbf{U}_0^H\} - \gamma_0(tr\{\mathbf{V}_0\mathbf{V}_0^H\} - P_0) \end{aligned} , \tag{17}$$

where γ_0 denotes the Lagrange multiplier. Based on the Lagrange dual problem, Karush-Kuhn-Tucker (KKT) conditions are given as [16]:

$$\frac{\partial L}{\partial \mathbf{V}_0^*} = \mathbf{H}_{0,0}^H\mathbf{U}_0^H\mathbf{U}_0\mathbf{H}_{0,0}\mathbf{V}_0 - \mathbf{H}_{0,0}^H\mathbf{U}_0^H + \gamma_0\mathbf{V}_0 = 0 , \tag{18}$$

$$\frac{\partial L}{\partial \mathbf{U}_0^*} = \mathbf{U}_0\mathbf{H}_{0,0}\mathbf{V}_0\mathbf{V}_0^H\mathbf{H}_{0,0}^H - \mathbf{V}_0^H\mathbf{H}_{0,0}^H + \sigma_0^2\mathbf{U}_0 = 0 , \tag{19}$$

$$tr\{\mathbf{V}_0\mathbf{V}_0^H\} - P_0 = 0 . \tag{20}$$

Then, the optimal beamforming matrices could be solved as

$$\mathbf{V}_0 = (\mathbf{H}_{0,0}^H\mathbf{U}_0^H\mathbf{U}_0\mathbf{H}_{0,0} - \gamma_0\mathbf{I})^{-1}\mathbf{H}_{0,0}^H\mathbf{U}_0^H , \tag{21}$$

$$\mathbf{U}_0 = \mathbf{V}_0^H\mathbf{H}_{0,0}^H(\mathbf{H}_{0,0}\mathbf{V}_0\mathbf{V}_0^H\mathbf{H}_{0,0}^H + \sigma_0^2\mathbf{I})^{-1} , \tag{22}$$

where γ_0 can be determined by the bisection method to meet the constraint (20).

Minimum MSE for Downlink Secondary Network

The sum of mean square errors of the primary receivers can be defined as

$$\begin{aligned} \Sigma MSE_i &= \sum_{i=1}^{K} \mathrm{E}[|\mathbf{r}_i - \mathbf{x}_i|^2] \\ &= \sum_{i=1}^{K}\mathrm{tr}\{\mathbf{U}_i\mathbf{H}_{i,i}\mathbf{V}_i\mathbf{V}_i^H\mathbf{H}_{i,i}^H\mathbf{U}_i^H\} - \sum_{i=1}^{K}\mathbf{U}_i\mathbf{H}_{i,i}\mathbf{V}_i \\ &\quad - \sum_{i=1}^{K} tr\{\mathbf{V}_i^H\mathbf{H}_{i,i}^H\mathbf{U}_i^H\} + \sum_{i=1}^{K} tr\{\mathbf{I}\} + \\ &\quad \sum_{i=1}^{K}\sum_{j=1,j\neq i}^{K}\mathbf{U}_i\mathbf{H}_{j,i}\mathbf{V}_j\mathbf{V}_j^H\mathbf{H}_{j,i}^H\mathbf{U}_i^H + \sigma_i^2\mathrm{tr}\{\mathbf{U}_i\mathbf{U}_i^H\} \end{aligned} , \tag{23}$$

Based on the equation (23), the beamforming matrices need to be formed to minimize the sum of MSEs under the constraint of transmission power. Therefore, the MMSE-based optimization criterion can be stated as the following problem,

$$\min_{\mathbf{U}_i,\mathbf{V}_i} \quad \sum_{i=1}^{K} MSE_i \qquad . \qquad (24)$$
$$s.t \quad tr\{\mathbf{V}_i\mathbf{V}_i^H\} - P_i$$

In order to find the optimal beamforming matrices, the Lagrange dual objective function could be constructed as,

$$L = \sum_{i=1}^{K} \mathrm{tr}\{\mathbf{U}_i\mathbf{H}_{i,i}\mathbf{V}_i\mathbf{V}_i^H\mathbf{H}_{i,i}^H\mathbf{U}_i^H\} - \sum_{i=1}^{K}\mathbf{U}_i\mathbf{H}_{i,i}\mathbf{V}_i - \sum_{i=1}^{K} tr\{\mathbf{V}_i^H\mathbf{H}_{i,i}^H\mathbf{U}_i^H\} + \sum_{i=1}^{K} tr\{\mathbf{I}\}$$
$$+ \sum_{i=1}^{K}\sum_{j=1,j\neq i}^{K} \mathbf{U}_i\mathbf{H}_{j,i}\mathbf{V}_j\mathbf{V}_j^H\mathbf{H}_{j,i}^H\mathbf{U}_i^H + \sigma_i^2\mathrm{tr}\{\mathbf{U}_i\mathbf{U}_i^H\} - \sum_{i=1}^{K}\gamma_i(tr\{\mathbf{V}_i\mathbf{V}_i^H\} - P_i) \quad , \qquad (25)$$

where γ_i are the Lagrange multipliers. Karush-Kuhn-Tucker (KKT) conditions for the Lagrange dual problem can be formed as follows [16],

$$\frac{\partial L}{\partial \mathbf{V}_i^*} = \sum_{j=1}^{K} \mathbf{H}_{i,j}^H\mathbf{U}_j^H\mathbf{U}_j\mathbf{H}_{i,j}\mathbf{V}_i - \mathbf{H}_{i,i}^H\mathbf{U}_i^H + \gamma_i\mathbf{V}_i = 0, \qquad (26)$$

$$\frac{\partial L}{\partial \mathbf{U}_i^*} = \sum_{j=0}^{K} \mathbf{U}_i\mathbf{H}_{j,i}\mathbf{V}_j\mathbf{V}_j^H\mathbf{H}_{j,i}^H - \mathbf{V}_i^H\mathbf{H}_{i,i}^H + \sigma_i^2\mathbf{U}_i = 0 \, , \qquad (27)$$

$$tr\{\mathbf{V}_i\mathbf{V}_i^H\} - P_i = 0 \qquad (28)$$

Therefore, the solution of the optimal beamforming matrices could be given as

$$\mathbf{V}_i = (\sum_{j=1}^{K} \mathbf{H}_{i,j}^H\mathbf{U}_j^H\mathbf{U}_j\mathbf{H}_{i,j} - \gamma_i\mathbf{I})^H\mathbf{H}_{i,i}^H\mathbf{U}_i^H \quad , \qquad (29)$$

and

$$\mathbf{U}_i = \mathbf{V}_i^H\mathbf{H}_{i,i}^H\sum_{j=0}^{K} \mathbf{H}_{j,i}\mathbf{V}_j\mathbf{V}_j^H\mathbf{H}_{j,i}^H + \mathbf{H}_{0,i}\mathbf{V}_0\mathbf{V}_0^H\mathbf{H}_{0,i}^H + \sigma_i^2\mathbf{I})^H, \qquad (30)$$

where γ_i can be solved by the bisection method to meet the constraint (28).

TABLE I
SIMULATION PARAMETERS

Symbol	Term	Value
P_i	Transmit power	1
$N_{t,i}$	Number of transmit antenna	4
$N_{r,i}$	Number of receive antenna	2
K	Number of secondary IoT transceiver	2

NUMERICAL RESULTS

In this section, we present numerical results to evaluate the performance of the proposed MMSE beamforming in terms of sum rate and MSE. Simulation parameters are briefly listed in Table 1. Simulation results are averaged over 1,000 independent channel realizations. The receivers and transmitters in the secondary network with beamforming have ideal channel knowledge. The channel inversion (CI) beamforming is compared with the proposed beamforming in terms of sum rate and MSE.

Fig. 2 shows how sum rate of the downlink primary network varies with Signal-to-Noise-Ratio (SNR). In this figure, the solid line with circle markers denotes the proposed beamforming and the dash line with square markers denotes the channel inversion beamforming. As observed, the base-MMSE proposed beamforming technique increases the sum rate of the primary network as SNR increases.

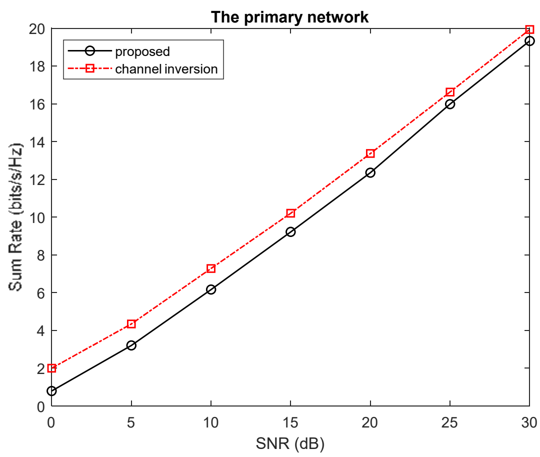

Fig. 2. Sum rate of the primary network as a function of SNR

Similar to Fig. 2, Fig. 3 denotes how sum rate of the downlink IoT cognitive network varies with SNR. As indicated, the MMSE-based proposed beamforming technique outperforms the channel inversion beamforming technique.

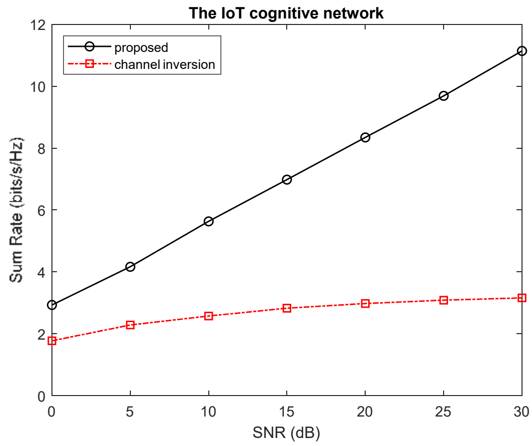

Fig. 3. Sum rate of the IoT cognitive network as a function of SNR

Fig. 4 and Fig.5 compare the proposed beamforming with the channel inversion beamforming in terms of MSE for the primary network and the IoT cognitive network, respectively. The results indicate that the improvement in MSE performance is achieved by implementing our technique in comparison to the channel inversion technique. The reason the proposed beamforming has the better performance, since it minimizes the leakage to the primary network and the interference in the IoT cognitive network.

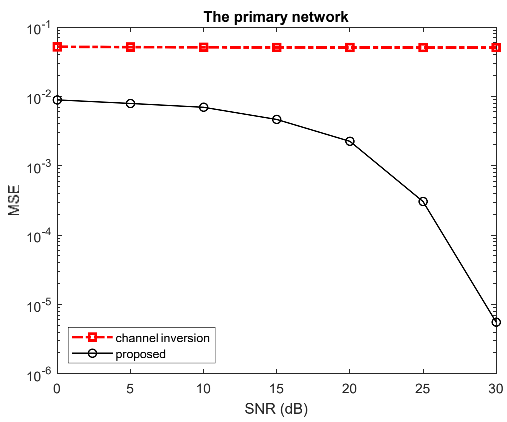

Fig. 4. The downlink MSE of the primary network as a function of SNR.

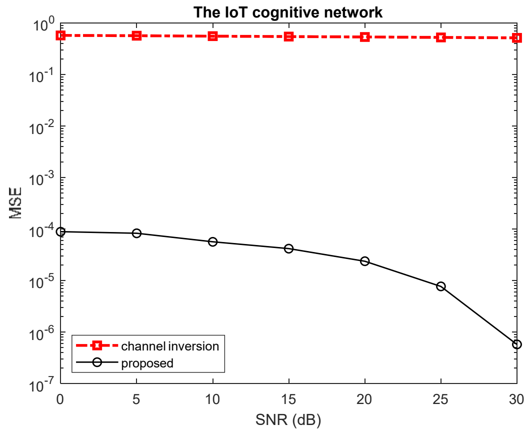

Fig. 5. The downlink MSEs of the IoT cognitive network as a function of SNR.

CONCLUSION

This paper studies an MMSE-based beamforming technique to IoT oriented heterogeneous networks. In order to improve MSE, an MMSE-base beamforming is proposed. The numerical results show that our proposed beamforming scheme obtains a performance gain in comparison to the channel inversion beamforming in both the primary network and the IoT cognitive network.

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