Power Optimization in Device to Device Communications Underlying 5G Cellular Networks

Qianchun WANG, Xiaobo SHEN

School of Electronic Engineering, Huainan Normal University, Huainan, Anhui Province, China

{wqc1982, SXB0017}@ outlook.com

Submitted September 27, 2021 / Accepted January 21, 2022

Abstract. *This paper investigates consumed power minimization and robust beamforming designs in the base station (BTS) in Device to Device (D2D) communications underlying 5G cellular network. It is supposed that BTS is not aware of the channel state information (CSI), and only an approximation of their covariance is available. Therefore, based on the estimation error of CSI covariance matrices, two optimization models are presented to minimize the power consumption and robust beamforming designs. The first model assumes that the upper bound of the estimation errors is limited to their Frobenius norms. So, the main objective of the first model is to calculate the beamforming at the BTS in such a way that the power consumption of the base station is minimized under the constraint that the SINR (signal-to-interference plus noise ratio) of all cellular users is guaranteed to be above a specified predetermined threshold. The second model considers the statistical distribution of the estimation error is known, and a probabilistic model is considered for the uncertainty of CSI covariance matrices. In this sense, the power consumption of the BTS is minimized in such a way that the non-outage probabilities of users are guaranteed to be above a certain predefined threshold. Although these optimization problems are non-convex, it is shown that they can be reformulated to a convex form using a semi-definite relaxation technique to obtain their lower bounds. The simulation results verify that the proposed methods perform much better than the Hybrid MRT-ZF, ZFBF and MRT beamforming methods.*

Keywords

5G cellular networks, Device to Device communications, power optimization

1. Introduction

Wireless network traffic is expected to increase a thousand times within the next ten years. It is estimated that by 2021, about eighty billion devices requiring ubiquitous data access will be connected to wireless networks. Due to the rapid growth in the number of users, wireless telecommunication networks are challenged by limited spectrum resources. Therefore, technologies that improve spectrum efficiency have received many attentions in the recent years [1], [2]. Device-to-Device (D2D) communication is one of these technologies. In a traditional cellular network, all communications must pass through the base station. But D2D communication allows two relatively close users to communicate directly. It has numerous advantages, including improved spectrum efficiency, increased throughput, enhanced energy efficiency, and delay reduction. Due to these properties, D2D communication is regarded as a key technology for the fifth-generation (5G) communication systems [4]. D2D communications are divided into in-band and out-band categories. In in-band communications, D2D users use cellular spectral resources, while in out-band communications, D2D users use spectral resources different from cellular spectrums. The in-band D2D communications can be established using overlay and underlay methods. In the overlay method, a specific part of the spectral resources is allocated to the D2D communications; but in the underlay method, D2D users can reuse the entire resources of the cellular spectrum. The underlay method is more popular because it allows both cellular and D2D users to use the spectrum simultaneously, which results in higher spectrum efficiency [3].

In underlay D2D communication, the studies have focused more on reusing the uplink spectrum than the downlink spectrum. Because in most cases, the cellular users download data from the cellular network rather than upload it [4]. Therefore, the uplink spectral resources are less engaged than the downlink spectral resources. However, in the recent years, applications such as voice over internet protocol (VOIP) and video conference applications that use the uplink spectral resources have become popular among cellular users. Therefore, the uplink and downlink spectrums are expected to carry nearly the same traffic in the future [5]. As a result, the allocation and reusing of the downlink spectral resources in underlay D2D communication is becoming an increasingly important problem. However, reusing the cellular spectrum in uplink and downlink modes causes cross-interference between cellular and D2D users.

As mentioned earlier, the interference management is a major challenge in underlay D2D communication and an interference coordination policy is needed to deal with

DOI: 10.13164/re.2022.0094

this concern. Power control is a method that can be effectively utilized to minimize the interferences between the cellular and D2D users. Distributed and centralized power control algorithms for single-input single-output communications are studied in [6]. In this study, the total transmit power of the users is set to a predefined value that maximizes the SINR of cellular users and simultaneously provides the minimum SINR required by D2D users. In [7], a dynamic power control mechanism is proposed to minimize the interferences caused by a pair of D2D users. All of the abovementioned studies suppose that the base station has a single antenna, and consider a system with a single cellular user and a pair of D2D users. But the existing mobile phone networks consist of multi-antenna base stations and multiple cellular users.

Few works have studied the power control mechanisms for underlay D2D communications in a cellular network with multi-antenna base stations and multiple cellular users. Minimizing the total transmission power of a multi-cellular network with uplink routes has been investigated in [8]. In this paper, a multi-cell network is considered where each base station supports a given number of cellular and D2D users. Cellular users are connected only to the base station, but D2D users can communicate directly or through the base station. It is proven that this is a non-deterministic polynomial time (NP-hard) problem. Due to its complexity, the authors have considered power allocation only in one cell and proposed a heuristic algorithm for this problem. In [9], a beamforming power control algorithm is presented. The algorithm aims to minimize the power consumption of the base station to guarantee a minimum QoS for both the cellular and D2D users. In the majority of underlay D2D communication investigations, it is assumed that perfect CSI of all channels is available at the base station. However, in practice, because of factors such as estimation error, quantization error, limited channel state feedback, and so on only imperfect or partial CSI are available at the transmitter. Therefore, providing robust beamforming methods that do not assume perfect CSI is essential to deal with uncertain environmental information.

Imperfect CSI can be divided into two major categories; imperfections in the instantaneous CSI and imperfections in the CSI covariance matrix. Since the changes in the second-order statistics of a channel vary slower than those of the channel itself, the covariance-based CSI requires fewer feedbacks than the instantaneous CSI. Therefore, using covariance-based CSI is more practical and logical, especially when experiencing fast fading channels. A partial CSI model is presented in [10], where it has been assumed that the perfect CSIs of the channels between cellular users and base station are available. Accordingly, a power control algorithm is presented based on game theory to minimize the interferences caused by D2D users. In [11], assuming that the instantaneous CSI is imperfect, a robust beamforming mechanism based on zero-forcing beamforming (ZFBF) is proposed to minimize the power consumption of the base station in an underlay D2D network.

Despite studies like [10] and [11], power control and robust beamforming mechanisms in D2D communications have not received enough attention. Furthermore, the growing number of wireless devices will increase CO_2 emissions [12]. Since 80% of the network energy is consumed by the base station, mechanisms that reduce energy consumption in the base station are very popular. Therefore, the present study aims to propose a set of power control and robust beamforming scenarios for an underlay D2D model in downlink mode, assuming that the CSI covariance matrix is imperfect. Our main objective is to define a beamforming mechanism in the base station to minimize its power consumption while guaranteeing that the QoS of the cellular and D2D users exceeds a minimum threshold. In this study two methods are investigated for modeling the CSI errors. In both methods, the errors are assumed to be additive in the covariance estimation of all the channels. In the first method, it is assumed that the Frobenius norm of the error is upper bounded which yields to a worst-case approach [13]. While in the second method, which is more logical and practical, the errors are assumed to be random with a specific statistical distribution which yields to outage probability approach. Like other beamforming optimization problems in multi-user systems, we have to solve a non-convex NP-hard problem due to rank-one constraints [14]. However, we will present that the problem can be reformulated as a convex optimization problem using a semi-definite relaxation technique in order to find a suboptimal beamforming and power assignment solution without loss of optimality.

Considering the previous investigations, our study is essentially different in the following aspects; firstly, in most of the earlier studies, there is only a single cellular user and a D2D pair in the network. Obviously, due to the popularity of cellular communication and the large number of cellular users, this assumption is not realistic. In our model, the network consists of multiple cellular users and a D2D pair. Also, our model can be easily extended to include more D2D pairs. Secondly, unlike earlier studies like [15] and [16] that ignore some of the interference links, in the present study, we have taken into consideration all interference signals and none of them have been ignored. Thirdly, unlike [17], imperfect CSI is not limited to interference links between cellular users and D2D users, and all links experience imperfect CSI. Finally, unlike research study works where same channel model is considered for cellular users and D2D pairs, a different individual channel model is considered for cellular users and D2D pairs in order to prepare a more realistic framework.

The rest of the paper is organized as follows. The system model is described in details in Sec. 2. In Sec. 3, the optimization problems and their solution methodologies are formulated based on channel covariance estimation for different proposed scenarios. The proposed algorithm is also presented in this section. The simulation results are provided in Sec. 4. Finally, Section 5 concludes the paper.

2. System Model

As shown in the system model presented in Fig. 1, the system consists of a cell with N cellular users with downlink communications, and underlay D2D pair. The cellular users are represented by CU_i where $i = 1,2,\ldots,N$, and the transmitter and receiver of the D2D pairs are represented by DT and DR, respectively. It is assumed that all users are equipped with one single antenna, while the base station is equipped with M antennas. Moreover, the whole bandwidth is divided to several frequency sub-channels while orthogonal frequency-division multiple access (OFDMA) technique is employed to let the BTS communicate with cellular users (CUs). According to [9], [7], it is also assumed that time division multiple access (TDMA) technique is employed to let D2D pairs reusing the total bandwidth in different time slots. Therefore, the base station can communicate with multiple cellular users simultaneously using its multiple antennas. Suppose that the BS has a full control on D2D communications, and it allows at most one D2D pair to communicate in each time slot. With no loss of assumptions, suppose that the i^{th} frequency subchannel is assigned to the i^{th} CU, where $i = 1,2,\ldots,N$, and a time slot is assigned to D2D pair. Considering that in a time slot at most one D2D pair is allowed to communicate, the received signals at the i^{th} cellular user and DR can be defined, respectively, as

$$y_r = \sqrt{P_0 s_0} h_{\mathrm{TR}} + \sum_{k=1}^{N} s_k \mathbf{h}_{\mathrm{R}}^{\mathrm{H}} \mathbf{w}_k + n_{\mathrm{R}}, \tag{1}$$

$$y_i = s_i \mathbf{h}_i^{\mathrm{H}} \mathbf{w}_i + \sum_{k=1,k\neq i}^{N} s_k \mathbf{h}_i^{\mathrm{H}} \mathbf{w}_k + \sqrt{P_0 s_0} h_{\mathrm{T}i} + n_i,\; i = 1,2,\ldots,N \tag{2}$$

where P_0 represents the transmission power of DT and s_0 represents the signal sent from DT to DR. Also s_i and $\mathbf{w}_i \in \mathbb{C}^{M\times 1}$, $i = 1, 2,\ldots,N$ represents the transmitted signal and beamforming weight vector corresponding to the i^{th} cellular user, respectively. h_{TR} is the channel coefficient between $\mathrm{D_T}$ and $\mathrm{D_R}$. $h_{\mathrm{T}i}$ is the channel coefficient between $\mathrm{D_T}$ and the i^{th} cellular user. $\mathbf{h}_{\mathrm{R}}$ and $\mathbf{h}_i$ indicate the coefficient vectors of the channel between the base station and $\mathrm{D_R}$ and the base station and the i^{th} cellular user, respectively. Also, n_{R} and n_i represent the additive zero-mean white Gaussian noise of the $\mathrm{D_R}$ and the i^{th} cellular user, with variances of σ_{R}^2 and σ_i^2, respectively. It can be assumed that in odd time slots, $\mathrm{D_T}$ transmits its signals to $\mathrm{D_R}$, while in even time slots $\mathrm{D_R}$ sends signals to $\mathrm{D_T}$. Since the equations for the received signals are similar, only the odd time slots are discussed here. It can also be assumed that there are multiple D2D pairs in a cell and derive similar equations for the signals received by these D2D pairs and the cellular users. In this case, the problem can still be solved by the proposed method. The only difference is that there will be more interference signals, and thus, the QoS of the users would be more complicated.

It can be assumed that $\mathbb{E}[S_0] = \mathbb{E}[S_i] = 0$ and $\mathbb{E}\left[|S_0|^2\right] = \mathbb{E}\left[|S_i|^2\right] = 1$, without losing the generality of the problem. It is also assumed that transmitted signals, channels vectors, and noises are statistically independent. Therefore, using (1) and (2), instantaneous SINR for $\mathrm{D_R}$ and the i^{th} cellular user can be formulated as (3) and (4), respectively:

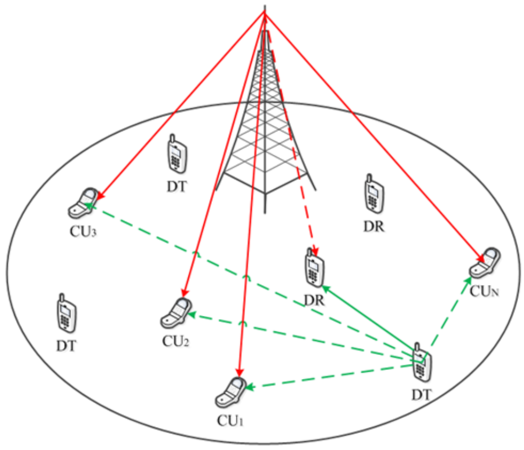

Fig. 1. System model presenting communication links in a single cell; solid lines represent the desired signals, while the dashed lines show interference signals.

$$\gamma_{\mathrm{R}} = \frac{P_0 |h_{\mathrm{TR}}|^2}{\sum_{k=1}^{N} |\mathbf{h}_{\mathrm{R}}^{\mathrm{H}} \mathbf{w}_k|^2 + \sigma_{\mathrm{R}}^2}, \tag{3}$$

$$\gamma_i = \frac{|\mathbf{h}_i^{\mathrm{H}} \mathbf{w}_i|^2}{P_0 |h_{\mathrm{T}i}|^2 + \sum_{k=1,k\neq i}^{N} |\mathbf{h}_i^{\mathrm{H}} \mathbf{w}_k|^2 + \sigma_i^2}. \tag{4}$$

As explained earlier, due to rapid fading, the constantly changing nature of wireless channels, quantization errors, and other factors, it is difficult to determine the perfect channel state information in practice. Therefore, it has been assumed that an estimation of the second-order statistics of the channels coefficients is available. The average SINR of the signal received by $\mathrm{D_R}$ and each cellular user is defined as follows:

$$\bar{\gamma}_{\mathrm{R}} = \mathbb{E}[\gamma_{\mathrm{R}}] = \frac{P_0 R_{\mathrm{TR}}}{\sum_{k=1}^{N} \mathbf{w}_k^{\mathrm{H}} \mathbf{R}_{\mathrm{R}} \mathbf{w}_k + \sigma_{\mathrm{R}}^2}, \tag{5}$$

$$\bar{\gamma}_i = \mathbb{E}[\gamma_i] = \frac{\mathbf{w}_i^{\mathrm{H}} \mathbf{R}_i \mathbf{w}_i}{P_0 R_{\mathrm{T}i} + \sum_{k=1,k\neq i}^{N} \mathbf{w}_k^{\mathrm{H}} \mathbf{R}_i \mathbf{w}_k + \sigma_i^2}, i = 1,2,\ldots,N \tag{6}$$

where $R_{\mathrm{TR}} = \mathbb{E}\left[h_{\mathrm{TR}} h_{\mathrm{TR}}^{\mathrm{H}}\right]$, $R_{\mathrm{T}i} = \mathbb{E}\left[h_{\mathrm{T}i} h_{\mathrm{T}i}^{\mathrm{H}}\right]$, $\mathbf{R}_{\mathrm{R}} = \mathbb{E}\left[\mathbf{h}_{\mathrm{R}} \mathbf{h}_{\mathrm{R}}^{\mathrm{H}}\right]$, and $\mathbf{R}_i = \mathbb{E}\left[\mathbf{h}_i \mathbf{h}_i^{\mathrm{H}}\right]$ are the estimated covariance of the channels. The power consumption of the base station is calculated using the following equation

$$P_{\mathrm{BS}} = \sum_{i=1}^{N} \mathrm{tr}(\mathbf{W}_i) \tag{7}$$

where $\mathbf{W}_i = \mathbf{w}_i \mathbf{w}_i^{\mathrm{H}}$ is the beamforming matrix. As can be observed, this matrix is a positive semi-definite Hermitian matrix of rank 1.

3. Problem Formulation

As mentioned earlier, unfortunately, it is too difficult to practically determine the perfect CSI. Therefore, it is assumed that the available estimations of the channels' covariance matrices contain some errors. We have used two methods to model these errors. The first method uses an approach inspired by [1] and [19] to describe the error using a bounded uncertainty model. In this method, it is assumed that all errors are additive and have bounded Frobenius norms. The second method is more realistic than the first one and uses an approach inspired by [2], [22]. In this approach, it is assumed that the errors have a specific statistical distribution. Accordingly, the estimation errors of the covariance matrices of channels between the base station and cellular users are additive with a Gaussian distribution. Also, the estimation errors of the covariance matrices of other channels are additive with bounded Frobenius norms, as in the first method.

3.1 Bounded Uncertainty Model

Assume that channels covariance estimations could be defined using (8) and (9):

$$\mathbf{R}_i = \hat{\mathbf{R}}_i + \mathbf{E}_i, \quad i \in \{1,2,\ldots,N\} \cup \{\mathbb{R}\}, \tag{8}$$

$$\mathbf{R}_{\mathrm{T}j} = \hat{\mathbf{R}}_{\mathrm{T}j} + \mathbf{E}_{\mathrm{T}j}, \quad j \in \{1,2,\ldots,N\} \cup \{\mathbb{R}\} \tag{9}$$

where $\hat{\mathbf{R}}_i$ and $\hat{\mathbf{R}}_{\mathrm{T}j}$ are the actual values of the channels' covariance matrices. $\mathbf{E}_i$ and $\mathbf{E}_{\mathrm{T}j}$ are estimation errors of $\hat{\mathbf{R}}_i$ and $\hat{\mathbf{R}}_{\mathrm{T}j}$, respectively, and satisfy $\|\mathbf{E}_i\| \le \varepsilon_i$ and $\|\mathbf{E}_{\mathrm{T}j}\| \le \delta_j$ conditions. Based on (8) and (9), Equations (5) and (6) can be rewritten as follows:

$$\bar{\gamma}_{\mathrm{R}} = \frac{P_0(\hat{R}_{\mathrm{TR}} + E_{\mathrm{TR}})}{\sum_{k=1}^{N} \mathbf{w}_k^{\mathrm{H}} (\hat{\mathbf{R}}_{\mathrm{R}} + \mathbf{E}_{\mathrm{R}}) \boldsymbol{w}_k + \sigma_{\mathrm{R}}^2}, \tag{10}$$

$$\bar{\gamma}_i = \frac{\mathbf{w}_i^{\mathrm{H}} (\hat{\mathbf{R}}_i + \mathbf{E}_i) \mathbf{w}_i}{P_0(\hat{R}_{\mathrm{T}i} + E_{\mathrm{T}i}) + \sum_{k=1, k\neq i}^{N} \mathbf{w}_k^{\mathrm{H}} (\hat{\mathbf{R}}_i + \mathbf{E}_i) \mathbf{w}_k + \sigma_i^2}, \quad i = 1,2,\ldots,N. \tag{11}$$

We aim to minimize the power consumption in the base station, provided that the SINR of all users exceeds a given threshold. Therefore, the optimization problem can be written as follows:

$$\begin{aligned} &\min P_{\mathrm{BS}} \\ &\text{subject to}: \ \bar{\gamma}_{\mathrm{R}} \ge \gamma_{\mathrm{th}} \\ &\qquad \bar{\gamma}_i \ge \gamma_{\mathrm{th}} \\ &\qquad \mathbf{W}_i \ge 0, \quad \mathbf{W}_i = \mathbf{W}_i^{\mathrm{H}}, \quad \mathrm{rank}(\mathbf{W}_i) = 1, \\ &\qquad i = 1,2,\ldots,N \end{aligned} \tag{12}$$

where γ_{th} represents the SINR threshold. Unfortunately, there is no closed-form solution for Problem (12) due to its complexity. However, to ensure that the first two conditions of (12) are satisfied, we can substitute the lower bounds of the SINRs to determine the worst-case results for both cellular users and the $\mathrm{D_R}$. Since the error norms are bounded, the $\bar{\gamma}_{\mathrm{R}}$ and $\bar{\gamma}_i$ lower bounds can be calculated using (13) and (14), respectively:

$$\begin{aligned} \min \bar{\gamma}_{\mathrm{R}} &= \frac{\min P_0 \left(R_{\mathrm{TR}} + E_{\mathrm{TR}}\right)}{\max \sum_{k=1}^{N} \mathbf{w}_k^{\mathrm{H}} \left(\hat{\mathbf{R}}_{\mathrm{R}} + \mathbf{E}_{\mathrm{R}}\right) \mathbf{w}_k + \sigma_{\mathrm{R}}^2} \\ &= \frac{P_0 \left(\hat{R}_{\mathrm{TR}} - \delta_{\mathrm{R}}\right)}{\sum_{k=1}^{N} \mathbf{w}_k^{\mathrm{H}} \left(\hat{\mathbf{R}}_{\mathrm{R}} + \varepsilon_{\mathrm{R}} \mathbf{I}\right) \mathbf{w}_k + \sigma_{\mathrm{R}}^2} \\ &= \frac{P_0 \left(\hat{R}_{\mathrm{TR}} - \delta_{\mathrm{R}}\right)}{\sum_{k=1}^{N} \mathrm{tr}\left(\left(\hat{\mathbf{R}}_{\mathrm{R}} + \varepsilon_{\mathrm{R}} \mathbf{I}\right) \mathbf{w}_k\right) + \sigma_{\mathrm{R}}^2}, \end{aligned} \tag{13}$$

$$\begin{aligned} \min \bar{\gamma}_i &= \frac{\min \mathbf{w}_i^{\mathrm{H}} \left(\hat{\mathbf{R}}_i + \mathbf{E}_i\right) \mathbf{w}_i}{\max P_0 \left(\hat{R}_{\mathrm{T}i} + E_{\mathrm{T}i}\right) \sum_{k=1,k\neq i}^{N} \mathbf{w}_k^{\mathrm{H}} \left(\hat{\mathbf{R}}_i + \mathbf{E}_i\right) \mathbf{w}_k + \sigma_i^2} \\ &= \frac{\mathbf{w}_i^{\mathrm{H}} \left(\hat{\mathbf{R}}_i + \varepsilon_i \mathbf{I}\right) \mathbf{w}_i}{P_0 \left(\hat{R}_{\mathrm{T}i} + \delta_i\right) + \sum_{k=1,k\neq i}^{N} \mathbf{w}_k^{\mathrm{H}} \left(\hat{\mathbf{R}}_i + \varepsilon_i \mathbf{I}\right) \mathbf{w}_k + \sigma_i^2} \\ &= \frac{\mathrm{tr}\left(\left(\hat{\mathbf{R}}_i + \varepsilon_i \mathbf{I}\right) \mathbf{w}_i\right)}{P_0 \left(\hat{R}_{\mathrm{T}i} + \delta_i\right) + \sum_{k=1,k\neq i}^{N} \mathrm{tr}\left(\left(\hat{\mathbf{R}}_i + \varepsilon_i \mathbf{I}\right) \mathbf{W}_k\right) + \sigma_i^2}, \end{aligned} \tag{14}$$

substituting (7), (13), and (14) in the optimization problem defined by (12) and simplifying the formula results in the optimization problem defined as follows:

$$\begin{aligned} &\min \sum_{i=1}^{N} \mathrm{tr}(\mathbf{W}_i) + P_0 \\ &\text{subject to:} \\ &P_0 \left(\hat{R}_{\mathrm{TR}} - \delta_{\mathrm{R}}\right) - \gamma_{\mathrm{th}} \sum_{k=1}^{N} \mathrm{tr}\left(\left(\hat{\mathbf{R}}_{\mathrm{R}} + \varepsilon_{\mathrm{R}} \mathbf{I}\right) \mathbf{W}_k\right) - \gamma_{\mathrm{th}} \sigma_{\mathrm{R}}^2 \ge 0, \\ &\mathrm{tr}\left(\left(\hat{\mathbf{R}}_i + \varepsilon_i \mathbf{I}\right) \mathbf{W}_i\right) - \gamma_{\mathrm{th}} P_0 \left(\hat{R}_{\mathrm{T}i} + \delta_i\right) - \sum_{k=1,k\neq i}^{N} \mathrm{tr}\left(\left(\hat{\mathbf{R}}_i + \varepsilon_i \mathbf{I}\right) \mathbf{W}_k\right) \\ &\qquad - \gamma_{\mathrm{th}} \sigma_i^2 \ge 0, \\ &\mathbf{W}_i \ge 0, \quad \mathbf{W}_i = \mathbf{W}_i^{\mathrm{H}}, \quad \mathrm{rank}(\mathbf{W}_i) = 1, \ i = 1,2,\ldots,N. \end{aligned} \tag{15}$$

In the optimization problem defined by (15), the objective function and all constraints, other than the beamforming matrix being rank-one are convex. Therefore, we can use the semi-definite relaxation method to eliminate this non-convex condition and get the optimization problem presented in (16), a convex semi-definite programing (SDP) problem that can be solved using convex optimization algorithms.

$$\begin{aligned} &\min \sum_{i=1}^{N} \mathrm{tr}(\mathbf{W}_i) \\ &\text{subject to:} \\ &P_0 \left(\hat{R}_{\mathrm{TR}} - \delta_{\mathrm{R}}\right) - \gamma_{\mathrm{th}} \sum_{k=1}^{N} \mathrm{tr}\left(\left(\hat{\mathbf{R}}_{\mathrm{R}} + \varepsilon_{\mathrm{R}} \mathbf{I}\right) \mathbf{W}_k\right) - \gamma_{\mathrm{th}} \sigma_{\mathrm{R}}^2 \ge 0, \\ &\mathrm{tr}\left(\left(\hat{\mathbf{R}}_i + \varepsilon_i \mathbf{I}\right) \mathbf{W}_i\right) - \gamma_{\mathrm{th}} P_0 \left(\hat{R}_{\mathrm{T}i} + \delta_i\right) - \sum_{k=1,k\neq i}^{N} \mathrm{tr}\left(\left(\hat{\mathbf{R}}_i + \varepsilon_i \mathbf{I}\right) \mathbf{W}_k\right) \\ &\qquad - \gamma_{\mathrm{th}} \sigma_i^2 \ge 0, \\ &\mathbf{W}_i \ge 0, \quad \mathbf{W}_i = \mathbf{W}_i^{\mathrm{H}}, \quad i = 1,2,\ldots,N. \end{aligned} \tag{16}$$

As mentioned above, the optimization problem (16) is convex and can be solved using any software package that uses interior point methods, including the CVX MATLAB Toolbox [21], [22]. It is also clear that if the rank of $\mathbf{W}_i$ is one, the optimal solution is achieved; but, if the rank of $\mathbf{W}_i$ is greater than one, a lower bound for the optimization problem is found.

3.2 Probabilistic Uncertainty Model

In Sec. 3.1, it was assumed that the error has a known bounded norm. However, such a deterministic and specific definition of error may not be acceptable in practice. Moreover, assuming the worst-case scenario might be too pessimistic; because the probability of all errors occurring at their maximum magnitude might be very small. Therefore, a probabilistic scheme can be a more realistic and flexible alternative for the worst-case schema.

In this section, we assume that the error matrix $\mathbf{E}_i$ is a zero-mean Hermitian complex Gaussian matrix with a variance of σ^2_{ei} [23]. Our objective is to minimize power consumption in the base station, provided that the non-outage probability of all cellular users is guaranteed to be above a predefined specific threshold, and the SINR of the D2D pair is also above a certain threshold. Therefore, the optimization problem can be formulated as follows:

$$\begin{aligned} &\min P_{\mathrm{BS}} \\ &\text{subject to: } \bar{\gamma}_{\mathrm{R}} \geq \gamma_{\mathrm{th}} \\ &\qquad \Pr\left(\bar{\gamma}_i \geq \gamma_{\mathrm{th}}\right) \geq p_i \\ &\qquad \mathbf{W}_i \geq 0, \quad \mathbf{W}_i = \mathbf{W}_i^{\mathrm{H}}, \quad \operatorname{rank}\left(\mathbf{W}_i\right) = 1, \\ &\qquad i = 1,2,\ldots,N \end{aligned} \tag{17}$$

where $\Pr(\cdot)$ is the probability operator, and p_i represents the non-outage probability threshold of the i^{th} cellular user. As shown in the above equations non-outage probability of a user is equal to the probability of the user's SINR being greater than the threshold (γ_{th}). Using (10) and (11) and assuming that norms of $\mathbf{E}_{\mathrm{R}}$, E_{TR}, and $E_{\mathrm{T}i}$ are bounded, the first two conditions of (17) can be rewritten as (18) and (19), respectively:

$$P_0\left(\hat{R}_{\mathrm{TR}} + \delta_{\mathrm{R}}\right) \geq \gamma_{\mathrm{th}}\left(\sum_{k=1}^{N} \operatorname{tr}\left(\left(\hat{\mathbf{R}}_{\mathrm{R}} + \varepsilon_{\mathrm{R}}\mathbf{I}\right)\mathbf{W}_k\right) + \sigma_{\mathrm{R}}^2\right), \tag{18}$$

$$\Pr\left\{ \operatorname{tr}\left(\left(\hat{\mathbf{R}}_i + \mathbf{E}_i\right)\mathbf{W}_i\right) \geq \gamma_{\mathrm{th}} \left(\begin{aligned} &P_0\left(\hat{R}_{\mathrm{T}i} + \delta_i\right) \\ &+ \sum_{k=1,k\neq i}^{N} \operatorname{tr}\left(\left(\hat{\mathbf{R}}_i + \mathbf{E}_i\right)\mathbf{W}_k\right) + \sigma_i^2 \end{aligned} \right) \right\} \geq \alpha_i, \quad i = 1,2,\ldots,N, \tag{19}$$

if $\mathbf{X}_i = \mathbf{W}_i - \gamma_{\mathrm{th}}(\sum_{k=1,\,k\neq i}^{N} \mathbf{W}_k)$, $y_i = \operatorname{tr}\left(\hat{\mathbf{R}}_i + \mathbf{E}_i\right)\mathbf{X}_i$, and $u_i = \gamma_{\mathrm{th}}\left(P_0\left(\hat{R}_{\mathrm{T}i} + \delta_i\right) + \sigma_i^2\right)$ for $i = \{1,2,\ldots,N\}$, equation (19) can be rewritten as follows:

$$\Pr\left(y_i \geq u_i\right) \geq \alpha_i, i = 1,2,\ldots,N. \tag{20}$$

Since $\hat{\mathbf{R}}_i + \mathbf{E}_i$ and $\mathbf{X}_i$ are both Hermitian complex Gaussian matrix, it is clear that y_i is real-valued. In [24], it is proved that y_i has a Gaussian distribution with mean $\mu_i = \operatorname{tr}(\mathbf{X}_i\hat{\mathbf{R}}_i)$ and variance of $\sigma^2_{ei}\operatorname{tr}(\mathbf{X}_i\mathbf{X}_i^{\mathrm{H}})$. (The proof is provided in Appendix A). Therefore, Pr is obtained as

$$\Pr\left(y_i \geq u_i\right) = Q\left(\frac{u_i - \mu_i}{\sqrt{\sigma_{\mathrm{ei}}^2 \operatorname{tr}\left(\mathbf{X}_i\mathbf{X}_i^{\mathrm{H}}\right)}}\right) = Q\left(\frac{u_i - \mu_i}{\sigma_{\mathrm{ei}}^2 \mathbf{X}_i}\right), \quad i = 1,2,\ldots,N \tag{21}$$

where $Q(x) = \int_x^{\infty} \frac{1}{2\sqrt{\pi}} \exp\left(\frac{-v^2}{2}\right) \mathrm{d}v \cdot$

As can be seen in (17), our objective is to ensure that the non-outage probability of the i^{th} user is above p_i. We know that in real-world systems non-outage probability must be above 0.5 and ideally equal to 1. Therefore, we assume in (17) that $0.5 \leq p_i \leq 1$ for $i = 1,2,\ldots,N$.

Since Q is a strictly decreasing function, the non-outage probability equation in Problem (17) can be simplified as follows:

$$\mathbf{X}_i \leq \frac{u_i - \mu_i}{\sigma_{\mathrm{ei}}^2 Q^{-1}\left(p_i\right)}. \tag{22}$$

If, as in the previous method, the non-convex constraint regarding the rank of the beamforming matrix is relaxed, we can use the previous equations to simplify and rewrite the optimization problem of (17) as follows:

$$\begin{aligned} &\min \sum_{i=1}^{N} \operatorname{tr}\left(\mathbf{W}_i\right) \\ &\text{subject to:} \\ &P_0\left(\hat{R}_{\mathrm{TR}} - \delta_{\mathrm{R}}\right) - \gamma_{\mathrm{th}} \sum_{k=1}^{N} \operatorname{tr}\left(\left(\hat{\mathbf{R}}_{\mathrm{R}} + \varepsilon_{\mathrm{R}}\mathbf{I}\right)\mathbf{W}_k\right) - \gamma_{\mathrm{th}}\sigma_{\mathrm{R}}^2 \geq 0, \\ &u_i - \mu_i - \mathbf{X}_i \sigma_{\mathrm{ei}}^2 Q^{-1}\left(p_i\right) \geq 0, \\ &\mathbf{W}_i \geq 0, \quad \mathbf{W}_i = \mathbf{W}_i^{\mathrm{H}}, \qquad i = 1,2,\ldots,N. \end{aligned} \tag{23}$$

The optimization problem presented in (23) is a convex problem with a linear objective function, which can be solved using optimization toolboxes such as CVX.

4. Simulation Results

In this section, some simulation results are presented to verify the performance of the proposed algorithms. It is assumed in all examples that there are three cellular users and one D2D pair in a single cell. It is also assumed in all simulations that the distance of $\mathrm{D_T}$ and $\mathrm{D_R}$ from the base station are θ_{T} and θ_{R}, respectively; while the cellular users (i.e. $\mathrm{CU_1}$, $\mathrm{CU_2}$ and $\mathrm{CU_3}$) are at the distances $\theta_1 = 10°$, $\theta_2 = \theta_1 + \alpha$, and $\theta_3 = \theta_1 - \alpha$, from the antenna array of the base station. According to [25], we assume that the base station is equipped with a uniform linear array antenna with elements positioned at half-wavelength spacing. Therefore, assuming that scatterers have a Gaussian distribution, the normalized channel covariance matrix between the base station and a cellular user can be estimated as follows:

$$\left[\hat{\mathbf{R}}_i\left(\theta_i,\sigma_\theta\right)\right]_{k,l} = \mathrm{e}^{\mathrm{j}\pi(k-l)\sin\theta_i}\,\mathrm{e}^{-0.5\left(\pi(k-l)\sigma_\theta\cos(\theta_i)\right)^2}, \quad i\in\{1,2,\ldots,N\}\cup\{\mathbb{R}\}. \tag{24}$$

The coefficients of the other channels are set to random values with normalized Gaussian distribution with zero mean and identity variance. It has been assumed that the power of D_T is constant and equal to $P_0 = 0$ dB. Also, noise powers in all cell users and D_R are assumed to have the same value, i.e., σ_n^2. Moreover, it was assumed that all errors have the same bound value of ε; in other words, $\varepsilon_i = \delta_i = \varepsilon$. Also, for $i = 1,2,\ldots,N$ we have assumed that $\sigma^2_{ei} = \sigma^2_e$ and $p_i = p$. The Matlab codes of our proposed algorithms are accessible via https://github.com/SXB0017/Xiaobo.Shen. The rest of system level simulation parameters are presented in Tab. 1 unless otherwise mentioned. In all simulations, the diagrams are provided only for the cases where the optimization problem could be solved.

Figure 2 shows the power consumption of the base station with respect to α for different ε values. Here, it is assumed that $M = 8$, $\gamma_{th} = 3$ dB, $\sigma_\theta = 2$, $\theta_T = 50°$ and $\theta_R = 55°$. As expected, increasing ε results in an increase in power consumption of the base station, while increasing the value of α reduces the power consumption, which is in line with our assumptions because increasing the distance between the users will contribute to more accurate beamforming.

Figure 3 shows the power consumption of the base station with respect to σ_θ for different $\varepsilon, \theta_T, \theta_R, \gamma_{th}$, and M values, where $\alpha = 10°$. It can be observed that increasing σ_θ

System parameters	Values
Base station antenna	Uniform linear transmitting antenna array (ULA) with half-wavelength spacing
Cell radius (meter)	420
D2D pair distance (meter)	25–55
The model for cellular link path loss	$22\log_{10}(d)+42+20\log_{10}\left(\frac{f_c}{5}\right)$ [26]
The model for D2D link path loss	$16.9\log_{10}(d)+46.8+20\log_{10}\left(\frac{f_c}{5}\right)$ [26]
Carrier frequency (GHz)	1.8
Noise power (dBm)	0
Maximum BTS transmit power (P_{max})	38
Maximum D2D transmit power (P^D_{max})	6
Minimum QoS requirements at CUs (dB)	2

Tab. 1. System level details of simulation parameters.

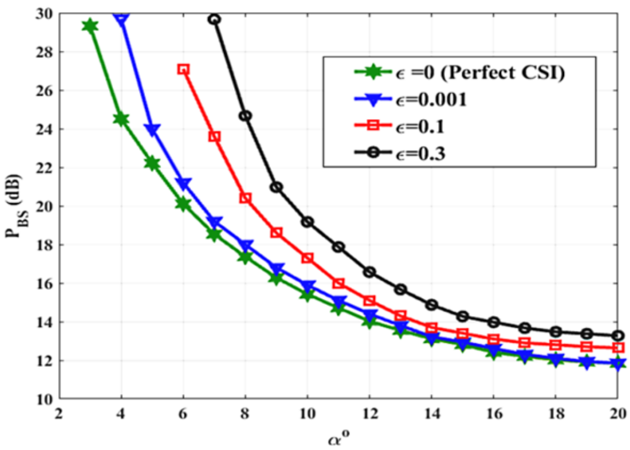

Fig. 2. Power consumption of the base station in scenario 1 with respect to α for different ε values, when $M = 8$, $\gamma_{th} = 3$ dB, $\sigma_\theta = 2$, $\theta_T = 50°$ and $\theta_R = 55°$.

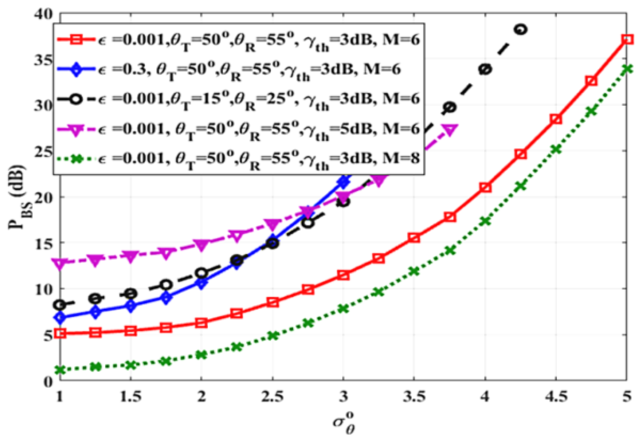

Fig. 3. Power consumption of the base station in scenario 1 with respect to σ_θ for different values of $\varepsilon, \theta_T, \theta_R, \gamma_{th}, M$ and $\alpha = 10°$.

increases the power consumption of the base station. Because the spatial correlation between antenna array elements of the base station corresponding to the spatial channels between the base station and cellular users is reduced, and the interference is increased from one link to another. Therefore, the power consumption is increased to guarantee the SINR. Figure 3 also shows that increasing ε results in increased power consumption in the base station, while increasing the number of antennas reduces the power consumption because beamforming using more antennas will be more accurate. Also, in cases that the D2D pair is not located between the cellular users ($\theta_T = 50°$, $\theta_R = 55°$), the power consumption is less than the case where the D2D pair is between the cellular users ($\theta_T = 15°$, $\theta_R = 25°$). It is also shown that increasing γ_{th} increases the power consumption; because achieving greater SINR requires more power.

Figure 4 compares the power consumptions of the proposed method with Hybrid MRT-ZF (maximum ratio transmission-zero forcing) [17], ZFBF (zero forcing beamforming) [11], and MRT (maximum ratio transmission) [27]. The figure depicts the power consumption of the base station with respect to the division angle of the cellular users α. Here, it is assumed that $\varepsilon = 0.1$, $\gamma_{th} = 3$ dB, $\sigma_\theta = 2$, $M = 6$, $\theta_T = 50°$, and $\theta_R = 55°$. It can be observed that our proposed algorithm has a better performance compared to the other methods. This difference is especially significant in cases with smaller α values where beamforming is more complicated due to the close distance between the users. Figure 5 shows the power consumption of the base station with respect to α for different non-outage probability p values. Here, it is assumed that $\varepsilon = 0.1$, $\gamma_{th} = 3$ dB, $\sigma_\theta = 2$, $M = 6$, $\theta_T = 50°$, and $\theta_R = 55°$. It can be observed that increasing α results in a decrease in power consumption for all p values because increasing the distance between the users will make beamforming simpler and more accurate.

Figure 6 shows power consumption in the base station with respect to α for different σ^2_e, ε, γ_{th}, and M values, where $p = 80\%$, $\sigma_\theta = 2$, $\theta_T = 50°$, and $\theta_R = 55°$. As expected, increasing γ_{th}, σ^2_e and ε result in higher power consumption in the base station. While, increasing M which contributes to more accurate beamforming, decreases the power consumption. Figure 7 shows the power consumption of the base station with respect to σ_θ for different positions of D2D pair and different σ^2_e values, where $p = 80\%$, $\sigma_\theta = 2$, $\varepsilon = 0.1$, $M = 6$ and $\gamma_{th} = 3$ dB. Relocating the D2D pair and positioning them between cellular users causes more interference for the cellular users and results in increased power consumption in the base station. It is also observed that increasing σ_θ increases the power consumption of the base station. Since the decrease in the spatial correlation between the cellular user and the antenna array elements corresponding to the spatial channels increases the interferences from one link to another, power consumption in the base station is increased to guarantee the users' QoS.

The performance of the proposed algorithm is compared with three beamforming algorithms, including Hybrid MRT-ZF, ZFBF, and MRT, in Fig. 8. Here, it is assumed that $p = 80\%$, $\sigma_e^2 = 0.001$, $\sigma_\theta = 2$, $\varepsilon = 0.1$, $\gamma_{th} = 3$ dB, and $M = 6$. The figure shows that our proposed algorithm consumes less power than the other methods, especially in smaller α values. Figure 9 compares the power consumption of the base station with respect to α for different σ_e^2 values in the two proposed algorithms, assuming that

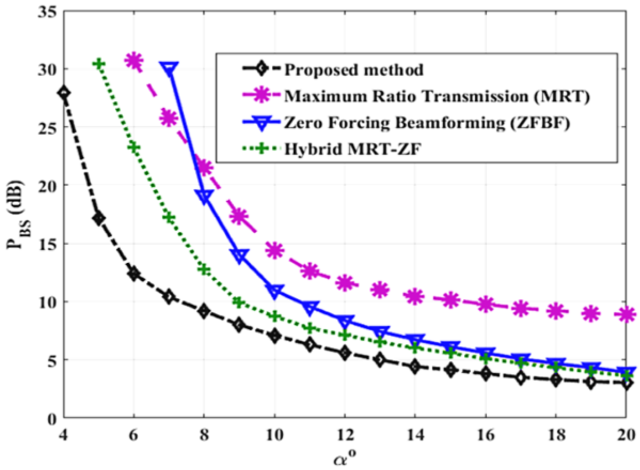

Fig. 4. Performance of the proposed algorithm scenario 1 compared to those of other beamforming methods including Hybrid MRT-ZF, ZFBF, and MRT when $\varepsilon = 0.1$, $\gamma_{th} = 3$ dB, $\sigma_\theta = 2$, $M = 6$, $\theta_T = 50°$, and $\theta_R = 55°$.

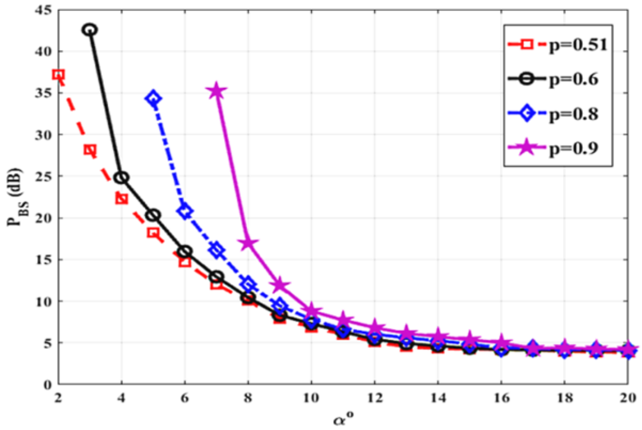

Fig. 5. Power consumption of the base station in scenario 2 for different p values where $\varepsilon = 0.1$, $\gamma_{th} = 3$ dB, $\sigma_\theta = 2$, $M = 6$, $\theta_T = 50°$, and $\theta_R = 55°$.

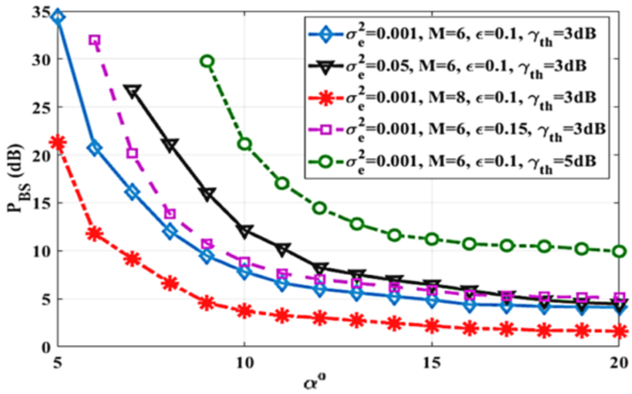

Fig. 6. Power consumption of the base station in scenario 2 with respect to α for different σ^2_e, ε, γ_{th}, and M values, where $p = 80\%$, $\sigma_\theta = 2$, $\theta_T = 50°$, and $\theta_R = 55°$.

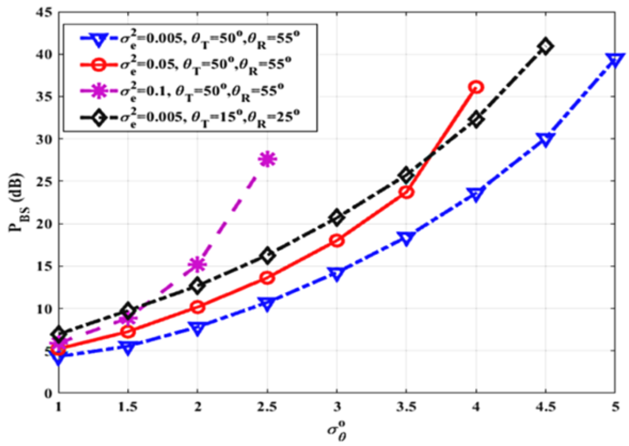

Fig. 7. Power consumption of the base station in scenario 2 with respect to σ_θ for different positions of D2D pair and different σ^2_e values, where $p = 80\%$, $\sigma_\theta = 2$, $\varepsilon = 0.1$, $M = 6$ and $\gamma_{th} = 3$ dB.

p = 80%, γ_{th} =3 dB, M = 6, θ_T = 50° and θ_R = 55°. For this comparison, in the first method, ε_i is determined using a numerical grid search to satisfy the condition p = 80%. It is also assumed in both methods that δ_i = 0.1. It is observed that the power consumption of the base station in the second method is less than the first method. This difference is more evident for smaller α values, where guaranteeing beamforming and QoS are more difficult to meet because users are closer to each other. In order to find out which algorithm is more efficient in terms of computational complexity, a running time comparison is carried out between the methods.

Considering the configuration of the used system with Intel Corei2, 8GB RAM in 64Bit-Matlab R2014b platform, the running time of the proposed methods is compared with the others in terms of number of users in Fig. 10. The running time of the reconstruction algorithms is partly close to

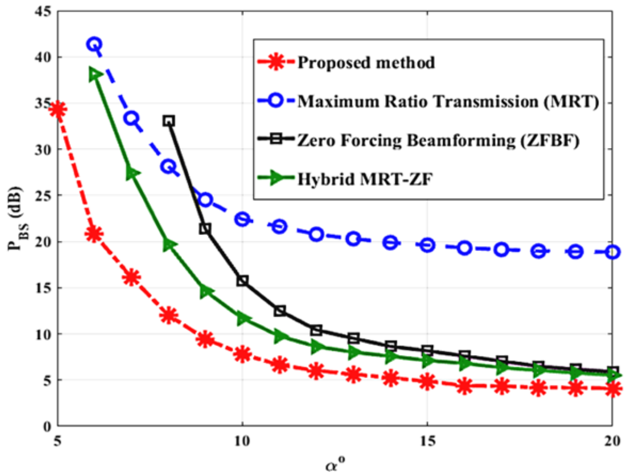

Fig. 8. Performance of the proposed algorithm in scenario 2 compared to the other methods, with respect to α where p = 80%, σ_e^2 = 0.001, σ_0 = 2, ε = 0.1, γ_{th} =3 dB, and M = 6.

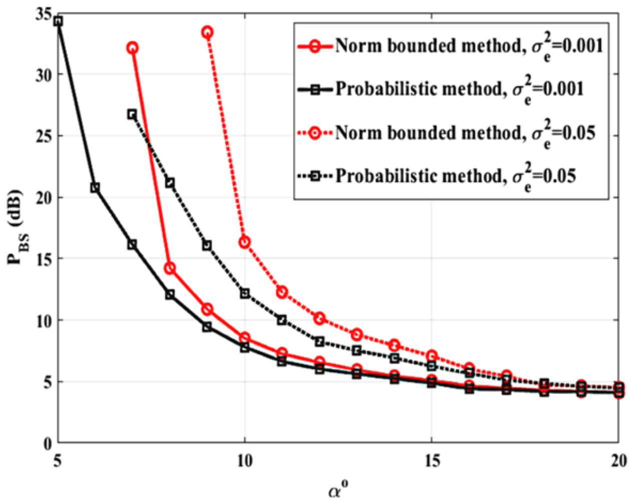

Fig. 9. Comparison two proposed algorithms (norm bounded (scenario 1) vs. probabilistic method (scenario 2)) for M = 6 and γ_{th} =3 dB.

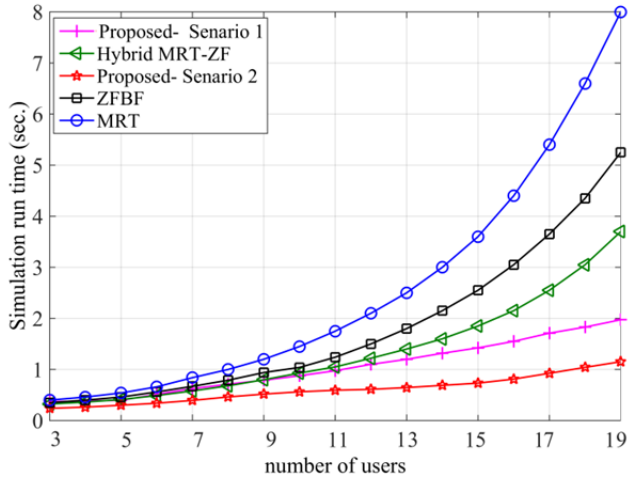

Fig. 10. Simulations run time (in seconds) with respect to number of users for different algorithms.

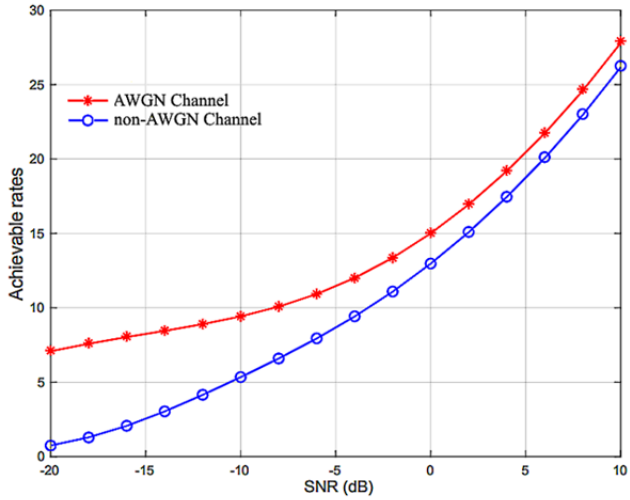

Fig. 11. Achievable solution rate of the optimization problem for the proposed method versus SNR in colored and white noisy conditions when M = 8, γ_{th} = 3 dB, σ_0 = 2, θ_T = 50°, and θ_R = 55°.

each other in the less number of users. Moreover, the proposed algorithm scenario 1 is much faster compared with especially Hybrid MRT-ZF, ZFBF and MRT. These results demonstrate that the proposed algorithms have both satisfactory speed and computational complexity compared with the state of the art algorithms.

Finally, the impact of non-AWGN (i.e. additive colored Gaussian noise as defined in [28]) with imperfect CSI estimation on the proposed model is evaluated with AWGN conditions in terms of achievable solution rate (i.e. when the optimization problem is solved). The results in Fig. 11 show that the achievable solution rate of the proposed method in presence of colored noise is lower than the white noise (i.e. AWGN channel) with decreasing SNR. Based on the gap between colored and white noise conditions, it is implied that the proposed model should be improved in such a way to demonstrate significant performance in more realistic environments in our future research work.

5. Conclusion

In this paper, beamforming and minimizing the power consumption of the base station in a cellular system underlying D2D communications were investigated in a more realistic environment. Knowing an imperfect CSI, only an approximation of their covariance is available in BTS. Therefore, based on the estimation error two optimization models were proposed to minimize the power consumption and robust beamforming designs. The first model assumes that the upper bound of the estimation errors is limited to their Frobenius norms. So, the main objective is to calculate the beamforming at the BTS in such a way that the power consumption of the base station is minimized under the constraint that the SINR of all cellular users is guaranteed to be above a specified predetermined threshold. The second model considers the statistical distribution of the estimation error is known, and a probabilistic model is considered for the uncertainty of CSI covariance matrices. In this sense, the power consumption of the BTS is minimized in such a way that the non-outage probabilities of users are guaranteed to be above a certain predefined threshold. Our proposed scenarios in this work were to understand first the effect of CSI error in a relatively simpler model, but not straightforward, leaving the general case to our future work which includes; a generalized framework that could cover the several cellular users scenario and eventually include out-of-cell interference and multiple antennas into the analysis in AWGN and non-AWGN channel conditions.

Acknowledgments

This research is sponsored through 2020 Key Research and Development Project of Anhui Province 'Key Technology and Product Development of Intelligent Fire Early Warning Equipment Based on Acoustic Array Multi-frequency Detection', project number: 202004a05020023.

References

[1] ZHANG, C., PATRAS, P., HADDADI, H. Deep learning in mobile and wireless networking: A survey. *IEEE Communications Surveys & Tutorials*, 2019, vol. 21, no. 3, p. 2224–2287. DOI: 10.1109/COMST.2019.2904897

[2] CAPPONI, A., FIANDRINO, C., KANTARCI, B., et al. A survey on mobile crowdsensing systems: Challenges, solutions, and opportunities. *IEEE Communications Surveys & Tutorials*, 2019, vol. 21, no. 3, p. 2419–2465. DOI: 10.1109/COMST.2019.2914030

[3] TEHRANI, M. N., UYSAL, M., YANIKOMEROGLU, H. Device-to-device communication in 5G cellular networks: Challenges, solutions, and future directions. *IEEE Communications Magazine*, 2014, vol. 52, no. 4, p. 86–92. DOI: 10.1109/MCOM.2014.6815897

[4] LIN, X., ANDREWS, J., GHOSH, A., et al. An overview of 3GPP device-to-device proximity services. *IEEE Communications Magazine,* 2014, vol. 52, no. 4, p. 40–48. DOI: 10.1109/MCOM.2014.6807945

[5] MALANDRINO, F., LIMANI, Z., CASETTI, C., et al. Interference-aware downlink and uplink resource allocation in HetNets with D2D support. *IEEE Transactions on Wireless Communications*, 2015, vol. 14, no. 5, p. 2729–2741. DOI: 10.1109/TWC.2015.2391126

[6] LEE, N., LIN, X., ANDREWS, J. G., et al. Power control for D2D underlaid cellular networks: Modelling, algorithms, and analysis. *IEEE Journal on Selected Areas in Communications*, 2015, vol. 33, no. 1, p. 1–13. DOI: 10.1109/JSAC.2014.2369612

[7] GU, J., BAE, S. J., CHOI, B. G., et al. Dynamic power control mechanism for interference coordination of device-to device communication in cellular networks. In *The Third International Conference on Ubiquitous and Future Networks (ICUFN).* Dalian (China), 2011, p. 71–75. DOI: 10.1109/ICUFN.2011.5949138

[8] BELLESCHI, M., FODOR, G., ABRARDO, A. Performance analysis of a distributed resource allocation scheme for D2D communications. In *Proceedings of IEEE Global Communications Conference (GLOBECOM).* Houston (TX, USA), 2011, p. 358–362. DOI: 10.1109/GLOCOMW.2011.6162471

[9] LIN, M., OUYANG, J., ZHU, W.P. Joint beamforming and power control for device-to-device communications underlying cellular networks. *IEEE Journal on Selected Areas in Communications*, 2016, vol. 34, no. 1, p. 138–150. DOI: 10.1109/JSAC.2015.2452491

[10] MAGHSUDI, S., STANCZAK, S. Hybrid centralized distributed resource allocation for device-to-device communication underlying cellular networks. *IEEE Transactions on Vehicular Technology*, 2016, vol. 65, no. 4, p. 2481–2495. DOI: 10.1109/TVT.2015.2423691

[11] MIRZA, J., ZHENG, G., WONG, K. K., et al. Joint beamforming and power optimization for D2D underlying cellular networks. *IEEE Transactions on Vehicular Technology*, 2018, vol. 67, no. 9, p. 8324–8335. DOI: 10.1109/TVT.2018.2845748

[12] VAN CHIEN, T., BJORNSON, E., LARSSON, E. G. Downlink power control for massive MIMO cellular systems with optimal user association. In *Proceeding IEEE International Conference on Communications (ICC)*. Kuala Lumpur (Malaysia), 2016, p. 1–6. DOI: 10.1109/ICC.2016.7510950

[13] NIU, H., ZHANG, B., HUANG, Y., et al. Robust secrecy beamforming and power-splitting design for multiuser MISO downlink with SWIPT. *IEEE Systems Journal*, 2018, vol. 13, no. 2, p. 1367–1375. DOI: 10.1109/JSYST.2018.2819993

[14] LIU, Y. F., DAI, Y. H., LUO, Z. Q. Coordinated beamforming for MISO interference channel: Complexity analysis and efficient algorithms. *IEEE Transactions on Signal Processing*, 2011, vol. 59, no. 3, p. 1142–1157. DOI: 10.1109/TSP.2010.2092772

[15] MIN, H., LEE, J., PARK, S., et al. Capacity enhancement using an interference limited area for device-to-device uplink underlying cellular networks. *IEEE Transactions on Wireless Communications*, 2011, vol. 10, no. 12, p. 3995–4000. DOI: 10.1109/TWC.2011.100611.101684

[16] MIN, H., SEO, W., LEE, J., et al. Reliability improvement using receive mode selection in the device-to-device uplink period underlying cellular networks. *IEEE Transactions on Wireless Communications*, 2011, vol. 10, no. 2, p. 413–418. DOI: 10.1109/TWC.2011.122010.100963

[17] NASLECHERAGHI, M., MARANDI, L., GHORASHI, S. A. A novel device-to-device discovery scheme for underlay cellular networks. In *Iranian Conference on Electrical Engineering (ICEE).* Tehran (Iran), 2017, p. 2106–2110. DOI: 10.1109/IranianCEE.2017.7985409

[18] FENG, D., LU, L., YI, Y. W., et al. QoS-aware resource allocation for device-to-device communications with channel uncertainty. *IEEE Transactions on Vehicular Technology*, 2016, vol. 65, no. 8, p. 6051–6062. DOI: 10.1109/TVT.2015.2479258

[19] LE, T. A., NAKHAI, M. R., NAVAIE, K. A robust transmission strategy for multi-cell interference networks. In *IEEE Global Communications Conference (GLOBECOM)*. San Diego (CA, USA), 2015, p. 1–6. DOI: 10.1109/GLOCOM.2015.7417142

[20] SHAKER, R., KHAKZAD, H., TAHERPOUR, A., et al. Hybrid underlay/overlay cognitive radio system with hierarchical modulation in the presence of channel estimation error. In *IEEE Global Communications Conference (GLOBECOM)*. Austin (TX, USA), 2014, p. 967–972. DOI: 10.1109/GLOCOM.2014.7036934

[21] GRANT, M., BOYD, S. *CVX: Matlab Software for Disciplined Convex Programming, Version 2.0 beta.* [Online] September 2013. Available at: http://cvxr.com/cvx

[22] JAHANSHAHI, J. A., DANYALI, H., HELFROUSH, M. S. A modified compressed sensing-based recovery algorithm for wireless sensor networks. *Radioengineering*, 2019, vol. 28, no. 3, p. 610–617. DOI: 10.13164/re.2019.0610

[23] CHU, Z., ZHU, Z., XIANG, W., et al. Robust beamforming and power splitting design in MISO SWIPT downlink system. *IET Communications*, 2016, vol. 10, no. 6, p. 691–698. DOI: 10.1049/iet-com.2015.0475

[24] COUILLET, R., DEBBAH, M. *Random Matrix Methods for Wireless Communications*. Cambridge University Press, 2011. ISBN: 9780511994746

[25] BENGTSSON, M., OTTERSTEN, B. Optimal downlink beamforming using semidefinite optimization. In *Proceedings of the 37th Annual Allerton Conference on Communication, Control and Computing*. 1999, p. 987–996.

[26] ITU. *Guidelines for Evaluation of Radio Interface Technologies for IMT-Advanced.* Report ITU-R M.2135-1, 12/2009. [Online] Available at: https://www.itu.int/dms_pub/itu-r/opb/rep/R-REP-M.2135-1-2009-PDF-E.pdf

[27] TIMOTHEOU, S., KRIKIDIS, I., ZHENG, G., et al. Beamforming for MISO interference channels with QoS and RF energy transfer. *IEEE Transactions on Wireless Communications*, 2014, vol. 13, no. 5, p. 2646–2658. DOI: 10.1109/TWC.2014.032514.131199

[28] BIGUESH, M., GAZOR, S., SHARIAT, M. H. Optimal training sequence for MIMO wireless systems in colored environments. *IEEE Transactions on Signal Processing*, 2009, vol. 57, no. 8, p. 3144–3153. DOI: 10.1109/TSP.2009.2018614

About the Authors …

Qianchun WANG was born in 1982, Dalian, Liaoning Province, China. In March 2011, she received her M.Sc. in Engineering, and is now a lecturer in the School of Electronic Engineering of Huainan Normal University. Her research interest is mainly wireless communication.

Xiaobo SHEN (corresponding author) was born in 1982, Zhaodong City, China. He received his master's degree in July 2008, and now he is an Associate Professor in the School of Electronic Engineering of Huainan Normal University. His research interests mainly include information processing and intelligent control.

Appendix A

If $\mathbf{G}\in \mathbb{C}^{N\times M}$ is a random Hermitian matrix, where the real-valued elements are located on the main diagonal, and the complex values of the other elements are independent random Gaussian variables with zero mean and variance of σ^2, the following equation shall apply to every definite matrix $\mathbf{A}\in \mathbb{C}^{N\times M}$

$$\operatorname{tr}\left(\mathbf{AG}\right) \sim N_{\mathrm{C}}\left(0, \sigma^2 \operatorname{tr}\left(\mathbf{AA}^{\mathrm{H}}\right)\right) \tag{A1}$$

where $N_{\mathrm{C}}(0,0)$ is a complex Gaussian distribution. If $MN\rightarrow\infty$, the central limit theorem implies that the distribution of tr(**AG**) is Gaussian, regardless of the distribution of G elements, because the elements of **G** are independent and extracted from the same statistical distribution.

Proof: Please note that,

$$\operatorname{tr}\left(\mathbf{AG}\right) = \sum_{i}^{M}\sum_{j}^{N} a_{ij} g_{ji}\,. \tag{A2}$$

Since **G** elements are independent and have a zero-mean Gaussian distribution, (24) also has a zero-mean Gaussian distribution, and its variance can be calculated using (27):

$$\begin{aligned} & E\left\{\operatorname{tr}\left(\mathbf{AG}\right)\left(\operatorname{tr}\left(\mathbf{AG}\right)\right)^{*}\right\} \\ & = E\left\{\operatorname{vec}\left(\mathbf{A}^{\mathrm{H}}\right)^{\mathrm{H}} \operatorname{vec}\left(\mathbf{G}\right)\operatorname{vec}\left(\mathbf{G}\right)^{\mathrm{H}} \operatorname{vec}\left(\mathbf{A}^{\mathrm{H}}\right)\right\} \\ & = \operatorname{vec}\left(\mathbf{A}^{\mathrm{H}}\right)^{\mathrm{H}} \sigma^2 \mathbf{I}_{NM} \operatorname{vec}\left(\mathbf{A}^{\mathrm{H}}\right) \\ & = \sigma^2 \operatorname{tr}\left(\mathbf{A}^{\mathrm{H}}\mathbf{A}\right) \end{aligned} \tag{A3}$$

where $\mathbf{I}_{NM}$ and vec(·) represent the identity matrix and vector operator, respectively. Thus, the proof is complete.