Research Article

Power Optimization of IRS-Assisted D2D System Based on Imperfect Channel

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1. Introduction

Recently, mobile edge computing (MEC) has become an effective technique for reducing computational latency in task-intensive applications by utilizing both local and edge computing [1]. However, the computing resources of the edge servers are limited, so the heavy computing burden of the edge servers needs to be relieved. Therefore, the authors of [2, 3] adopt D2D technology to reduce the burden of edge servers and improve energy efficiency through user cooperative offloading. However, due to the limitation of user transmit power and the link used for transmission may be blocked by obstructions, D2D user pairs who are far apart generally have a lower success rate of offloading. By adopting intelligent reflecting surface (IRS) to assist communication, the communication environment can be changed to resist the influence of a bad communication environment on system performance [4]. Therefore, the performance of the D2D offload system can be improved from the perspective of saving device power and communication.

1. Introduction

Recently, mobile edge computing (MEC) has become an effective technique for reducing computational latency in task-intensive applications by utilizing both local and edge computing [1]. However, the computing resources of the edge servers are limited, so the heavy computing burden of the edge servers needs to be relieved. Therefore, the authors of [2, 3] adopt D2D technology to reduce the burden of edge servers and improve energy efficiency through user cooperative offloading. However, due to the limitation of user transmit power and the link used for transmission may be blocked by obstructions, D2D user pairs who are far apart generally have a lower success rate of offloading. By adopting intelligent reflecting surface (IRS) to assist communication, the communication environment can be changed to resist the influence of a bad communication environment on system performance [4]. Therefore, the performance of the D2D offload system can be improved from the perspective of saving device power and communication.

IRS technology has attracted much attention in recent years [5–7]. IRS is a metasurface with a large number of reconfigurable passive components. Each component can independently produce phase shifts to incident signals. All elements work together to change the transmission path of the reflected signals [8]. In contrast to the traditional amplification and forwarding (AF) relay phase, IRS uses passive reflection beamforming to process the incident signal, reducing the energy consumption of the system [9]. These characteristics make IRS technology more promising from an energy efficiency perspective. Fortunately, by subtly tweaking reflective components, IRS helps create a good wireless propagation environment to greatly optimize spectral efficiency and energy efficiency [10–12]. The authors of [13, 14] adopted IRS to assist communication, which greatly improved the reachable rate of the communication system. The authors of [15] investigated the role of IRS-assisted communication in improving system security performance. Therefore, IRS can solve the problems of long communication distance and communication link blockage mentioned above.
The authors of [10] aimed to jointly design the transmit beamforming of access points (AP) and the phase shift of IRS to minimize the power of the system. The authors of [11] explored the block coordinate descent method to optimize delays in IRS-assisted MEC systems. The authors of [16] studied the physical layer security and data transmission of IRS-assisted D2D networks. The authors of [17] studied the IRS-assisted D2D wireless communication system, using IRS to regulate its reflecting components to enhance the data transmission of D2D communication. To maximize the energy efficiency of the system, the authors of [18] adopted IRS to assist the D2D communication network and jointly optimize the device power control and passive beamforming of IRS to maximize the energy efficiency of the system.

However, all above researches about IRS-assisted D2D communication networks were all carried out under the premise of perfect channel state information (CSI). Unfortunately, perfect CSI between users and the IRS is difficult to obtain in practice because the IRS reflecting elements are passive, and its signal processing power is limited. Generally, there are two main ways to get the communication channels associated with the IRS. One method estimates the base station (BS)-IRS channel and IRS-user channel, respectively [19]. However, this method requires the introduction of active components, which can increase hardware costs and add additional power consumption. Fortunately, the cascaded BS-IRS-user channels are sufficient to support joint beamforming designs [20, 21].

The literature [10–18] mentioned above did not consider the influence of imperfect CSI on transmission design. Because of the inevitable channel estimation errors, simply treating channels as perfect ones in the analysis process will lead to the loss of system performance. In addition, although nonorthogonal multiple access (NOMA) can increase system throughput, the processing capacities of users are not as strong as those of the BS, so it is difficult to achieve multi-user detection and interference elimination at the user end.

Considering the errors in the estimation of the wireless channel and the requirement of the worst-case transmit rate of the devices and the IRS power budget, the authors of [22] developed an optimization problem to minimize the transmit power of the AP. In the imperfect CSI case, the authors of [23] investigated the worst-case joint optimization design for IRS-assisted MISO systems to minimize the transmit power of the system. By jointly optimizing the transmit beamforming at the AP and the phase shift at IRS, the authors of [24] aimed to minimize the transmit power of the system constrained by the worst-case quality of service of the device.

The literature [22–24] mentioned above considered the channel estimation error of the IRS-aided communication system, but the authors only considered direct communication between the user and the base station. With the rapid increase of Internet of Things (IoT) devices, the computing resources of edge servers are limited, and the heavy computing burden of edge servers needs to be relieved. Therefore, D2D technology can be adopted to reduce the burden of edge servers and improve spectrum efficiency through user cooperative offloading.

To overcome the impact of long-distance transmission and harsh wireless communication environment on system performance, we adopt IRS-assisted wireless communication. With the large-scale popularization of intelligent terminal equipment, spectrum efficiency and power consumption have become a nonnegligible problem. D2D technology can be adopted to reduce the burden of edge servers and improve spectrum efficiency and energy efficiency through user cooperative offloading. In this context, this paper studies the robust design of an IRS-assisted D2D network with the assumption of imperfect cascaded channels. And D2D users communicate with each other using orthogonal frequency division multiple access (OFDMA). Specifically, our goal is to design a robust joint optimization scheme for transmit beamforming and IRS phase shift to minimize the system transmit power of D2D systems under a bounded CSI error model.

The contributions of our work are summarized below: (1) Our goal is to jointly optimize the transmit beamforming and IRS phase to minimize the system transmit power, while requiring each user’s rate to meet the minimum rate constraint in the presence of channel errors. (2) The problem presented is nonconvex, and the imperfection of CSI makes it even more difficult. We convert the problem to two effectively solvable semidefinite programming (SDP) subproblems using S-Procedue and then solve them through the convex-concave procedure (CCP) algorithm and the alternate optimization method. (3) Numerical results show the effectiveness of the algorithm and verify that the deployment of IRS could significantly reduce the system transmit power.

2. System Model

2.1. Communication Model. We consider an IRS-assisted D2D network, and users communicate with each other with OFDMA. As shown in Figure 1, there are L single-antenna D2D link pairs in the system and an IRS with N reflection elements. The phase shift of IRS is a diagonal matrix \( \Theta = \text{diag}(\theta_1, \ldots, \theta_N) \in \mathbb{C}^{N \times N} \), where \( \theta_n \in [0, 2\pi] \) denotes the reflection angle of reflection element \( n \). Denote by \( g_l \in \mathbb{C} \) the link coefficient from transmitter \( DT_l \) to receiver \( DR_l \), where \( l \in \mathcal{L} = \{1, 2, \ldots, L\} \). The channel vectors from transmitter \( DT_l \) to IRS and from IRS to receiver \( DR_l \) are represented by \( \mathbf{f}_l \in \mathbb{C}^{N \times 1} \) and \( \mathbf{h}_l \in \mathbb{C}^{N \times 1} \), respectively.

L signals offloaded by the transmit users are denoted by \( \mathbf{x} = [x_1, \ldots, x_L]^T \in \mathbb{C}^{L \times 1} \). The transmit data for user \( DT_l \) is assumed to have zero mean and unit variance, i.e., \( E(x_lx_l^H) = 1 \). The received signal of \( DR_l \) is as follows:

\[
y_l = (g_l^H + h_l^H \Theta \mathbf{f}_l)a_l x_l + n,
\]

where \( \mathbf{a} = [a_1, \ldots, a_L] \in \mathbb{C}^{L \times L} \) is the corresponding precoding vector for the transmit users and \( n \in \mathbb{C} \sim \mathcal{CN}(0, \sigma^2) \) is the additive noise. Denote by \( H_l = \text{diag}(h_l^H) \) the cascaded channels from \( DT_l \) to \( DR_l \) through the IRS, and the vector
D2D communication network can be expressed as

\[ \text{the system transmit power subject to the constraints of the} \]

transmit beamforming and IRS phase shifts to minimize

\[ \text{with imperfect CSI. Specifically, we jointly optimize} \]

the system transmit power subject to the constraints of the worst-case quality of service (QoS). Thus, this problem can be expressed as

\[ \min_{a,c} |a|^2, \quad \text{(5a)} \]

containing diagonal elements of \( \Theta \) is denoted by \( e = (e^{θ_1}, \ldots, e^{θ_N})^T \in \mathbb{C}^{N \times 1} \). Then, the received signal of \( DR_i \) can be redescribed as

\[ y_i = \left( g_i^H + e^H_i H_i \right) a_i x_i + n_i. \quad \text{(2)} \]

Then, the achievable rate of link \( l \) in the OFDMA-based D2D communication network can be expressed as

\[ R_l = \log_2 \left( 1 + \frac{|\left( g_l^H + e^H_l H_l \right) a_l |^2}{\sigma^2} \right). \quad \text{(3)} \]

In IRS-assisted D2D networks, there are two different types of links: the direct channel \( g_l \) and the cascaded channel \( H_l \). IRS-related cascade channels are more difficult to estimate than direct channels due to the passivity of IRS. Therefore, we assume that the cascaded channels are imperfect. We define the cascaded channel as an error bounded model, which can be expressed as

\[ H_l = \tilde{H}_l + \Delta H_l, \quad \| \Delta H_l \|_F \leq \epsilon, \forall l \in \mathcal{L}, \quad \text{(4)} \]

where \( \tilde{H}_l \) represents the estimated cascaded channel vector, \( \Delta H_l \) represents the corresponding channel error vector, and \( \epsilon \) is the range of the uncertainty region defined by the transmitter.

2.2. Robust Problem Formulation. Here, our goal is to minimize the transmit power of the IRS-assisted D2D system with imperfect CSI. Specifically, we jointly optimize the transmit beamforming and IRS phase shifts to minimize the system transmit power subject to the constraints of the worst-case quality of service (QoS). Thus, this problem can be expressed as

\[ \begin{align*}
\text{s.t.} & \quad \log_2 \left( 1 + \frac{|\left( g_l^H + e^H_l H_l \right) a_l |^2}{\sigma^2} \right) \geq r_l, \quad \| \Delta H_l \|_F \leq \epsilon, \forall l \in \mathcal{L}, \\
& \quad \| e^H_l |^2 = 1, \forall n \in \mathcal{N}. \quad \text{(5b)} \\
& \quad \| e^H_l |^2 = 1, \forall n \in \mathcal{N}. \quad \text{(5c)}
\end{align*} \]

Here, \( r_l \) is the minimum rate target for each user. Constraints in (5b) are the lowest targets for users, while constraints in (5c) are the IRS phase shift constraints. It is a tricky problem to solve due to the nonconvex constraints in (5b) and constant-modulus constraints in (5c). In addition, \( e \) and \( a \) are coupled. We will use the CCP algorithm and the alternative optimization (OA) method to solve the problem (5) in the next section.

3. Robust Beamforming Design Subheadings

Here, we tackle the power minimization problem of the IRS-assisted D2D networks. First, we equivalently convert the nonconvex constraints in (5b) to a form that is easy to deal with and then optimize \( e \) and \( a \) using the OA method, respectively.

3.1. Problem Transformation. To start with, constraints in (5b) can be equivalently described as

\[ \left( |(g_l^H + e^H_l H_l) a_l|^2 \right) \geq \sigma^2 (2^n - 1), \quad \| \Delta H_l \|_F \leq \epsilon, \forall l \in \mathcal{L}. \quad \text{(6)} \]

First, the left side of inequality constraints in (6) is approximated by a linear lower bound. Then, the S-Procedure is used to deal with the semi-infinite inequalities after approximation. Specifically, Lemma 1 shows the linear lower bound of (6).

**Lemma 1.** Assume that \( a_l^{(n)} \) and \( e^{(n)} \) are the optimal solutions gained at the \( n \)-th iteration, and \( |(g_l^H + e^H_l H_l) a_l|^2 \) can be equivalent to a linear lower bound at \( (a_l^{(n)}, e^{(n)}) \) as follows:

\[ H_l^H A_l H_l + 2 \text{ Re } (B_l^H H_l) + C_l, \quad \text{(7)} \]

where

\[ A_l = a_l a_l^{(n)H} + e^{(n)} e^{(n)H} a_l + a_l^{(n)H} e^{(n)} a_l - a_l^{(n)} a_l^{(n)H} e^{(n)} - e^{(n)} a_l^{(n)H} e^{(n)}, \]

\[ B_l = e^{(n)} a_l^{(n)H} g_l + e a_l^{(n)H} g_l - e^{(n)} a_l^{(n)} g_l, \]

\[ C_l = g_l^H \left( a_l^{(n)H} a_l + a_l^{(n)H} - a_l^{(n)} a_l^{(n)H} \right) g_l. \quad \text{(8)} \]

**Proof.** According to Appendix B of [25]. Assuming \( w \) be a complex scalar variable, then the following inequality holds.

\[ |w|^2 \geq w^{*(n)} w + w^{*(n)} w^{*(n)} - w^{*(n)} w^{*(n)}. \quad \text{(9)} \]
For any fixed \( w^{(n)} \), (7) can be obtained by replacing \( w \) and \( w^{(n)} \) with \( |(g_i^H + d_i^H H_i) a_i| \) and \( |(g_i^H + e_i^{(n)} H_i) a_i^{(n)}| \), respectively. Lemma 1 is proved.

By substituting \( H_i = \tilde{H}_i + \Delta H_i \) into (7), the constraints in (5b) can be expressed as follows:

\[
\vec{c}_1^T (\Delta H_i) A \vec{c}_1 + 2 \Re \left\{ b_1^T \vec{c}_1 \right\} + c_1 \geq \sigma^2 (2^n - 1), \forall \Delta H_{iF} \leq e, \forall l \in \mathcal{L} ,
\]

where

\[
b_1 = \vec{c}_1 \left( e \left( g_i^H + e_i^{(n)} H_i \right) a_i^{(n)} a_i^H \right) + \vec{c}_1 \left( e_i^{(n)} \left( g_i^H + e_i^{(n)} H_i \right) a_i a_i^{(n)} H_i \right) - \vec{c}_1 \left( e \left( g_i^H + e_i^{(n)} H_i \right) a_i a_i^{(n)} H_i \right),
\]

\[
c_1 = 2 \Re \left\{ \left( g_i^H + e_i^{(n)} H_i \right) f_1^H \left( g_i + H_i e \right) \right\} - \left( g_i^H + e_i^{(n)} H_i \right) f_1^H f_1^{(n)} H_i \left( g_i + H_i H_i e \right).
\]

Lemma 2 (S-Procedure). Let Hermitian matrix \( B_1, B_2 \in \mathbb{C}^{n \times n} \), and \( c_1, c_2 \in \mathbb{C}^{n \times 1} \). Define the following inequality of variable \( x \in \mathbb{C}^{n \times 1} \):

\[
x^H B_2 x + 2 c_2^H x + d_2 < 0 .
\]

The inequality \( x^H B_2 x + 2 c_2^H x + d_2 \geq 0 , \forall x \in \mathbb{C}^{n \times 1} \) holds only if there exists \( \lambda \geq 0 \) such that

\[
\begin{pmatrix}
B_1 & c_1 \\
\lambda & c_2
\end{pmatrix}
\begin{pmatrix}
x^H \\
d_1
\end{pmatrix} \geq 0 .
\]

According to Lemma 2, inequality (10) can be transformed into the following linear matrix inequalities:

\[
\begin{bmatrix}
\lambda I_N + A_1 & b_1 \\
b_1^T & D_1
\end{bmatrix} \succ 0, \forall l \in \mathcal{L} ,
\]

where \( D_1 = c_1 - \sigma^2 (2^n - 1) - \lambda e \) and \( \lambda = [\lambda_1, \ldots, \lambda_N]^T \geq 0 \) are slack variables.

Replace (5b) with (14), and then, optimization problem (5) is restated as

\[
\mathcal{P}_A : \min_{a, \sigma, \lambda} ||a||^2,
\]

\[
s.t. (5c), (14), \lambda \geq 0 .
\]

Due to the coupling between \( a \) and \( e \), problem \( \mathcal{P}_A \) is still nonconvex and difficult to tackle. Next, we will alternately optimize the transmit beamforming \( a \) and phase shift matrix \( e \) to solve the problem \( \mathcal{P}_A \).

3.2. Alternate Optimization. Specifically, for a given phase shift \( e \), the problem \( \mathcal{P}_A \) reduces to a convex subproblem as follows:

\[
\mathcal{P}_{A1} : \min_{a, \sigma, \lambda} ||a||^2,
\]

\[
s.t. (14), (15c).
\]

Problem \( \mathcal{P}_{A1} \) is convex and can be easily tackled by using CVX toolkit. Problem \( \mathcal{P}_{A1} \) is an SDP, and when the difference between the target value of the iteration \( n + 1 \) and the iteration \( n \) is lower than the preset threshold, the iteration stops.

Then, for a given transmit beamforming vector \( a \), the problem \( \mathcal{P}_A \) becomes a feasibility-check problem. According to [23], to improve the convergence of the optimal solution of the feasibility-check problem, we would introduce an auxiliary variable \( t = [t_1, \ldots, t_L] \geq 0 \) to modify inequality (6) as follows:

\[
||g_i^H + e_i^{(n)} H_i a_i||^2 \geq \sigma^2 (2^n - 1) + t_L, \forall l \in \mathcal{L} .
\]

In addition, the linear matrix inequalities of (14) also can modify as follows:

\[
\begin{bmatrix}
\lambda I_N + A_1 & b_1 \\
b_1^T & D_1 - t_L
\end{bmatrix} \succ 0, \forall l \in \mathcal{L} .
\]

Thus, \( \mathcal{P}_A \) can be written as the following feasibility-check problem:

\[
\mathcal{P}_{A2} : \max_{e, \sigma, \lambda} ||t||_1,
\]

\[
s.t. (5c), (15c), (18),
\]

\[
t = [t_1, \ldots, t_L] \geq 0 .
\]

We can notice that \( \mathcal{P}_{A2} \) is still nonconvex due to (5c). Here, we can address the nonconvexity via the semidefinite relaxation (SDR) method [26]. It is worth noting that if the optimal solutions of the SDP problems are not rank-one, the feasibility of these problems cannot be guaranteed. In addition, when the variable dimension is large, the complexity of the SDR method is high. To avoid the drawbacks of the SDR method, the penalty CCP method [27] is used to address nonconvex constraints in (5c). In particular, the constraints \( e_i^{(n)} = 1, \forall n \in \mathcal{N} \) can be equivalent to \( 1 \leq |e_i^{(n)}|^2 \leq 1, \forall n \in \mathcal{N} \). According to the CCP framework, (5c) can be further linearized by \( |e_i^{(n)}|^2 \) Re \((e_i^{(n)} t_i^{(n)}) \leq -1, \forall n \in \mathcal{N} \) at fixed \( t_i^{(n)} \). We introduce the slack variable \( b = [b_1, \ldots, b_N] \) with the unit-modulus constraints. Then, the problem \( \mathcal{P}_{A2} \) can be reprogrammed as follows:

\[
\mathcal{P}_{A3} : \max_{e, t, a, b} ||t||_1 - \beta \sum_{n=1}^{N} b_n ,
\]

where \( \beta \) is a penalty parameter. Problem \( \mathcal{P}_{A3} \) is a convex feasibility problem.
and receive user-IRS link, respectively. And of transmit user-IRS link, transmit user-receive user link, P optimization problem 2 to be large-scale and small-scale fading. The large-scale channels of the user-user link, user-IRS-user, are assumed α loss index and ff efficiency of IRS deployment and evaluate the e 4. Numerical Result 5.0) and ([5, −5],0) meters, respectively. The assisted D2D network with proposed algorithm. The simulated system is an IRS- single-antenna D2D user pairs. The IRS is located at (0,0,0), and the transmit users and the receive user link, respectively. And d is the link distance. The small-scale fading channel model is Rayleigh fading distribution. Define e = η||H||, ∀l ∈ L where η ∈ [0, 1), as the channel error boundary, represents the relative uncertainty of the channel. All users in the system have the same rate constraint, i.e., r = r2 · · · = rL = r.

Figure 2 illustrates the system transmit power versus minimum rate constraint of users when η = 0.02. As shown in Figure 2, the system transmit power in all cases increases as the constraint rate increases. This result shows that the price of good user QoS is high in system power consumption. We also analyse the relationship between the transmit power of the system and the reflector number of IRS. As can be seen from Figure 2, the transmit power of the system decreases with the increase of the number of reflection elements of IRS. This shows that a large number of IRS reflection elements can bring a better system gain. We can also see that the transmit power of the system is greatly increased without the deployment of IRS, demonstrating the superiority of IRS deployment in system performance improvement.

Figure 3 illustrates the transmit power of the system versus minimum rate constraint of users under different channel estimation errors when the reflection elements number of IRS N = 10. As shown in Figure 3, the transmit power of the system increases as the channel estimation error increases, and the transmit power of robust design is higher than that of without robust. This result illustrates that the robust design of the system requires additional power costs.
The higher the channel errors, the greater the power consumption of the system, which means that additional power is needed to compensate for the influence caused by the channel errors.

Figure 4 illustrates the transmit power of the system versus channel estimation error $\eta$ under different number of user pairs when $N = 10$. As shown in Figure 4, the transmit power of the system in all cases increases as the channel estimation error increases. This shows that in order to compensate for the loss of system performance caused by channel error, the system needs to consume additional power. We can also see that the transmit power rises dramatically with the increase of user pairs. The simulation results show that the more users participate in collaborative offloading, the more additional power is paid.

Figure 5 illustrates the transmit power of the system versus the iteration number when $N = 10, \eta = 0.02$. The results show that the convergence rate of this algorithm is fast, and 10 iterations are enough to ensure convergence of the proposed algorithm. This shows that the algorithm proposed in this paper is guaranteed in terms of effectiveness and complexity.
5. Conclusion

In this paper, we investigated the power optimization of IRS-aided D2D offloading system under imperfect channels and considered the robust design of the system. We jointly optimized transmit beamforming and IRS phase shifts to minimize system transmit power while requiring each user’s rate to meet the minimum rate constraint in the presence of channel errors. The CSI uncertainties were transformed by using S-Procedure, and the unit-modulus constraints of phase shift were tackled by using the penalty CCP method.

From the analysis of the simulation results, we can get the following conclusions: (1) Deploying an IRS can significantly reduce the transmit power of the system, and the transmit power of the system decreases with the increase of IRS reflectors. (2) The system needs to consume extra power.
to compensate for the performance loss caused by channel errors. (3) The algorithm proposed in this paper has a fast convergence rate.

For our future work, we can consider using nonorthogonal multiple access to communicate between devices to improve the spectral efficiency of the system and reduce transmission delay.

**Data Availability**

The code used to support the findings of this study is available from the corresponding author upon request. Correspondence should be addressed to Guoping Zhang: gpzhang@mail.ccnu.edu.cn.

**Conflicts of Interest**

The authors declare that there is no conflict of interest regarding the publication of this paper.

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