Uplink Transceiver Design and Optimization for Transmissive RMS Multi-Antenna Systems

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Abstract—In this paper, a novel uplink communication for the transmissive reconfigurable metasurface (RMS) multi-antenna system is investigated. Specifically, a transmissive RMS-based receiver equipped with a single receiving antenna is first proposed, and a far-near field channel model is also given. Then, in order to maximize the system sum-rate, we formulate a joint optimization problem over subcarrier allocation, power allocation and RMS transmissive coefficient design. Since the coupling of optimization variables, the problem is non-convex, so it is challenging to solve it directly. In order to tackle this problem, the alternating optimization (AO) algorithm is used to decouple the optimization variables and divide the problem into two subproblems to solve. Numerical results verify that the proposed algorithm has good convergence performance and can improve system sum-rate compared with other benchmark algorithms.

Index Terms—Transmissive RMS, far-near field channel model, system sum-rate, alternating optimization (AO).

I. INTRODUCTION

The power consumption of a single fifth-generation (5G) base station (BS) is about 3500W, which is about three times that of fourth-generation (4G) BS. Since the 5G network operates in a higher frequency band, to achieve the same coverage as the 4G network, the number of 5G BSs is about three to four times that of the 4G BSs, which greatly increases the deployment cost. In addition, since the massive multiple-input multiple-output (MIMO) system of 5G networks requires a large number of radio frequency (RF) chains and complex signal processing units, the cost of a single station is also greatly increased [1]. Therefore, it is urgent to seek a novel multi-antenna system that can reduce power consumption and cost for next generation communication networks.

Recently, reconfigurable metasurface (RMS) as a revolutionary technology has attracted attention from academia and industry [2], [3]. In the current research, RMS mainly has two modes: reflective mode [4], [5] and transmissive mode [6]. At present, more research focuses on the RMS-assisted communication in reflective mode or transmissive mode. The RMS in reflective mode is mainly used to enhance the spectral- and energy-efficiency of the networks. Moreover, the transmissive RMS is mainly used to solve the blind coverage problem and enhance the network coverage. These works are all based on the perspective of RMS with different modes for communication assistance.

In addition to being used for auxiliary communication, RMS can also be considered as transceivers for communication, which is in its infancy and also very promising. Currently, some studies have proposed that the reflective RMS can be used as a transmitter [7]. However, compared to the reflective RMS transceiver, the transmissive RMS can be designed to be more efficient due to no feed blocking, no self-interference, higher aperture efficiency, and more stable operating bandwidth [8]. Therefore, we have proposed a transmissive RMS transmitter architecture in [9]. Our target is to propose a transmissive RMS multi-antenna system, which greatly motivates the research on uplink transceiver design for transmissive RMS multi-antenna systems.

In this paper, since the proposed transmissive RMS multi-antenna system is equipped with a single receiving antenna, we consider orthogonal frequency division multiple access (OFDMA) for uplink multi-user communications. Our goal is to solve a problem of maximizing system sum-rate by jointly optimizing multi-user power allocation, subcarrier allocation and RMS transmissive coefficient. Due to the high coupling of optimization variables, it is difficult to obtain the optimal solution, so an approximate optimal algorithm is expected.

II. SYSTEM MODEL AND PROBLEM FORMULATION

As shown in Fig. 2, we consider an uplink multi-user OFDMA network based on the transmissive RMS multi-antenna system. The network consists of a receiving antenna, RMS with $M_c \times M_r$ transmissive elements, and $K$ single-antenna users. Let $c = [c_{1,1}, ..., c_{M_c,M_r}]^T \in \mathbb{C}^{M_c \times M_r \times 1}$ denote the RMS transmissive coefficient vector, where $c_{m_c,m_r} = \beta_{m_c,m_r} e^{j\theta_{m_c,m_r}}$. $\beta_{m_c,m_r} \in [0,1]$ and $\theta_{m_c,m_r} \in [0,2\pi]$ respectively represent the transmissive amplitude and phase shift of the $(m_c,m_r)$-th element of RMS. The RMS transmissive coefficient needs to meet

$$|c_{m_c,m_r}| \leq 1, \forall m_c, m_r.$$  \hspace{1cm} (1)

The controller equipped with RMS can adjust the amplitude and phase shift of each transmissive element. To facilitate the analysis, we assume that the RMS is fully transmissive, i.e., no incident signal is reflected. In this paper, the elements of RMS are modeled in the way of uniform planar array (UPA). Specifically, each column has $M_c$ elements arranged at equal
The channel with bandwidth $B$ is divided into $N$ subcarriers, and the bandwidth of each subcarrier is $W = B/N$. Then, the EM wave radiation field in the wireless communication network can be divided into far field and near field. On the $n$-th subcarrier, the channel from the $k$-th user to the RMS is denoted as $g_{k,n} \in \mathbb{C}^{M_{c} \times 1}$, which can be modeled as a far-field channel. Herein, we can model the channel as a Rician fading channel. Hence, the channel gain from the $k$-th user to the RMS on the $n$-th subcarrier can be expressed as

$$g_{k,n} = \sqrt{\frac{C_{0}}{(d_{k})^{\alpha}} \left( e^{-j2\pi nW \frac{d_{k}}{d_{k}}} g_{k}^{\text{LoS}} + \frac{1}{1+\kappa} g_{k,n}^{\text{NLoS}} \right)},$$

where $g_{k,n}^{\text{NLoS}} \sim \mathcal{CN}(0,\mathbf{I}_{M_{c}})$ and $g_{k}^{\text{LoS}}$ can be given by

$$g_{k,n}^{\text{LoS}} = \begin{bmatrix}
1, e^{-j2\pi f_{c}d_{k} \sin \theta_{k} \cos \psi_{k}}, \ldots, e^{-j2\pi f_{c}(N_{c}-1)d_{k} \sin \theta_{k} \cos \psi_{k}}
\end{bmatrix}^{T}$$

where $C_{0}$ is channel gain when reference distance is 1 meter, $d_k$ denotes the distance between RMS and the $k$-th user, $\alpha$ denotes path loss exponent of the channel, $c$ represents speed of light, $\kappa$ is Rician factor and $f_{c}$ denotes carrier frequency. $\theta_{k}$ and $\psi_{k}$ respectively denote vertical and horizontal angle-of-arrival (AoA). Besides, on the $n$-th subcarrier, the channel from the RMS to the receiving antenna can be denoted as $h_{n} \in \mathbb{C}^{M \times 1}$, which can be regarded as a near-field channel. We can model it as a line-of-sight (LoS) channel as

$$h_{n} = \rho e^{-j2\pi nW \frac{r}{c}} \left[ e^{-j2\pi f_{c} \frac{r}{c}}, \ldots, e^{-j2\pi f_{c}(M_{c}-1) \frac{r}{c}} \right]^{H},$$

where $\rho$ and $\tilde{r}$ denote complex gain and the the distance from the center of the RMS to the receiving antenna, respectively. $r_{m_{c},m_{r}}$ is the distance from the $(m_{c},m_{r})$-th RMS element to the receiving antenna, and $r_{m_{c},m_{r}} = \sqrt{\sqrt{d_{m_{c}}^{2} + d_{m_{r}}^{2}}}$, where $d_{m_{c}} = \sqrt{d_{m_{c}}^{2} + d_{m_{r}}^{2}}$ denotes the distance from the $(m_{c},m_{r})$-th RMS element to the center of the RMS, $\delta_{m_{c}} = \frac{2m_{c}-M_{c}-1}{2}$ and $\delta_{m_{r}} = \frac{2m_{r}-M_{r}-1}{2}$. Accordingly, on the $n$-th subcarrier, the signal of the $k$-th user received by receiving antenna can be expressed as

$$y_{k,n} = \sqrt{p_{k,n}} h_{n}^{H} \text{diag}(g_{k,n}) c_{x_{k,n}} + n_{0}, \forall k, n,$$

where $x_{k,n}$ represents the transmitting signal of the $k$-th user on the $n$-th subcarrier, which is assumed to be $x_{k,n} \sim \mathcal{CN}(0,1)$. $n_{0} \sim \mathcal{CN}(0,\sigma^{2})$ denotes the additive white Gaussian noise (AWGN), $\sigma^{2} = N_{0}W$, $N_{0}$ is the noise power spectral density (PSD). Hence, on the $n$-th subcarrier, the signal-to-noise ratio (SNR) of the $k$-th user can be given by

$$\gamma_{k,n} = \frac{p_{k,n} |h_{n}^{H} \text{diag}(g_{k,n}) c_{x_{k,n}} |^{2} \nu_{k}}{N_{0}W}, \forall k, n,$$

where $p_{k,n}$ is the transmit power of the $k$-th user on the $n$-th subcarrier, and $\nu_{k}$ describes the imperfections of the channel and modulation, which can be given by $\nu_{k} = -1.5/\log(5 \text{BER}_{k})$, $\forall k$, with $\text{BER}_{k}$ denotes the maximum allowable bit error rate of the $k$-th user. Therefore, the system sum-rate can be given by

$$R(A, P, c) = \sum_{k=1}^{K} \sum_{n=1}^{N} a_{k,n} \log_{2}(1 + \gamma_{k,n}),$$

where $A = [a_{k,n}], \forall k, n$ is subcarrier allocation matrix, $a_{k,n} \in \{0,1\}$. When the $n$-th subcarrier is allocated to the $k$-th user, $a_{k,n} = 1$. Otherwise, $a_{k,n} = 0$. It should satisfy

$$a_{k,n} \in \{0,1\}, \forall k, n, \sum_{k=1}^{K} \sum_{n=1}^{N} a_{k,n} p_{k,n} \leq p_{k}^{\text{max}}, \forall k.$$
\[ \mathcal{L}(\bar{P}, \bar{A}, \lambda, \mu) = W \sum_{k=1}^{K} \sum_{n=1}^{N} \tilde{a}_{k,n} \log_2 \left( 1 + \frac{\tilde{p}_{k,n} \Gamma_{k,n}}{\tilde{a}_{k,n}} \right) - \sum_{k=1}^{K} \lambda_k \left( \sum_{n=1}^{N} \tilde{p}_{k,n} - \tilde{p}_{k}^{\text{max}} \right) - \mu_k \left( r_k^{\text{min}} - \sum_{n=1}^{N} \tilde{a}_{k,n} \log_2 \left( 1 + \frac{\tilde{p}_{k,n} \Gamma_{k,n}}{\tilde{a}_{k,n}} \right) \right). \] (12)

Then, given power allocation and subcarrier allocation, the RMS transmissive coefficient is optimized in the second subproblem. Finally, the two subproblems are optimized alternately until convergence is achieved. However, the existence of the binary variable \( a_{k,n} \) makes the problem (P0) non-convex. We first relax the binary variable \( a_{k,n} \) to obtain \( \tilde{a}_{k,n} \), i.e., \( a_{k,n} \in \{0, 1\} \Rightarrow \tilde{a}_{k,n} \in [0, 1] \). The auxiliary variable \( \tilde{p}_{k,n} = \tilde{a}_{k,n} p_{k,n} \) is also introduced. Then, the optimization problem (P0) can be divided into two subproblems to solve by using the AO algorithm framework as follows.

A. Joint optimization of multi-user power allocation and subcarrier allocation

We first fix the RMS transmissive coefficient \( c \) to solve the user’s power allocation \( \bar{P} \) and subcarrier allocation \( \bar{A} \). Let \( \Gamma_{k,n} = \left[ h_{k,n}^H \text{diag}(g_{k,n}) c^2 \right] r_k / N_0 W \), the problem (P0) can be transformed into the problem (P1), which can be expressed as

\[ \text{(P1)} \quad \max_{\Delta, \bar{A}} \quad W \sum_{k=1}^{K} \sum_{n=1}^{N} \tilde{a}_{k,n} \log_2 \left( 1 + \frac{\tilde{p}_{k,n} \Gamma_{k,n}}{\tilde{a}_{k,n}} \right), \]

s.t. \( \tilde{a}_{k,n} \in [0, 1], \forall k, n, \sum_{k=1}^{K} \tilde{a}_{k,n} \leq 1, \forall n, \) (11a)

\( \tilde{p}_{k,n} \geq 0, \forall k, n, \sum_{n=1}^{N} \tilde{p}_{k,n} \leq p_{k}^{\text{max}}, \forall k, \) (11b)

\( \sum_{n=1}^{N} \tilde{a}_{k,n} \log_2 \left( 1 + \frac{\tilde{p}_{k,n} \Gamma_{k,n}}{\tilde{a}_{k,n}} \right) \geq r_k^{\text{min}}, \forall k. \) (11c)

**Theorem 1**: The function \( h(x, t) = t \log_2 (1 + \frac{x}{t}) \) is concave with respect to (w.r.t) \( x > 0 \) and \( t > 0 \).

According to Theorem 1, the objective function in the problem (P1) is the sum of several concave functions, so it is concave w.r.t \( \tilde{a}_{k,n} \) and \( \tilde{p}_{k,n} \). In addition, Eq. (11a) and Eq. (11b) are affine, and Eq. (11c) is convex, so this problem is a standard convex optimization problem. Herein, we apply the Lagrangian dual decomposition technique to solve the problem (P1). Define \( \lambda = [\lambda_1, ..., \lambda_K] \) and \( \mu = [\mu_1, ..., \mu_K] \) as the Lagrangian multipliers corresponding to constraints (11b) and (11c), respectively. The Lagrangian function of problem (P1) can be written as Eq. (12). Note that other constraints will be considered in the later solving section, which will not be ignored. The Lagrangian dual function can be expressed as

\[ g(\lambda, \mu) = \sup_{\bar{P}, \bar{A}} \mathcal{L}(\bar{P}, \bar{A}, \lambda, \mu). \] (13)

Therefore, the Lagrangian dual problem can be given by

\[ \min_{\lambda, \mu} \quad g(\lambda, \mu), \]

s.t. \( \lambda, \mu \geq 0. \) (14a)

Next, the Lagrangian dual decomposition method will be elaborated in detail. First, in the \( i \)-th iteration, given the Lagrangian multipliers \( \lambda \) and \( \mu \), we solve an unconstrained maximization problem, which can be expressed as

\[ \bar{P}^i, \bar{A}^i = \arg \max_{\bar{P}, \bar{A}} \mathcal{L}(\bar{P}, \bar{A}, \lambda, \mu), \] (15)

where \( \bar{P}^i \) and \( \bar{A}^i \) are the subcarrier allocation and power allocation schemes obtained in the \( i \)-th iteration, respectively.

**Theorem 2**: The function \( \mathcal{L}(\bar{P}, \bar{A}, \lambda, \mu) \) of Eq. (12) is a concave function w.r.t \( \tilde{a}_{k,n} \) and \( \tilde{p}_{k,n} \).

Since the problem (P1) is a convex problem, the solution that satisfies the Karush-Kuhn-Tucker (KKT) condition is also the optimal solution of the problem (P1) and its dual problem [\( \Pi \)]. Therefore, we use the gradient condition in the KKT condition to solve the user’s power allocation and subcarrier allocation. Since \( \mathcal{L}(\bar{P}, \bar{A}, \lambda, \mu) \) is concave w.r.t \( \tilde{a}_{k,n} \) and \( \tilde{p}_{k,n} \), we take the partial derivative of \( \mathcal{L}(\bar{P}, \bar{A}, \lambda, \mu) \) to \( \tilde{p}_{k,n} \), and the multi-user power allocation scheme can be obtained as follows

\[ p_{k,n}^i = \left[ \frac{W + \mu_k}{\lambda_k \ln 2 \Gamma_{k,n}} - \frac{1}{\Gamma_{k,n}} \right]^+, \]

where \([\cdot]^+ \) returns the maximum value of \((\cdot)\) and zero. In addition, in order to obtain the subcarrier allocation scheme, we take the partial derivative of \( \mathcal{L}(\bar{P}, \bar{A}, \lambda, \mu) \) to \( \tilde{a}_{k,n} \), and the subcarrier allocation criterion can be obtained, denoted by \( \chi_{k,n}^i \), which can be further expressed as

\[ \chi_{k,n}^i = \left( W + \mu_k \right) \left( \log_2 \left( 1 + p_{k,n}^i \Gamma_{k,n} \right) - p_{k,n}^i \right) \ln 2 \sum_{n=1}^{N} \tilde{a}_{k,n} \log_2 \left( 1 + \frac{\tilde{p}_{k,n} \Gamma_{k,n}}{\tilde{a}_{k,n}} \right). \] (17)

This subcarrier allocation criterion can be regarded as the sum-rate growth rate when the \( n \)-th subcarrier is allocated to the \( k \)-th user. Meanwhile, for \( p_{k,n}^i > 0, \chi_{k,n}^i > 0 \) means that when the \( n \)-th subcarrier is allocated to the \( k \)-th user, the system sum-rate is guaranteed not to be reduced. We can allocate subcarriers for users according to the subcarrier allocation criterion. Specifically, in order to maximize the sum-rate of the system, the \( n \)-th subcarrier is allocated to the user with the largest \( \chi_{k,n}^i \), which can be expressed as

\[ a_{k,n}^i = \begin{cases} 1, & \text{if } \chi_{k,n}^i = \max_k \chi_{k,n}^i \text{ and } \chi_{k,n}^i > 0, \\ 0, & \text{otherwise}. \end{cases} \] (18)

Since \( \mathcal{L}(\bar{P}, \bar{A}, \lambda, \mu) \) is differentiable and the solution of Eq. (15) is unique, the Lagrangian multipliers \( \lambda \) and \( \mu \) can be obtained by the method of gradient update. In the \( i \)-th iteration,
the Lagrangian multipliers can be updated by
\[ \lambda_k^i = \left( \lambda_k^{i-1} - \varsigma_k \left( p_k^{\max} - \sum_{n=1}^{N} a_{k,n}^i p_{k,n}^i \right) \right)^+ , \]
and
\[ \mu_k^i = \left( \mu_k^{i-1} - \psi_k \left( \sum_{n=1}^{N} a_{k,n}^i \log_2 \left( 1 + p_{k,n}^i \Gamma_{k,n} \right) - \rho_k^{\min} \right) \right)^+ , \]
where \( \varsigma_k \) and \( \psi_k \) are the update step sizes of the corresponding multipliers.

B. Optimization of RMS transmissive coefficient

Given the subcarrier allocation matrix \( A \) and the user power allocation \( P \), we solve the RMS transmissive coefficient. Let \( \Xi_{k,n} = p_{k,n} \nu_k / N_0 W, \forall k, n \), the problem (P0) can be transformed into the problem (P2), which can be given by

\[
\begin{aligned}
\text{(P2)} \quad \max_C & \quad W \sum_{k=1}^{K} \sum_{n=1}^{N} \tilde{a}_{k,n} \log_2 \left( 1 + \Xi_{k,n} |h_{n}^H \text{diag} (g_{k,n}) c|^2 \right) \\
\text{s.t.} & \quad (1), \quad (22a), (22b). \\
\end{aligned}
\]

Let \( v_{k,n}^H = h_{n}^H \text{diag} (g_{k,n}) \in \mathbb{C}^{1 \times M} \), then
\[ |h_{n}^H \text{diag} (g_{k,n}) c|^2 = \left| v_{k,n}^H c \right|^2 = v_{k,n}^H c c^H v_{k,n}. \] Herein, let \( C = c c^H \in \mathbb{C}^{M \times M} \), where \( C \succeq 0 \) and \( \text{rank} (C) = 1 \). In addition, let \( v_{k,n} = v_{k,n}^H v_{k,n} \in \mathbb{C}^{M \times M} \), then
\[ |h_{n}^H \text{diag} (g_{k,n}) c|^2 = \text{tr} (CV_{k,n}). \] The problem (P2) is equivalently expressed as the problem (P3) as follows

\[
\begin{aligned}
\text{(P3)} \quad \max_C & \quad W \sum_{k=1}^{K} \sum_{n=1}^{N} \tilde{a}_{k,n} \log_2 \left( 1 + \Xi_{k,n} \text{tr} (CV_{k,n}) \right) \\
\text{s.t.} & \quad (1), (22a), (22b). \\
\end{aligned}
\]

Due to the existence of the non-convex rank-one constraint (22c), the problem (P3) is still a non-convex optimization problem. We apply Proposition 1 to transform the constraint.

**Proposition 1:** For the positive semi-definite matrix \( B \in \mathbb{C}^{N \times N} \), \( \text{tr} (B) > 0 \), the rank-one constraint can be equivalent to the difference between two convex functions as follows,
\[ \text{rank} (B) = 1 \Rightarrow \text{tr} (B) - ||B||_2 = 0, \]
where \( \text{tr} (B) = \sum_{n=1}^{N} \sigma_n (B), ||B||_2 = \sigma_1 (B) \) is spectral norm, and \( \sigma_n (B) \) represents the \( n \)-th largest singular value of \( B \).

According to Proposition 1, we can transform the constraint (22c) in the problem (P3) into
\[ \text{rank} (C) = 1 \Rightarrow \text{tr} (C) - ||C||_2 = 0. \]

We introduce the penalty factor \( \eta \), and add Eq. (24) to the objective of the problem (P3). The problem (P3) can be transformed into the problem (P4), which can be given by

\[
\begin{aligned}
\text{(P4)} \quad \max_C & \quad W \sum_{k=1}^{K} \sum_{n=1}^{N} \tilde{a}_{k,n} \log_2 \left( 1 + \Xi_{k,n} \text{tr} (CV_{k,n}) \right) \\
\text{s.t.} & \quad (22a), (22b). \\
\end{aligned}
\]

Since \( ||C||_2 \) is convex, the problem (P4) is a difference-convex (DC) programming problem, which is still a non-convex optimization problem. We apply SCA to obtain the lower bound of \( ||C||_2 \), which can be expressed as
\[ ||C||_2 \geq \left( \max_{x \in X} \text{tr} (C) \right) ||C||_2 \]
where \( \text{rank} (C) = 1 \Rightarrow \text{tr} (C) - ||C||_2 \geq 0 \).
RMS is equipped with $M = 25$ transmissive elements. We set the antenna spacing to be half of the carrier wavelength. Meanwhile, we set $P_{k}^{\text{max}} = 200\text{mW}$, BER$_{k} = -30\text{dB}$, $N_0 = -174\text{dBm/Hz}$, $f_c = 3\text{GHz}$ and $r_k^{\text{min}} = 10\text{bps}$. In addition, the path loss exponent is set as $\alpha = 3$, $\rho$ is randomly generated from a distribution that obeys $CN(0, 1)$. We set $C_0 = -30\text{dB}$, Rician factor $\kappa$ to 3dB, and the convergence threshold of the proposed algorithm to $10^{-3}$.

In order to evaluate the performance of the proposed algorithm, we consider the following benchmark algorithms. Benchmark 1 (three-stage algorithm): The algorithm does not perform alternate iterations. Benchmark 2 (random coefficient algorithm): This algorithm still uses the problem (P2) solution, and uses a random scheme for the problem (P5). Benchmark 3 (random allocation algorithm): This algorithm uses a random scheme for the problem (P0).

In Fig. 2 (a), when the user’s maximum transmit power changes, we compare the performance of the proposed algorithm with different benchmark algorithms. As the user’s maximum transmit power increases, the system sum-rate increases. This is mainly due to the increase in the user’s maximum transmit power makes the power allocated by each user larger, and therefore the uplink sum-rate of the system becomes larger. In addition, the performance of our proposed algorithm is better than that of other benchmark algorithms. Then, we compare the variation of system sum-rate with the number of subcarriers as shown in Fig. 2 (b). It can be seen that as the number of subcarriers increases, the system sum-rate under is constantly increasing. This is because we are considering an uplink OFDMA network, where the greater the number of subcarriers, the greater the frequency diversity gain brought by them, so the performance is superior, as well as the performance of our proposed algorithm is still better than other benchmark algorithms. Finally, Fig. 3 (c) depicts the change of system sum-rate with the number of RMS elements. We can see that the performance of the proposed algorithm still outperforms other benchmark algorithms. Moreover, the system sum-rate increases as the number of RMS elements increases. This is because the RMS transmissive element will strengthen the users uplink transmission signal. Therefore, more RMS elements can bring more high performance gains.

V. CONCLUSIONS

A novel uplink transceiver design in the transmissive RMS multi-antenna systems has been investigated in this paper. Specifically, a problem of maximizing system sum-rate by jointly optimizing subcarrier allocation, power allocation, and RMS transmissive coefficient design is formulated. In order to solve this challenging problem, the original problem is decomposed into two subproblems by the AO algorithm and solved sequentially. Then, the two subproblems are iterated optimized until convergence is achieved. Numerical simulation results verify that our proposed algorithm can improve system sum-rate, which has great potential for next generation communication networks.

REFERENCES

[1] M. Shafi, A. F. Molisch, P. J. Smith, T. Haustein, P. Zhu, P. De Silva, F. Tufvesson, A. Benjebbour, and G. Wunder, “5G: A tutorial overview of standards, trials, challenges, deployment, and practice,” IEEE J. Sel. Areas Commun., vol. 35, no. 6, pp. 1201–1221, Apr. 2017.
[2] Q. Wu and R. Zhang, “Intelligent reflecting surface enhanced wireless network via joint active and passive beamforming,” IEEE Trans. Wireless Commun., vol. 18, no. 11, pp. 5394–5409, Aug. 2019.
[3] Z. Li, W. Chen, Q. Wu, H. Cao, K. Wang, and J. Li, “Robust beamforming design and time allocation for IRS-assisted wireless powered communication networks,” IEEE Trans. Commun., vol. 70, no. 4, pp. 2838–2852, Feb. 2022.
[4] Z. Li, W. Chen, Q. Wu, K. Wang, and J. Li, “Joint beamforming design and power splitting optimization in IRS-assisted SWIPT NOMA networks,” IEEE Trans. Wireless Commun., pp. 1–1, Sept. 2021.
[5] H. Cao, Z. Li, and W. Chen, “Resource allocation for IRS-assisted wireless powered communication networks,” IEEE Wireless Commun. Lett., vol. 10, no. 11, pp. 2450–2454, Aug. 2021.
[6] S. Zhang, H. Zhang, B. Di, Y. Tan, Z. Han, and L. Song, “Beyond intelligent reflecting surfaces: Reflective-transmissive metasurface aided communications for full-dimensional coverage extension,” IEEE Trans. Veh. Technol., vol. 69, no. 11, pp. 13 905–13 909, Sept. 2020.
[7] W. Tang, J. Y. Dai, M. Z. Chen, K. K. Wong, X. Li, X. Zhao, S. Jin, Q. Cheng, and T. J. Cui, “MIMO transmission through reconfigurable intelligent surface: System design, analysis, and implementation,” IEEE J. Sel. Areas Commun., vol. 38, no. 11, pp. 2683–2699, Jul. 2020.
[8] X. Bai, F. Kong, Y. Sun, G. Wang, J. Qian, X. Li, A. Cao, C. He, X. Liang, R. Jin et al., “High-efficiency transmissive programmable metasurface for multimode OAM generation,” Adv. Opt. Mater., vol. 8, no. 17, p. 2000570, Jun. 2020.
[9] Z. Li, W. Chen, and H. Cao, “Beamforming design and power allocation for transmissive RMS-based transmitter architectures,” IEEE Wireless Commun. Lett., pp. 1–1, Oct. 2021.
[10] M. Cui and L. Dai, “Channel estimation for extremely large-scale MIMO: Far-field or near-field?” arXiv preprint arXiv:2108.07581, 2021.
[11] S. Boyd, S. P. Boyd, and L. Vandenberghe, *Convex optimization*. Cambridge university press, 2004.

[12] M. Grant and S. Boyd, “CVX: Matlab software for disciplined convex programming, version 2.1.” 2014.