Transmissive Reconfigurable Meta-surface Empowered 6G Ultra Massive MIMO

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In this paper, we investigate a more efficient transmissive reconfigurable meta-surface (RMS) transmitter, which is potential to realize the sixth-generation (6G) mobile communication ultra massive multiple input multiple output (MIMO) due to its low cost and low power consumption. Since RMS is passive, it can reduce power consumption while satisfying the high-capacity requirements of 6G networks. For the proposed architecture, we elaborate transmissive RMS transmitter architecture, channel model, channel estimation, downlink (DL) signal modulation, and beamforming design, etc. Finally, several potential research directions in the future are given.

Introduction

In recent years, with the rapid development of mobile communication technology, the number of traffic has continued to surge. With the global commercialization of the fifth-generation (5G) mobile communications, many business requirements of users have been met. Meanwhile, many emerging applications and scenarios have put forward higher requirements on the network, e.g., holographic video conference, remote surgery, augmented reality (AR), virtual reality (VR), and autonomous driving, etc. The requirements for network performance of these promising applications in the future obviously exceed the capacity of the existing 5G network. Therefore, both industry and academia have set their sights on the sixth-generation (6G) mobile communication network [1]. The vision of the 6G network is to realize a data-driven intelligent network world. Users have also put forward higher requirements for 6G networks, such as ultra-low latency, ultra-high reliability, low energy consumption, massive connection support, ultra-high speed, etc. [2]. Many new technologies will emerge in 6G to fully support these needs. At the same time, 6G networks will continue to benefit from many key technologies of 5G networks, but new technologies are still expected, so we need to consider some more novel network paradigms.

In order to support the higher-capacity communication requirements in the 6G network, the ultra massive multiple input multiple output (MIMO) technology is proposed. Similar to the concept of the 5G massive MIMO technology, the ultra massive MIMO further increases the scale of the transmitter antenna. In theory, the more antennas there are, the system capacity will increase exponentially. Therefore, the ultra massive MIMO technology can well satisfy the 6G business requirements for higher capacity. However, as the number of antennas increases, the number of radio frequency links required by the system and the complexity of signal processing will increase, which will lead to greater network power consumption and deployment costs. Therefore, we have to find a solution that can improve system performance and reduce power consumption and deployment costs.

Reconfigurable meta-surface (RMS), also called reconfigurable intelligent surface (RIS) and intelligent reflecting surface (IRS), is proposed as a revolutionary technology, which can be used to reduce system energy consumption and improve network spectral efficiency and energy efficiency [3] [4]. To be clear, RMS is a planar array composed of a large number of low-cost passive elements. Its deployment is very convenient. The artificial adjustment of these elements can be realized through intelligent controllers, and the amplitude and phase of incident electromagnetic (EM) waves can be changed, thereby realizing the reconstruction of the electromagnetic environment. Since the RMS can control the amplitude and phase of the incident EM wave, it can enhance the desired signal and eliminate the interference signal [5]. In addition, since RMS is a passive device, it only adjusts the amplitude or phase of the incident EM wave and does not perform signal processing, so it does not introduce unnecessary noise [6] [7]. Meanwhile, compared with the traditional multi-antenna technology, the required hardware cost and power consumption are much lower. These have greatly promoted the application of RMS in 6G networks [8].

At present, the research on RMS in academia is mainly divided into two modes: reflection and transmission. First, for the reflection model, the reflective RMS is mainly used for auxiliary communication to enhance the throughput and energy efficiency of the system [9]. There are also some studies that consider using reflective RMS for the transmitter to achieve
communication [10]. For the transmission mode, some scholars have put forward the concept of intelligent omni-surface (IOS), which can serve mobile users on both sides of the surface. Multi-dimensional communication can be realized through its reflection and transmission characteristics, which can mainly guarantee the communication quality in the blind area of the reflective RMS [11]. However, as far as we know, the architecture of transmissive RMS as the transmitter has not been proposed yet. Because the reflective RMS feed blockage is serious and the phase difference is unstable, the radiation efficiency is severely affected by these defects. By combining the receiver, transmitter and phase shifter in one element, the transmissive RMS can avoid the effects of the defects of the reflective RMS, which is very similar to the working mechanism of the transmitter array [12]. Thus, the efficiency of the transmissive RMS is higher than the reflective RMS. Therefore, we propose the transmissive RMS as the transmitter architecture. Since the reconfigurability of RMS helps it expand the number of passive elements without increasing the number of expensive active antennas, the transmissive RMS with a feed antenna as the transmitter is a very potential design to achieve 6G ultra massive MIMO.

The purpose of this paper is to propose a basic framework to stimulate more promising 6G ultra massive MIMO research. Nowadays, 6G research is still in its infancy, and some system and algorithm designs may not be implemented until a few years later. The following mainly introduces and reviews the proposed transmitter architecture based on transmissive RMS, channel model, channel estimation, signal modulation, beamforming design, and then looks forward to the potential research directions in the future. Finally, we draw conclusions.

Transmissive RMS Transmitter Architecture

We first introduce a transmitter architecture based on a transmissive RMS equipped with a feed antenna as shown in Figure 1. The user first sends the pilot sequence to the transmissive RMS transmitter, and then the transmitter estimates the channel to obtain the channel state information (CSI). Then, the feed antenna radiates EM waves to RMS. The RMS controller uses the acquired CSI to perform different signal modulation and beamforming design algorithms on the incident EM waves, i.e., change its phase shift and amplitude, and then transmit to the user, and the user adopts the corresponding demodulation method to recover signal. Since the transmitter uses transmissive RMS, a transmitter architecture that increases the number of antennas with a lower cost and lower power consumption can be realized. This architecture is very potential and effective for 6G ultra massive MIMO in the future.

![Figure 1 Transmissive RMS transmitter architecture.](image)

Channel Model

According to our proposed architecture, the feed antenna first radiates single-frequency EM waves to the transmissive RMS, and the RMS sends the signal to the user through the controller’s modulation of the source signal and beamforming design. Therefore, the channel model is mainly divided into two parts: feed antenna to RMS and RMS to user. For the former, according to the definition of Fresnel number, generally speaking, the feed antenna and RMS are in the near field, and we can use the characteristics of Fresnel diffraction to calculate the loss. Next, we consider the RMS to user channel model. Considering that the channel from the RMS to the user has line-of-sight (LOS) components, we model it as a Rician channel, which is composed of LOS components and non-line-of-sight (NLOS) components. When the Rice factor is 0, the channel is transformed into a Rayleigh channel. Furthermore, each element of the NLOS component is an independent and identically distributed circularly symmetric complex Gaussian (CSCG) random vector with zero mean and unit variance. For the LOS component, it can be modeled in two ways: uniform linear array (ULA) and uniform planar array (UPA). It is obvious that UPA is more practical.

Channel Estimation

Since the beamforming design requires CSI, it is important to estimate the channel from the transmissive RMS transmitter to the user. However, since the RMS is a passive device, it can only reflect or transmit the incident signal, so it is challenging to obtain the CSI of the transmissive RMS transmitter. Since the research on the transmissive RMS transmitter is still in its infancy, we first introduce some current channel estimation methods for RMS-assisted communication in this section. Then, we combine the characteristics of our proposed architecture to explain some suitable channel estimation methods.

It is not easy to obtain the CSI of the RMS-assisted communication network. The main consideration is that the RMS passively reflects or transmits signals. Therefore, the channel estimation of the RMS-assisted communication network is completed by the active base station (BS) directly sending the training sequence. At the same time, generally
speaking, a larger number of RMS elements will lead to larger training overhead, and from the expression of channel gain, the channels of BS-RMS and RMS-user are coupled, and it is difficult to estimate separately. The channel of the RMS-assisted communication network consists of two parts: a direct channel and a cascade channel. The estimation of the direct channel can be obtained by setting two suitable reflection matrices to obtain the expression and adopting the classical channel estimation method. As for the cascade channel, the current research mainly consists of two parts: the separable cascade channel and the direct cascade channel. For the separable cascaded channel estimation, there are currently studies that propose the use of a semi-passive RMS channel estimation method and a fully passive RMS channel estimation method. For semi-passive RMS, it is equipped with a part of active elements to receive the transmitted signal from the BS or user, and then estimate the angle and path loss of the BS-RMS and RMS-user [13]. However, this method needs to be fed back to the BS and the user for beamforming design again, which will reduce efficiency. In addition, it will also increase the cost of hardware. Full-passive RMS can solve this limitation well. For the full-passive RMS, the user transmits different pilot sequences to the base station through the RMS, and through the analysis of the received signal, a two-stage method is used to estimate the cascade channel. For direct cascade channel estimation, there are currently binary reflection estimation and total reflection estimation for single users, and joint channel estimation for multiple users.

Inspired by the channel estimation of the RMS-assisted communication network, for our proposed architecture, we can adopt a semi-passive RMS structure. The user transmits a pilot sequence to the RMS, and the active elements of the RMS estimate the angle and path loss after the sequence is received. Then, by using the classical compressed sensing algorithm, the CSI from the user to the RMS can be recovered from the CSI from the user to the active elements. In addition, the controller at the transmitter can demodulate the signal sent by the user and then transmit it to the feed antenna to realize the reception of the signal sent by the user. Some traditional channel estimation methods can also be well suited to the architecture we proposed. In this way, when we adopt the RMS transmitter architecture for the 6G network in the future, the traditional algorithm can be well applied after the improvement, which is expected.

Downlink (DL) Signal Modulation and Transmission

Without loss of generality, here we consider the transmissive RMS transmitter for quadrature phase shift keying (QPSK) modulation, which can be achieved by deploying two diodes in each element of the RMS. The Figure 2 shows the modulation diagram of the transmitter. The RMS transmissive coefficient is obtained by multiplying the signal modulation and beamforming design. Specifically, the feed antenna emits a single-frequency EM wave to the RMS, and the information source is mapped to the phase shift $e^{\varphi}$. The mapping principle is shown in the Figure 3. The other part of the transmission coefficient $\beta e^{\varphi}$ is designed by the beamforming algorithm, which will be explained below. Therefore, the transmissive coefficient of the transmissive RMS transmitter can be expressed as $f = \beta e^{\varphi} e^{\theta}$. Then RMS controller can adjust the transmissive coefficient of each element by setting corresponding control signal to realize the signal modulation and transmission.

The process is as follows: (a) Get the information bit streaming (0100111...) from the information source. (b) Map the bit stream into the corresponding QPSK phase shift. (c) Obtain the beamforming design according to beamforming design algorithm described later. (d) Obtain the transmissive coefficient of RMS according to step (b) and step (c) and determine the RMS control signal of controller. (e) Control the transmissive coefficient of RMS according to the control signal obtained in step (d) and then the transmissive EM wave modulated with the information is transmitted once the incident EM wave arrives the RMS.

**DL Beamforming Design**

After obtaining the CSI based on the above channel estimation, the transmitter can perform beamforming. Since the transmissive coefficient of the transmissive RMS is similar to the reflective coefficient of the reflective RMS, many of the state-of-art algorithms for beamforming design (i.e., reflective coefficient design) for reflective RMS can well stimulate our research. The following briefly introduces the potential beamforming design algorithms that may be used in our proposed architecture. Currently, the mainstream beamforming design algorithms are divided into two categories: beamforming design based on optimization and beamforming design based on reinforcement learning (RL).

![Figure 2 DL Transmissive RMS transmitter modulation and transmission diagram.](image1)

![Figure 3 Transmitter modulation mapping principle.](image2)
**DL beamforming design based on optimization**

When we only consider the beamforming design of the transmitter, if considering a single-user multiple input single output (MISO) scenario, in order to solve the non-convex rank-one constraint, we can use matrix lifting and semi-definite relaxation (SDR) to obtain the beamforming design, and then use Gaussian randomization (GR) to obtain an approximate rank-one solution. The algorithm can also be extended to multi-user MISO scenarios. When the optimization problem we consider is not only beamforming design, such as power allocation, physical layer security, energy transmission and other issues, we can use the alternating optimization (AO) method. The framework of the AO algorithm is to divide the problem into several sub-problems, and then solve each sub-problem. In the process of solving each sub-problem, methods such as successive convex approximation (SCA), matrix lifting, SDR and penalty function can be used [14]. Finally, several sub-problems are alternately optimized to achieve convergence. Although easy to implement, the AO method alternately updates a variable block in each iteration, which usually requires a large number of iterations to guarantee convergence, especially for high-dimensional optimization variables. In addition to the above optimization algorithms, according to the unique rank-one constraint of RMS, a manifold optimization method can also be used to design its beamforming of transmissive RMS transmitter.

**DL beamforming design based on RL**

The classic optimization-based beamforming design usually considers the optimization of a time slot. In the practical problem, each time slot needs to be re-evaluated and optimized again, which is expensive. At the same time, the channel state may change due to the mobility of the user, and the optimization in this case may not be very effective. Therefore, the beamforming can be designed based on RL. Unlike the optimization of a single slot, the RL considers the long-term benefits of a process, which is more practical. Model-free RL is a dynamic programming pool, which can learn the optimal solution in a dynamic environment to solve decision-making problems. Therefore, this method is very suitable for the beamforming design problem under our proposed architecture. We can regard the proposed wireless communication networks as an environment, and the central controller of the transmitter as a learning agent. Then the channel information, quality-of-service (QoS) threshold, etc., are regarded as the state space, the optimization variable is regarded as the action space, the objective function combined with the partial constraints of the problem are regarded as the reward function, and the transition probability is defined. Finally, algorithms such as Q-learning, policy gradient and deep Q-Network (DQN) can be used to solve the problem. In order to speed up the convergence speed and avoid falling into the local optimum, some improved algorithms can be adopted on the basis of classic algorithms, such as post-decision state and prioritized experience replay. The DL beamforming design based on classic optimization and RL can be summarized as Figure 4.

**Uplink (UL) Transmissive RMS Receiver**

For the transmissive RMS empowered wireless communication networks, similar to the signal modulation, consider that the controller is equipped with a baseband with demodulation function, i.e., when the user sends the modulated signal to the RMS, the controller can demodulate the signal and perform receiving beamforming, this process is reciprocal with the DL process, so we won't elaborate on it here.

**Potential Research Directions**

**Wireless power transmission with transmissive RMS transmitter**

Considering that there will be more large-scale, low-power, energy-constrained Internet-of-things (IoT) devices in the 6G network to provide continuous information transmission and energy transmission requirements, simultaneous wireless information and power transfer (SWIPT) and wireless powered
communication networks (WPCN) can serve them well. We can combine the proposed architecture and wireless power transmission (WPT) to realize a new network paradigm for 6G WPT. Meanwhile, considering the limitation of system performance degradation due to distance limitation, we can also consider using reflective RMS to further strengthen, greatly improving the transmission efficiency and coverage, so as to realize the transmissive-reflective RMS-empowered WPT network architecture.

**Non-orthogonal multiple access (NOMA) with transmissive RMS transmitter**

NOMA can well meet the large-scale connections of 6G networks and the higher service requirements of users. Unlike traditional orthogonal multiple access (OMA), NOMA can support multiple users to share the same resources, such as time, frequency, coding, etc., therefore, it can support large-scale access of users. Specifically, taking NOMA in the power domain as an example, the transmitter can use the same resources to serve multiple users, which can greatly improve the spectrum efficiency to meet the user's service requirements. For NOMA transmission in the downlink power domain, superposition coding and serial interference cancellation (SIC) technologies are applied at the transmitter and the user, respectively. By applying SIC technology, users with stronger channel gains can remove co-channel interference caused by users with weaker channel gains before decoding. The research of NOMA under the proposed framework will be a brand new attempt.

**DRL-enabled transmissive RMS transmitter**

The future 6G network is an intelligent ubiquitous network, with huge data volume and user scale, and the communication environment is complex and changeable. Deep reinforcement learning (DRL) is a very promising technology for future 6G networks. DRL combines the advantages of RL and deep learning well, and it is very suitable for the decision-making, scheduling and allocation problems of high-dimensional variables in wireless communications. Nowadays, there are many researches on DRL used in the resource management of wireless communication systems, and some DRL algorithms have already begun to solve the problem of reflective RMS-assisted communication [15]. However, DRL has not been applied to our proposed architecture. Therefore, it is very potential to use DRL to solve a series of communication problems for our proposed transmissive RMS transmitter architecture.

**Conclusions**

In this paper, we have proposed a more efficient transmissive RMS transmitter architecture for the business requirements and characteristics of 6G networks. Due to its low cost and low power consumption, this architecture has great potential for the realization of 6G ultra massive MIMO. Combined with some existing work, we also have introduced and reviewed the architecture from several aspects such as transmissive RMS transmitter design, channel model, channel estimation, signal modulation, and beamforming design. In addition, we have made a concise summary of several potential research directions in the future. In addition, the reflective RMS can also well assist our proposed architecture to improve communication performance in different scenarios.

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