

Reconfigurable Intelligent Surfaces: Principles and Opportunities

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Abstract

Reconfigurable intelligent surfaces (RISs), also known as intelligent reflecting surfaces (IRSs)¹, have received significant attention for their potential to enhance the capacity and coverage of wireless networks by smartly reconfiguring the wireless propagation environment. Therefore, RISs are considered a promising technology for the sixth-generation (6G) communication networks. In this context, we provide a comprehensive overview of the state-of-the-art on RISs, with focus on their operating principles, performance evaluation, beamforming design and resource management, applications of machine learning to RIS-enhanced wireless networks, as well as the integration of RISs with other emerging technologies. We describe the basic principles of RISs both from physics and communications perspectives, based on which we present performance evaluation of multi-antenna assisted RIS systems. In addition, we systematically survey existing designs for RIS-enhanced wireless networks encompassing performance analysis, information theory, and performance optimization perspectives. Furthermore, we survey existing research contributions that apply machine learning for tackling challenges in dynamic scenarios, such as random fluctuations of wireless channels and user mobility in RIS-enhanced wireless networks. Last but not least, we identify major issues and research opportunities associated with the integration of RISs and other emerging technologies for application to next-generation networks.

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¹Without loss of generality, we use the name of RIS in the remainder of this paper.

Index Terms

6G, intelligent reflecting surface (IRS), machine learning, performance optimization, reconfigurable intelligent surface (RIS), wireless networks

I. INTRODUCTION

The unprecedented demands for high quality and ubiquitous wireless services impose enormous challenges to existing cellular networks. Applications like rate-centric enhanced mobile broadband (eMBB), ultra-reliable, low latency communications (URLLC), and massive machine-type communications (mMTC) services are the targets of designing the fifth-generation (5G) communication systems. However, the goals of sixth-generation (6G) wireless communication systems are expected to be transformative and revolutionary encompassing applications like data-driven, instantaneous, ultra-massive, and ubiquitous wireless connectivity, as well as connected intelligence [1], [2]. Therefore, new transmission technologies are needed in order to support these new applications and services. Reconfigurable intelligent surfaces (RISs), also called intelligent reflecting surfaces (IRSs) [3], [4] or large intelligent surfaces (LISs) [5], [6], comprise an array of reflecting elements for reconfiguring the incident signals. Owing to their capability of proactively modifying the wireless communication environment, RISs have become a focal point in the wireless communications research field for mitigating a wide range of challenges encountered in diverse wireless networks [7], [8]. The advantages of RISs are listed as follows:

- **Easy to deploy:** An RIS is a passive device, made of electromagnetic (EM) material. As illustrated in Fig. 1, RISs can be deployed on several structures, including but not limited to building facades, indoor walls [9], aerial platforms, roadside billboards, highway polls, vehicle windows, as well as pedestrians' clothes due to their low-cost.
- **Spectrum efficiency enhancement:** An RIS is capable of reconfiguring the wireless propagation environment by compensating for the power loss over long distances. Virtual line-of-sight (LoS) links between base stations (BSs) and mobile users can be formed via passively reflecting their received signals. The throughput enhancement becomes more significant when the LoS link between BSs and users is blocked by high-rise buildings with high probability. Due to the intelligent deployment and design of RISs, a software-defined

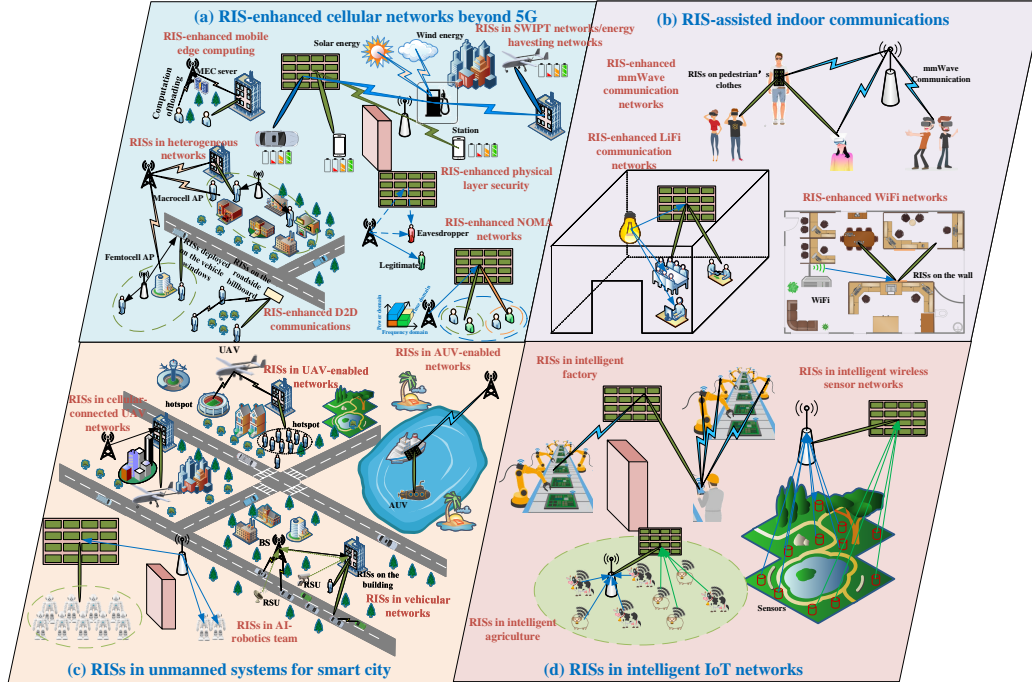


Figure 1: RISs in wireless communication networks.

wireless environment may be constructed, which in turn, provides potential enhancements in the received signal-to-interference-plus-noise ratio (SINR).

- **Environment friendly:** In contrast to conventional relaying systems, e.g., amplify-and-forward (AF) and decode-and-forward (DF) [10], an RIS is capable of shaping the incoming signal by controlling the phase shift of each reflecting element instead of employing a power amplifier [11], [12]. Thus, deploying an RIS is more energy-efficient and environment friendly than conventional AF and DF systems.
- **Compatibility:** RISs support full-duplex (FD) and full-band transmission due to the fact that they only reflect EM waves. Additionally, RIS-enhanced wireless networks are compatible with the standards and hardware of existing wireless networks [13].

Due to the aforementioned attractive characteristics, RISs are recognized as an effective solution for mitigating a wide range of challenges in commercial and civilian applications. There have been many recent studies on RISs and their contributions focus on several application scenarios under different assumptions. As a result, the system models proposed by these research

contributions tend to be different. Thus, there is an urgent need to categorize the existing research contributions, which is one of the main goals of this paper.

Fig. 1 illustrates the application of RISs in diverse wireless communication networks. In Fig. 1 (a), RIS-enhanced cellular networks are illustrated, where an RIS is deployed for bypassing the obstacles between BSs and users. Thus, the quality of service in heterogeneous networks and the latency performance in mobile edge computing (MEC) networks are improved [14], [15]. On the other hand, an RIS can act as a signal reflection hub to support massive connectivity via interference mitigation in device-to-device (D2D) communication networks [16], or an RIS can cancel undesired signals by smartly designing the passive beamforming in the context of physical layer security (PLS) networks [17]. Additionally, an RIS can be deployed to strengthen the received signal power of cell-edge users and mitigating interferences from neighbor cells [18], while the significant power loss over long distances can also be compensated in simultaneous wireless information and power transfer (SWIPT) networks [19]–[22]. In Fig. 1 (b), RIS-assisted indoor communications are illustrated, where an RIS can be deployed on the wall for enhancing the quality of service in some rate-hungry scenarios, such as virtual reality. Additionally, a virtual RIS-aided LoS link can be formed for guaranteeing no blind spots in the coverage area of some block-sensitive scenarios, such as visible light communications [23] and wireless fidelity (WiFi) networks. In Fig. 1 (c), RIS-enhanced unmanned systems are illustrated. An RIS can be leveraged for enhancing the performance of unmanned aerial vehicle (UAV) enabled wireless networks [24], cellular-connected UAV networks [25], autonomous vehicular networks and autonomous underwater vehicle (AUV) networks by fully reaping the aforementioned RIS benefits. In Fig. 1 (d), RIS-enhanced Internet of Things (IoT) networks are illustrated, where an RIS is exploited for assisting intelligent wireless sensor networks [26], intelligent agriculture, and intelligent factory.

In contrast to the existing literature, this paper provides both a comprehensive discussion of RIS-enhanced wireless networks principles, and research opportunities for exploiting RISs in diverse applications, such as unmanned systems, non-orthogonal multiple access (NOMA) in RIS-enhanced wireless networks and machine learning in RIS-enhanced wireless networks. Our main contributions are as follows.

- We introduce the fundamental principles that govern the operation of RISs and their inter-

action with the EM signals. We also survey typical RIS functions and their corresponding principles. Specifically, we focus on patch-array based implementation and compared the ray-optics perspective with the wave-optics perspective.

- We develop performance evaluation techniques for multi-antenna assisted RIS systems. Research contributions are also summarized by providing their advantages and limitations.
- We investigate RISs from the information theory perspective, based on which we review the protocols and approaches for jointly designing beamforming and resource allocation with different optimization objectives. Additionally, the major open research problems are discussed.
- We discuss the need of amalgamating machine learning and RISs. After reviewing the most recent research contributions, we propose a novel framework for optimizing RIS-enhanced intelligent wireless networks, where big data analytics and machine learning are leveraged for optimizing RIS-enhanced wireless networks.
- We identify major research opportunities associated with the integration of RISs into other emerging technologies and discuss potential solutions.

The remainder of this paper is structured as follows. Section II elaborates on the fundamental operating principles of RIS-enhanced wireless networks. Section III focuses on the performance evaluation of multi-antenna assisted RIS systems and the main advantages of using RISs in wireless networks. In Section IV, the latest research activities on the joint design of beamforming and resource allocation are discussed. The framework of machine learning empowered RIS-enhanced intelligent wireless networks is illustrated in Section V. Finally, Section VI investigates the integration of RIS with other emerging technologies towards the design and optimization of 6G wireless networks. Fig. 2 illustrates the organization of this paper.

II. RIS: FROM PHYSICS TO WIRELESS COMMUNICATIONS

RIS is a two-dimensional (2D) material structure that is reconfigurable in terms of its EM wave response. In contrast to conventional wireless communication networks, RIS-aided networks can control and configure the channel between the transmitters and the receivers to achieve an enhanced received signal at the terminal devices. In this section, we introduce the fundamental

Table I: LIST OF ACRONYMS

AF	Amplify-and-Forward
AO	Alternatng Optimization
AUV	Autonomous Underwater Vehicle
BC	Broadcast Channel
BS	Base Station
CSI	Channel State Information
D2D	Device-to-Device
DF	Decode-and-Forward
DL	Deep Learning
EE	Energy Efficiency
EM	Electromagnetic
FD	Full-Duplex
FDMA	Frequency Division Multiple Access
HD	Half-Duplex
IRS	Intelligent Reflecting Surface
IoT	Internet of Things
LiFi	Light Fidelity
LIS	Large Intelligent Surfac
LoS	Line-of-Sight
MEC	Mobile Edge Computing
MIMO	Multiple-Input and Multiple-Output
MISO	Multiple-Input and Single-Output
ML	Machine Learning
MOS	Mean Opinion Score
NP	Non-deterministic Polynomial-time
NOMA	Non-Orthogonal Multiple Access
OFDM	Orthogonal Frequency Division Multiplexing
OMA	Orthogonal Multiple Access
PDF	Probability Density Function
PLS	Physical Layer Security
QoS	Quality of Service
RIS	Reconfigurable Intelligent Surface
RL	Reinforcement Learning
SCA	Successive Convex Approximation
SCMA	Sparse Code Multiple Access
SE	Spectral Efficiency
SG	Stochastic Geometry
SIC	Successive Interference Cancellation
SIMO	Single-Input and Multiple-Output
SINR	Signal-to-Interference-plus-Noise Ratio
SISO	Single-Input and Single-Output
SNR	Signal-Noise Ratio
SWIPT	Simultaneous Wireless Information and Power Transfer
UAV	Unmanned Aerial Vehicle
VLC	Visible Light Communication
VR	Virtual Reality
WiFi	Wireless Fidelity
5G	Fifth-Generation
6G	Sixth-Generation

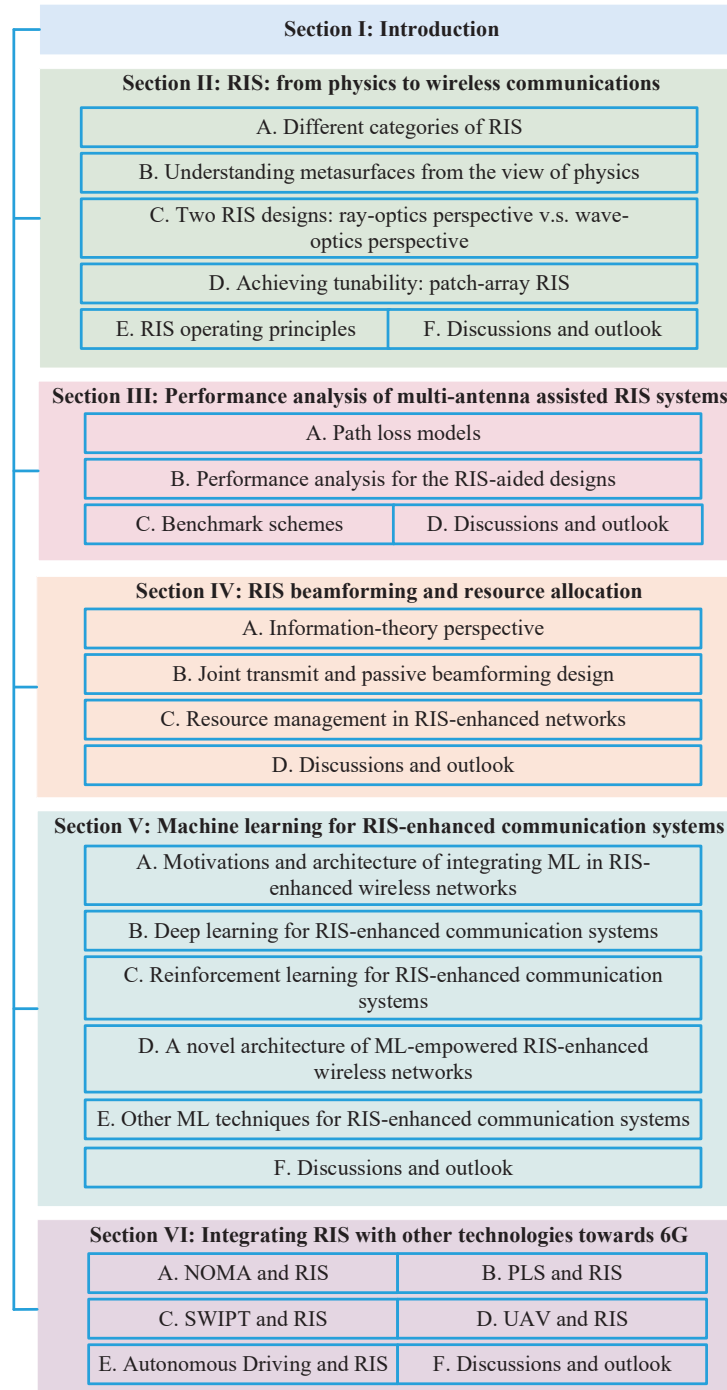


Figure 2: Organization of the present paper.

principles which govern the operation of RISs and their interaction with the EM signals. We also survey the typical RIS functions and their corresponding principles.

A. Different Categories of RISs

Considering their structures, RISs can be realized by using metamaterial or patch-array based technologies. Metamaterial-based RISs are referred to as metasurfaces. Deployed at different locations, they can be designed to work as reflecting/refracting RIS between the BS and the user or waveguide RIS operating at the BS. Considering the tuning mechanisms, RISs can be reconfigured electrically, mechanically, or thermally. Depending on their energy consumptions, RISs can be categorized as passive-lossy, passive-lossless, or active. The active or passive nature of RISs determine their ultimate performance capabilities. It is worth mentioning, however, that RISs cannot be completely passive because of their inherent property of being configurable. Here, we discuss three important RIS working conditions: waveguide [27], refraction [28] and reflection [29]. With the aid of Love's field equivalence principle [30], the reflected and refracted EM field can be studied by introducing equivalent surface electric and magnetic current [28]. In the three working conditions, the RIS converts and radiates wave (either induced by an incident wave or fed by a waveguide) into a desired propagating wave in free space. The surface equivalence principle (SEP) including Love's field equivalence principle and Huygens' principle will be introduced in Section II-B.

1) *Waveguide RIS*: R. Smith *et al.* [27] presented a theoretical study of waveguide-fed metasurfaces. The elements in the metasurface are modeled as uncoupled magnetic dipoles. The magnitude of each dipole element is proportional to the product of the reference wave and each element's polarizability. By tuning the polarizability, the metasurface antenna can perform beamforming. Each element on the metasurface serves as a micro-antenna. Compared to conventional antenna arrays, the compact waveguide metasurface occupies less space and can transmit wide angles of radiation patterns.

2) *Refracting RIS*: Viktor S *et al.* [31] proposed a theoretical design of a perfectly refracting and reflecting metasurface. The authors used an equivalent impedance matrix model so that the tangential field components at the two sides on the metasurface are appropriately optimized. Moreover, three possible device realizations are discussed: self-oscillating teleportation metasurfaces, non-local metasurfaces, and metasurfaces formed by only lossless components. The crucial role of omega-type bianisotropy in the design of lossless-component realizations of perfectly refractive surfaces is discussed.

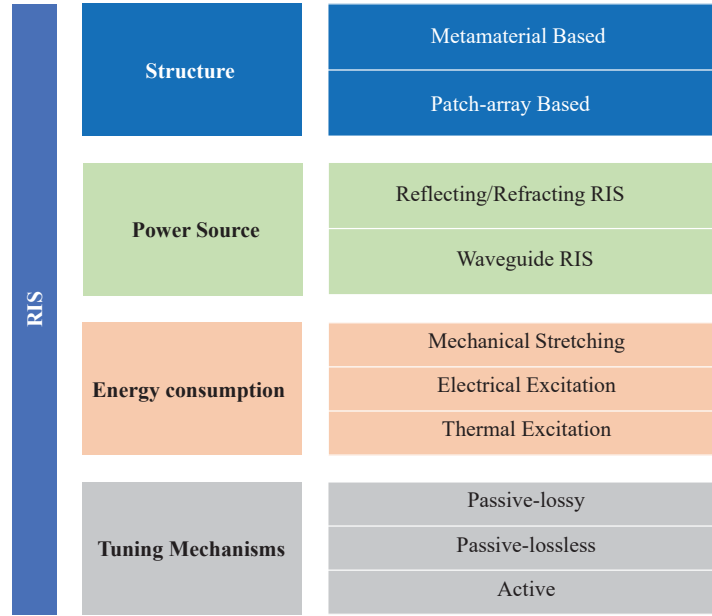


Figure 3: Different types of metasurfaces.

3) *Reflecting RIS*: Dai *et al.* [29] designed a digital coding reflective metasurface. The elements in the metasurface contain varactor diodes with a tunable biasing voltage. By pre-designing several digitized biasing voltage levels, each element can perform discrete phase shifts and achieve beamforming for the reflected wave.

The rest of this section will be focused on the operating principles for RISs that operate as reflectors.

B. Understanding Metasurfaces From the View of Physics

A wireless signal is essentially an EM wave propagating in a three-dimensional (3D) space. Attenuation or reduction of the signal's strength occurs as the EM wave propagates through space and interacts with scattering objects. From basic principles of electromagnetism, the signal power per unit area is proportional to the square of the electric field of the corresponding wave, in a given media. For the reflective and refractive smart surfaces, this result enables us to study the EM wave to gain an understanding of the wireless signal and its interaction with reflective objects. The equivalence principle, especially the SEP is the building block for all these studies of EM wave manipulation. Two views can be adopted in the context of RIS designs: the Huygens' principle and the Love's field equivalence principle. The first view is the Huygens' principle, according

to which the EM wave manipulation boils down to the controllable change in amplitudes and phases at each position on the surface wavefront. The Love's field equivalence principle is another important view because it can be adopted for both the external problem (source-free region) and the internal problem. As shown in Fig. 4, the equivalent problem for region I can be set up by placing equivalent currents on S that satisfy the boundary condition for each particular case and filling region II with the same medium of constitutive parameters ϵ and μ . Thus, the equivalent currents $(-J_s, -M_s)$, together with the original source (J_1, M_1) , will radiate the correct fields in region I. The equivalent problem for region II can be set up similarly.

The operating principle of waveguide-based RISs can be summarized as follows. In [32], the EM wave manipulation of the waveguide metasurface performs the coupling between 3D free space waves and two-dimensional surface waves. As a result, the metasurface can be regarded as a hologram, which carries additional information about its radiated signal propagating in the 3D space. After being excited by the source, this pre-designed information is coupled into the radiated field. As illustrated in Fig. 5, the figure conceptually represents a pre-designed holographic waveguide-based RIS.

C. Two RIS Designs: Ray-optics Perspective v.s. Wave-optics Perspective

To characterize the interaction between an RIS and the impinging EM waves, one can adopt approximations and tools either from ray-optics or wave-optics. These two perspectives have been used by physicists for a long time. Even though they are based on some approximations, these two methods of analysis are useful in order to obtain important insight into the interaction of light or radio waves with materials. In the RIS literature, both methods of analysis are often employed. However, the assumptions behind their use and their physical assumptions are intrinsically different. To shed light on their differences and similarities, we compare the two in this subsection. As shown in Fig 6 (a), from the ray-optics perspective, the EM wave is modeled as a collection of geometrical rays with varying phases. The phase of each ray increases linearly with the optical path length as it traverses through the vacuum or other media. As a result, at each location of the i -th ray, a phase (denoted by ϕ_i) can be defined. When the ray interacts with an optical material, the phenomenon is studied by determining the relationship between the change in the phase and the material's refraction index. Finally, the desirable reflected wave

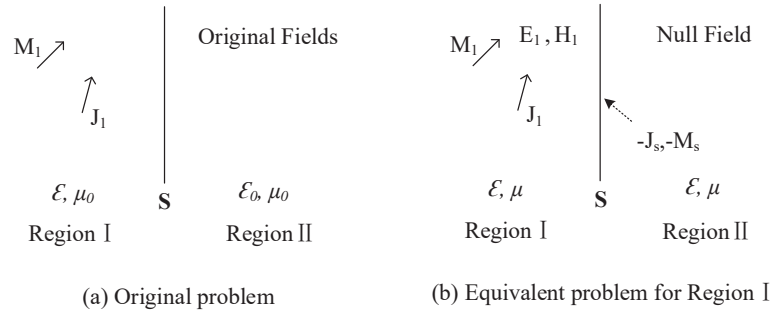


Figure 4: Love's equivalence internal problem (for region I).

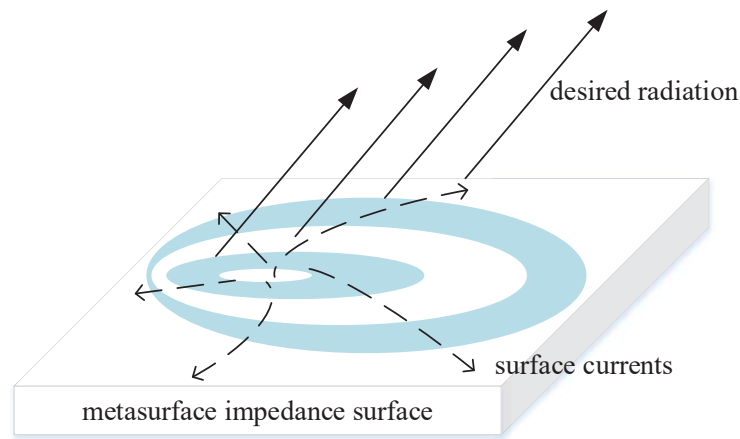


Figure 5: Conceptual illustration of the holographic impedance smart surface.

can be achieved if the ray collection obeys the proper co-phase condition. The wave-optics perspective is shown in Fig 6 (b), where the EM wave is represented by the corresponding electric field and magnetic field. At each position, these two vector fields can be characterized by a time-varying complex-valued vector, with a direction, an amplitude, and a phase. From the wave-optics perspective, the interaction between the wave and the reflective material can be studied using the various equivalent principles, as discussed in the last subsection (II-B). The points with equal phase values form series surfaces in space, which we refer to as wavefronts. As a result, the desirable reflected wave can be achieved if proper wavefront transformation is performed at the RIS.

1) *Comparing Ray-optics and Wave-optics Perspectives:* Table II highlights some of the differences between the two perspectives. Compared with wave-optics, the ray-optics perspective

	Ray-optics	Wave-optics
Wave representation	Geometrical rays	Vector fields
Theoretical foundation	Snell's law	Maxwell's equations
Surface profile	Phase discontinuity	Surface impedance
Requirement of the reflected wave	Co-phase condition	Proper wavefront
Power flow	Not accurate	Accurate

Table II: Comparing different wave representation perspectives

is a stronger simplification of the real system. As a result, it is easier to be adopted and can produce a quick prediction about the RIS design. However, ray-optics fails when considering the RIS power flow. Wave-optics, on the other hand, predict the power flow by the Poynting vector, which enables us to study the local and overall RIS power consumption. This is an important issue to consider in the real design and manufacture of the RIS. For example, both [31] and [33] point out that it is impossible to achieve a lossless plane-wave beam steering with locally passive RIS. One has to adopt the wave-optics perspective to study the power flow of the system. Moreover, [33] states that, according to their simulation results, one can expect increasingly improved performance for RIS designed based on wave-optics in comparison to those designed based on the ray-optics approximation. In conclusion, both perspectives have their benefits. However, adopting the wave-optics perspective is the most appropriate choice for most cases. A study of the differences, in terms of power flow and reflection coefficient, between ray-optics and wave-optics methods of analysis is reported in [7].

D. Achieving Tunability: Patch-array RIS

The electromagnetic characteristics of the RIS, such as phase discontinuity, can be reconfigured by tuning the surface impedance, using various mechanisms. Apart from electrical voltage, other mechanisms are reported, including thermal excitation, optical pump, and physical stretching. Among them, electrical control is the most convenient choice, since the electrical voltage is easier to be quantized and controlled by FPGA chips. The choices of RIS materials include semiconductors [34] and graphene [35].

Regardless of the tuning mechanisms, we focus on patch-array smart surfaces in the following discussion. The general geometry layout of this type of RIS can be modeled as a periodic (or quasi-periodic in the most general case) unit cells integrated on a substrate. For ease of

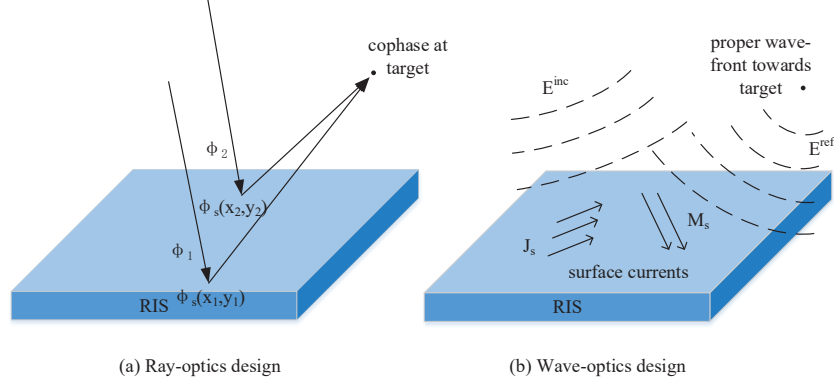


Figure 6: Comparison between Ray-optics and wave-optics perspective.

description, in addition, we limit our discussion to RISs that are based on a local design, in which the cells do not interact with each other (which is referred to as a non-local design). A local design usually results in the design of sub-optimal RISs. A comprehensive discussion about local and non-local designs can be found in [7]. When designing RIS-assisted communication systems based on a local design, the most important RIS parameter is the reflection coefficient of r at each element (unit cell, or scatter). To characterize the tunability of the RIS, the method of equivalent lumped-element circuits can be adopted. As shown in Fig. 7, the unit cell is equivalent to a lumped-element circuit with a load impedance of Z_l . Particularly, the equivalent load impedance could be tuned by changing the bias voltage of the varactor diode. When modeling the patch-array RIS in wireless communication systems, we can characterize, under a local design, each of its unit cells only by the reflection coefficients. For example, the i -th cell can be modeled as:

$$r_i = \beta_i \cdot e^{j\phi_i} \quad (1)$$

where β_i and ϕ_i correspond to the amplitude response and the phase response, respectively. The reflection coefficient is a function of the unit cell impedance. Moreover, according to [36], β_i and ϕ_i in (1) are correlated and related through a compact function: $\beta_i = f(\phi_i)$. In the following sections, $\Phi(\vec{r}_x)$ refers to the phase discontinuity as a function of position on the RIS, and ϕ_{mn} refers to the phase discontinuity of the (m, n) -th element in the case of patch-array RIS.

Existing designs of patch-array RIS achieve discrete phase control or amplitude control. Arun *et al.* [37] designed *RFocus*, which is a two-dimensional surface with a rectangular

array of passive antennas. Each passive unit is $\lambda/4 \times \lambda/10$ of size and either let the signal go through or reflect it. The authors show that the *RFocus* surface can be manufactured as an inexpensive thin wallpaper, requiring no wiring, and improves the median signal strength by 9.5 times. Welkie *et al.* [38] developed a low-cost device embedded in the walls of a building to passively reflect or actively transmit radio signals. Dunna *et al.* [39] present *ScatterMIMO*, which uses a smart surface to increase the scattering in the environment. In their hardware design, each reflector unit uses a patch antenna which further connects to 4 open-ended transmission lines. The transmission lines provide $0, \pi/2, \pi$ or $3\pi/2$ phase shifts. Moreover, each unit has its addressable memory. The *ScatterMIMO* achieves a throughput gain of 2 times and a multiple-input and multiple-output (MIMO) SNR impartment of 4.5dB compared to the baseline.

E. RIS Operating Principles

Considering single-beam reflection, the patch-array based RIS can be configured to serve a terminal device in both far-field and near-field regions. In the literature, the RIS functions under these two working scenarios are often referred to as *anomalous reflection* and *beamforming*. Adopting the wave-optics perspective, anomalous reflection is a wavefront transformation from a plane wave to another plane wave, while beamforming is a wavefront transformation from a plane wave to a desirable wavefront. Adopting the ray-optics perspective, we present the operating principles of these two cases in the following discussion. For the case of anomalous reflection, the RIS is designed to reflect an incident beam to a far-field terminal, following the generalized laws of refraction and reflection [40]. For the case of beamforming (also called focusing), the incident wave is reflected and focused in a targeted region, often referred to as the *focal point*. The required RIS configuration follows the co-phase condition [41]. Before we present these two different principles, the physical distinction between the near-field region and the far-field region needs to be clarified.

1) *Near-field v.s. Far-field*: In the spirit of dimensional analysis, the characteristics of a system can be represented by dimensionless numbers. In order to separate the near-field region from the far-field region, a proper dimensionless number is needed. Let L and R_F denote the antenna aperture size of the RIS and the focal distance, respectively. Suppose z is the distance of a particular field point to the RIS. We define a dimensionless parameter $\gamma = z/(2L^2/\lambda)$ as the

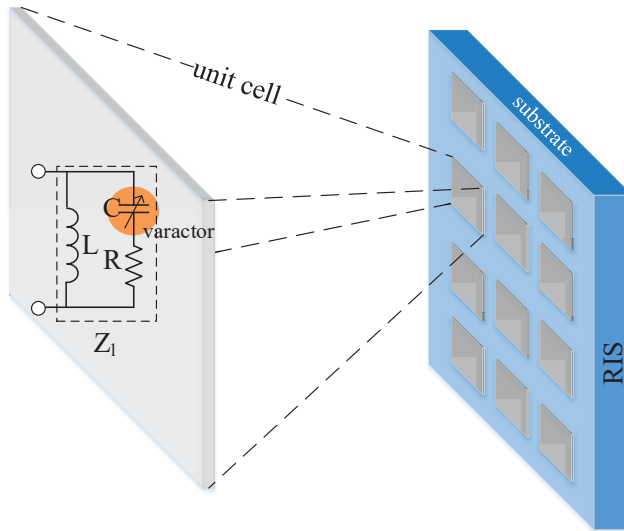


Figure 7: Schematic diagram of the varactor RIS.

field point indicator. The position corresponding to $\gamma = 1$ is the boundary between the near-field region and the far-field region. This result comes from the inspection of the power density variation with the distance between a field point and the RIS. As the field point approaches the boundary, the power density reaches its asymptotic limit determined by the z^{-2} factor, as reported in [42] and [43]. However, within the near field where $\gamma < 1$, the power density shows drastic variations. The peak position of the power density in the near-field region, namely R_F , changes with the different RIS configurations. Using the proper co-phase condition, beam focusing can be achieved within the near-field of the RIS.

Based on the above discussion, the essential difference between the near-field region and the far-field region is how the power density changes with distance. Consider that the beam focusing RIS focuses the wave within an area of a . The total energy incident on the RIS is proportional to the solid angle (Ω) spanned by the surface area of the RIS w.r.t the transmitter. After the reflection, the transmitted energy is spread over an area denoted by a . Thus, the power density around the focal point is proportional to Ω/a . Moreover, according to [37], the area a is proportional to $\lambda^2(1 + 4z^2/L^2)$, as a result of the Abbe diffraction limit. In the far-field region, the latter term inside the brackets dominates. Thus Ω/a is proportional to $A\Omega/z^2$, which is the typical spherical dissipation of signal power. In the near-field region, the former term dominates and the area a becomes very small. As a result, the desirable focus gain can be achieved.

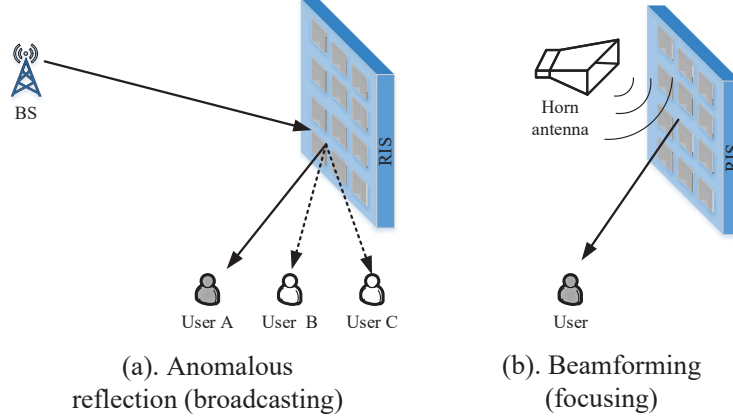


Figure 8: Typical functions of reflecting metasurface.

Next, adopting the ray-optics perspective, we discuss the generalized laws of refraction and reflection, as well as the co-phase condition.

2) *The generalized laws of refraction and reflection:* From the geometrical optics perspective, the anomalous reflection and refraction at the metasurface can be described by the generalized laws of refraction and reflection [40]. This generalized law is a natural derivation of both the Fermat's principle and the boundary conditions governed by Maxwell equations, which can be stated as follows:

Principle 1. *Achieving anomalous reflection (Fig. 8(a))*

Suppose that the phase discontinuity at the boundary is a function of the position along the x direction $\Phi(\vec{r}_x)$, where \vec{r}_x is the position vector on the boundary surface. Moreover, suppose that the phase discontinuity changes are continuous with the position and its derivative corresponding to the direction of the incident ray ($d\Phi/dx$) is constant. Then, the reflected (θ_1) and refracted angles (θ_2) are [44]:

$$\theta_1 = \sin^{-1} \left[\sin\theta_i + \frac{\lambda}{2\pi n_1} \frac{d\Phi}{dx} \right], \quad (2)$$

$$\theta_2 = \sin^{-1} \left[\frac{n_1}{n_2} \sin\theta_i + \frac{\lambda}{2\pi n_2} \frac{d\Phi}{dx} \right], \quad (3)$$

where θ_i is the incident angle, λ is the wavelength of the transmitted signal in vacuum, and n_1, n_2

are the refractive indexes, as shown in Fig. 9. Considering the discretization of the patch-array implementation, the phase of the n -th element is as follows:

$$\phi_n = (\sin\theta_1 - \sin\theta_i) \frac{d_x}{\lambda} \cdot 2\pi n \quad (4)$$

where n is the elements index along x -axis, d_x is the length of the RIS element along x -axis. \square

In the literature, the quantity is often referred to as $X = |\lambda/(\sin\theta_1 - \sin\theta_i)|$ as the surface *super-lattice*. Thus, the optimal phase design can be rewritten as the ratio between the super-lattice length and the element period length: $\phi_n = (d_x/X) \cdot 2\pi n$. There are other results related to the generalized laws of refraction and reflection, including the critical angles for total internal reflection or refraction. The main result we present here states that when a phase discontinuity is introduced at the boundary surface, the reflection and refraction angles depend not only on the incident angle but also on the wavelength, refractive indexes, and the gradient of the phase discontinuity. This gives us extra controllable parameters to manipulate the reflected and refracted EM waves. As a result, anomalous reflection can be achieved by tuning the phase gradient ($d\Phi/dx$) based on (2) or, in the discrete case of the patch-array implementation, by tuning the length of the super-lattice. However, the assumption that the derivative of the phase discontinuity is constant ($d\Phi/dx = Const.$) does not hold in other designs involving multiple beams. In those situations, the reflected and refracted wave scatters and propagates in multiple directions. Consequently, the EM manipulation properties of the RIS cannot be characterized by the gradient of the phase discontinuity or by the super-lattice length.

3) *Co-phase condition*: The beamforming (focusing) function is usually implemented when the RIS is within the near field of the source or the terminal is close to the RIS. In these cases, the curvatures of the incident and reflected wavefront are non-negligible. Phase shift adjustment aims to produce a pencil-beam pointing towards the direction of the terminal. When the link between the source and the RIS, as well as the link between the RIS and the terminal, are LoS links, the co-phase condition [41] can be applied as in the theory of reflectarray antennas.

Principle 2. *Achieving beamforming (focusing) (Fig. 8(b))*

Suppose r_{mn} indicates the position of the (m, n) -th RIS element, r_s is the source position, \hat{u}

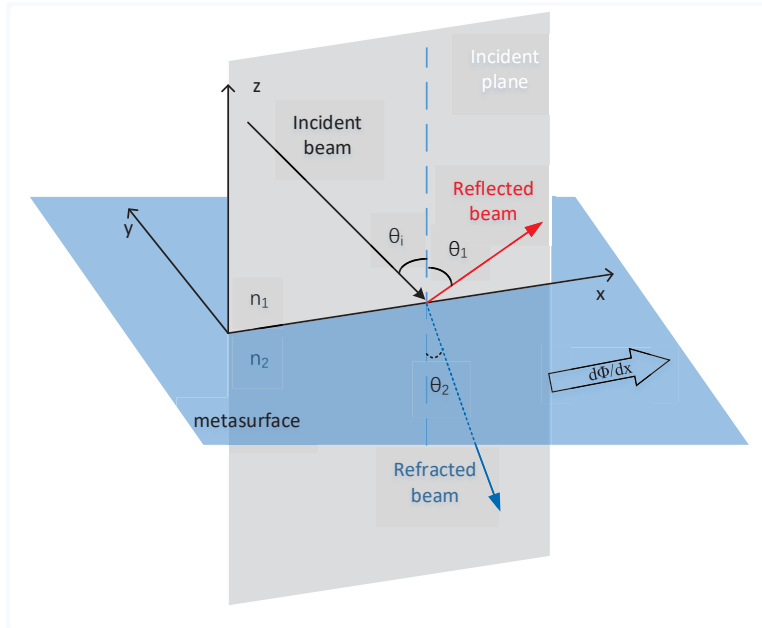


Figure 9: Illustration of the generalized laws of refraction and reflection.

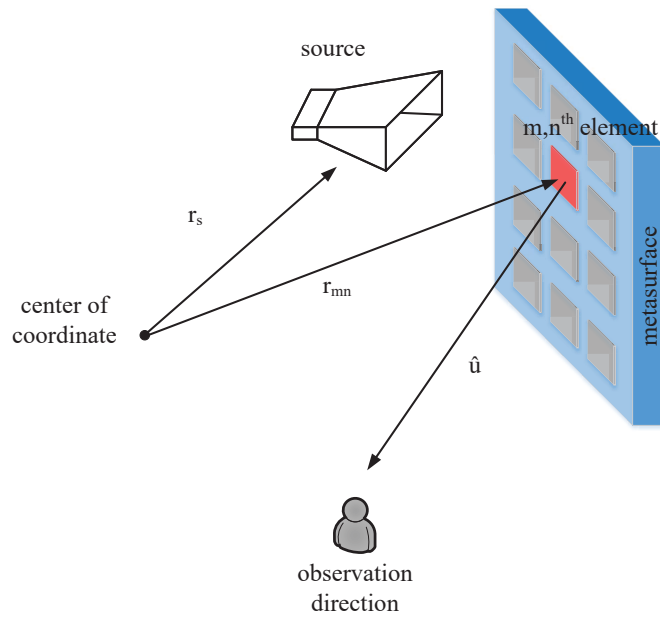


Figure 10: Coordinate representation of co-phase condition.

indicates the direction of the observer w.r.t the metasurface. As shown in Fig. 10, ϕ_{mn} can be determined by [45]:

$$-k_0(|\vec{r}_{mn} - \vec{r}_s| - \vec{r}_{mn} \cdot \hat{u}) + \phi_{mn} = 2\pi \cdot t \quad (5)$$

where $t = 1, 2, 3, \dots$ and $k_0 = 2\pi/\lambda_c$. □

It is worth mentioning that anomalous reflection and beamforming can be achieved with RIS implementations other than the patch-array RIS. For example, PIVOTAL COMMWARE proposed a new technique called *Holographic Beam Forming (HBF)*. The proposed holographic beamformer has a lower cost compared to the patch-array based implementations and can realize beamforming by configuring the bias states of the hologram.

The above two principles provide guidance on how to configure the RIS phase shift patterns under typical scenarios. In more complex wireless communication systems, the RIS role is more intricate, thus cannot be categorized by the two working functions described in Fig. 8. In these cases, to determine the RIS configuration, an optimization problem needs be formulated. Different objective functions have different optimal solutions for the RIS configurations. The research contributions for these complex cases with different objective functions are surveyed in the following sections.

F. Discussions and Outlook

In the design and configuration of RISs, both theoretical limitations and hardware implementation limitations affect the overall performance of the resulting system. Theoretical limitations are the results of setting up simplified assumptions or adopting naive perspectives during the modeling of the RIS and its interaction with the EM wave. Hardware implementation limitations come from the discretization of the ideally continuous RIS profile. In order to further study RISs in various application scenarios, it is crucial to understand that these limitations are inevitable in any RIS design.

For the RIS patch-array implementation, although the ray-optics approximation can produce effective designs for some cases (as shown in Section II-E), it is still preferable to adopt the wave-optics design in most cases to utilize the best potential of the patch-array RIS. The ray-optics perspective has been adopted in the literature for designing RIS-assisted wireless systems. On the other hand, system models adopting the wave-optics perspective are less common. Further research efforts are expected to bridge the complex physical models of the different RIS implementations to the widely used communication models.

III. PERFORMANCE ANALYSIS OF MULTI-ANTENNA ASSISTED RIS SYSTEMS

In Section II, we have discussed the fundamental physical properties of the RISs. However, how RIS affects the communication performance is still an open problem. To systematically survey existing designs for RIS-aided networks, we discuss the following topics: (1) path loss models, (2) performance analysis, and (3) benchmark schemes.

A. Path Loss Models

A survey of the path-loss for RISs is available in [7], [43] and [46]. In these papers, it is shown that the power scattered by an RIS is usually formulated in terms of an integral that accounts, by leveraging the Huygens principle, for the impact of the entire surface. Closed-form expressions of the integral are, on the other hand, difficult to obtain, except for some asymptotic regimes, which correspond to viewing the RIS as electrically small and electrically large (with respect to the wavelength and the transmission distances). It is worth mentioning, in addition, that the path-loss model depends on the particular phase gradient applied by the RIS. Notably, the scaling laws can be different if the RIS operates as an anomalous reflector and as a focusing lens. In the following, we briefly discuss two scaling laws that have recently been reported for RISs that operate as anomalous reflectors (described in the previous text). Further information and details can be found in [7] and [46].

- **Electrically Small RISs:** In this asymptotic regime, the RIS is assumed to be relatively small in size compared with the transmission distances. In this regime, the RIS can be approximated as a small-size scatterer. In general, the path-loss scales with the reciprocal of the product of the distance between the transmitter and the center of the RIS and the distance between the center of the RIS and the receiver. In addition, the received power usually increases with the size of the RIS. The received power is usually maximized in the direction of anomalous reflection.
- **Electrically Large RISs:** In this asymptotic regime, the RIS is assumed to be large (ideally infinitely large) in size compared with the transmission distances and the wavelength. In this regime, the RIS can be approximated as a large flat mirror. Let us denote by x_0 the point of the RIS (if it exists) at which the first-order derivative of the total phase response of the combined incident signal, reflected signal, and the surface reflection coefficient of

the RIS is equal to zero. In general, the path-loss asymptotically scales with the reciprocal of a weighted sum of the distance between the transmitter and x_0 and the distance between x_0 and the receiver. In addition, the received power is not dependent on the size of the RIS, which is viewed as asymptotically infinite. This result substantiates the fact that the power scaling law of the RIS is physically correct, since it does not grow to infinity as the size of the RIS goes to infinity. This is because the scaling law and the behavior of the RIS are different with respect to the electrically small regime.

1) *Spatial Analysis*: Stochastic geometry (SG) tools are capable of capturing the location randomness of users thus enabling the derivation of computable or closed-form expressions of key performance metrics. Specifically, several well-accepted processes are selected for modeling the location randomness of users in different wireless networks, i.e. the homogeneous Poisson point process (HPPP) [47], [48], the Poisson cluster process (PCP) [49], [50], the Binomial point process (BPP) as well as the Hard core point process (HCPP) [51]. Below we list some of the promising approaches in the field of SG enhanced RIS networks in Table III. In [52], the RIS elements are employed on the obstacles, and it is assumed that the randomly distributed users are located in the serving area of RISs. By locating the RIS elements at the center of the cell, which could be a potential solution to the RIS-aided networks [5], the network's performance can be evaluated. In [53], the objects are modeled by a modified random line process of fixed length and with random orientations and locations. where the probability that a randomly distributed object that is coated with an RIS acts as a reflector for a given pair of transmitter and receiver was investigated. However, since the user locations are randomly distributed, the evaluation of the length of the BS-user or RIS-user links is still an open problem. Generally speaking, large-scale fading includes path loss and shadowing. There is no research yet focusing on the shadowing of the RIS-aided networks, which is a promising direction to investigate.

Table III: Summary of the RIS-aided SG Networks

Approaches	Advantages	Disadvantages	Ref.
RIS-aided HPPP	Fairness-oriented design	Restricted user distribution	[5]
RIS-aided two layer HPPP	Coverage-hole enhancement	RISs are deployed at obstacles	[52]
HPPP conditioned on angle	Practical design	Not tractable	[54]
RIS-aided HPPP conditioned on angle	Practical design for the RIS-aided networks	Complicated	–

B. Performance Analysis for the RIS-aided Designs

In this section, we briefly discuss currently available papers on the performance analysis of RISs that are realized as large arrays of tiny and inexpensive antennas whose phase response is locally optimized.

Currently, two main approaches have been used for performance analysis: (1) central-limit-theorem-based (CLT-based) distribution, (2) approximated distribution.

- **CLT-based Distribution:** The CLT-based technique is an approximation tool for analyzing the performance in the low-medium-SNR regime. This is due to fact that the distribution of the probability density function (PDF) in the range 0 to $0+$ is not precise by using the CLT-based technique, which indicates that the system performance in the high-SNR regime is not precise [55]. For the case of Rayleigh fading channels, it is also shown that the distribution of the RIS-aided network follows a modified Bessel function [55]. Since both the transmitter and RISs are part of the infrastructure, and the RISs are typically positioned to exploit the LoS path with respect to the location of the transmitter for increasing the received signal power. Zhang *et al.* [56] focused on the Rician fading channels, and the results illustrate that the signal power follows a non-central chi-squared distribution with two degrees of freedom. Ding and Poor [57] proposed an RIS-aided network, where RISs are utilized for effectively aligning the directions of users' channel gains, and hence the cell-edge users can be served.
- **Approximated Distribution:** The exact distribution of the received SNR of the signal reflected from an RIS is non-trivial to obtain, and hence an approximated distribution may be a solution. Qian *et al.* [58] proposed a simple approximated distribution of the received SNR, and proved that the received SNR can be approximated by two (or one) Gamma random variables and the sum of two scaled non-central chi-square random variables. Specifically, in order to provide further engineering insights, a prioritized signal enhancement design was proposed by Hou *et al.* [59], where both the outage performance and ergodic rate of the user with the best channel gain were calculated, where all other users rely on RIS-aided beamforming. Lyu and Zhang [60] proposed a single-input and single-output (SISO) network with multiple randomly deployed RIS arrays, and showed that the exact distribution in terms

of signal power can be approximated by a Gamma distribution. Makarfi *et al.* [26] proposed an RIS-aided network, whose equivalent channel is modelled by the Fisher-Snedecor \mathcal{F} distribution.

Based on the above mentioned contributions [26], [55]–[57], [59], [60], the exact distribution of RIS networks is still an open problem. For the CLT-based distribution in [55], the diversity gain is $\frac{1}{2}$ in the high-SNR regimes, whereas the diversity gain is $\frac{N}{3}$ for the approximated Gamma distribution, where N denotes the number of RISs. Note that both the CLT-based and approximated distributions are not exact, making the performance analysis of RIS-aided networks an interesting problem for future research.

1) **RIS-aided Designs:** By offering extra diversity in the spatial domain, multiple antenna techniques are of significant importance. The application of multiple antenna assisted RIS network has attracted substantial interest from academia [5], [59], [60] and industry [12], [61], [62]. Given the increasing research contributions on RIS, its advantages are becoming clear, especially in terms of its high spectral efficiency (SE) and energy efficiency (EE). There are several key challenges for performance analysis in RIS-aided networks. One of the main challenges is to evaluate the exact distributions of the cascade channels between the BS and users through the RISs. Another challenge is evaluating the effective channel gain after passive beamforming at the RIS. Table IV summarizes the existing contributions on RISs with multiple antennas and illustrates their comparisons. The single user designs were introduced in **Section IV.A**. We then turn our attention to the multi-user cases. Note that the single user design can be further extended to multi-user design, a prioritized signal-enhancement-based (SEB) was proposed by Hou *et al.* [59], where the passive beamforming is designed for the user with the best channel gain, and all other users rely on RIS-aided beamforming.

- **RIS-aided Signal Enhancement Designs:** In order to further enhance the SE of the RIS-aided networks, multiple antenna techniques are deployed at both the BS and users. Ntontin *et al.* [63] considered a pair of extreme scenarios, where the diffuse scattering and anomalous reflecting scenarios were investigated. Yuan *et al.* [65] proposed a cognitive-radio-based RIS-aided multiple-input and single-output (MISO) network, where both the perfect and imperfect channel state information (CSI) cases were considered. However, in most literature, continuous amplitude coefficients and phase shifts were assumed at the RISs,

Table IV: Important contributions on RIS-aided MIMO. “DL” and “UL” represent downlink and uplink, respectively. The “sum-rate gain” implies that the gain brought by invoking RIS technique

Ref.	Scenarios	Direction	Users	Main Objectives	Techniques
[5]	MIMO	DL	Multiple users	OP and Throughput	Fairness SEB
[12]	SISO	DL	Single user	sum-rate gain	Compare with Relay
[26]	SISO	UL	Single user	OP and Throughput	Effective Channel gain
[55]	SISO	DL	Single user	Effective channel gain	Compare with random phase shifting
[56]	SISO	DL	Single user	Effective channel gain	SEB
[57]	SISO	DL	Single user	OP	SEB
[59]	SISO	DL	Multiple users	OP and Throughput	Prioritized SEB
[60]	SISO	DL	Single user	Effective channel gain	SEB
[58]	MIMO	DL	Single users	Effective channel gain	Random matrix theory and CLT
[63]	MIMO	DL	Multiple users	sum-rate gain	SEB
[62]	MIMO	DL	Multiple users	Interference Cancellation	SCB and less constraint at RAs
[64]	SISO	UL	Multiple users	Sum-rate	Minimum required finite resolution
[65]	MISO	DL	Multiple users	Sum-rate	Multi-RIS distribution
[66]	MISO	DL	Multiple users	Sum-rate	Discrete phase shifts

whilst in practice, the phase shifts of RISs may not be continuous. Thus You *et al.* [66] proposed a discrete phase shifts model for a MISO assisted RIS network. Zhang *et al.* [64] then evaluated the required number of bits for the finite resolutions at the RISs in a UL SISO network, which indicated that 1-bit would be enough. Hou *et al.* [5] investigated an RIS-aided MIMO network, where a fairness oriented design was considered by applying SG tools for modelling the impact of the users’ locations.

- RIS-aided Signal Cancellation Designs:** Two wave sources are perfectly coherent if they only have a constant phase difference but with the same frequency, as well as the same waveform. Specifically, in contrast to conventional RIS designs to enhance the received signal strength, another reason for implementing RISs is to align the reflected signals for signal cancellation. By doing so, some promising applications can be realized, i.e. physical layer security and interference cancellation. On the one hand, by assuming that perfect CSI is available at the RIS controller, the inter-cell and inter-cluster interferences can be eliminated. On the other hand, considering the physical layer security requirements, RISs also stand as a potential solution for cooperative jamming techniques, i.e. RISs act as artificial noise sources. By adopting this approach, several contributions have been made to RIS-aided networks. Hou *et al.* [62] proposed an RIS-aided interference cancellation technique in a MIMO network, where the inter-cluster interference can be eliminated without active beamforming weights and detection vectors. Furthermore, this work can be

readily adopted for application to coordinated multi-point (CoMP) networks for inter-cell interference cancellation in the cellular networks. Shi *et al.* [67] investigated an RIS-aided secure beamforming technique, where the secrecy rate of the legitimate user was derived. Lyu *et al.* [68] investigated an RIS jamming scenario, where RISs act as jammers for attacking legitimate communication without using any internal energy.

C. Benchmark Schemes

In order to assess the advantages and limitations of RISs, two benchmark transmission technologies are usually considered: 1) surfaces with random phase shifts; and 2) relay networks.

- **Random Phase Shifts:** RISs are capable of shifting the phase of the incident signal, and hence multiple signals can be boosted or eliminated at the user side or at the BS side. Hence, a well-accepted benchmark scheme to quantify the performance enhancement by RIS elements is given by a surface that is not configurable and that can ideally be modeled by a surface with random phase shifts [55].
- **Relay Networks:** Generally speaking, relay-aided networks can be classified into two pairs of classic relaying protocols, which are 1) FD and half-duplex (HD) relay networks; and 2) AF and DF relay networks. Specifically, Bjornson *et al.* [12] compared the achievable data rate of both the RIS-aided and DF-relay-aided SISO network, where the direct links between the BS and users are blocked. It was pointed out that when the number of tunable elements of the RISs is large enough, an RIS-aided network is capable of outperforming a relay-aided network. In an effort to provide a comprehensive analysis for both RIS-aided and relay-aided networks, Ntontin *et al.* [63] compared the system performance of classic maximal ratio transmission (MRT) and maximal ratio combination (MRC) techniques. Fig. 11 illustrates the potential benefits of RIS-aided compared with both the HD-relay and FD-relay networks in terms of network throughput [59]. Here, the performance of the HD-relay is obtained for an equal time-split ratio. We can see that the network throughput gap between the RIS-aided network and the other pair of relay aided networks becomes smaller, when the number of RISs is increased. Observe that for the case of $N = 18$, the proposed RIS-aided network is capable of outperforming both the FD and HD relay aided networks, which indicates that the RIS-aided NOMA network becomes more competitive, when the number of RISs

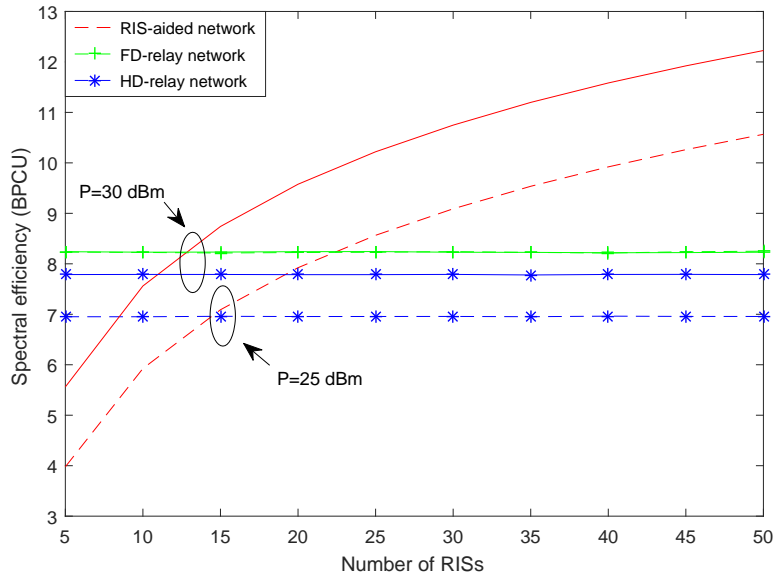


Figure 11: Spectral efficiency of the RIS-aided, FD-relay as well as HD-relay networks versus the number of RISs. Please refer to [59] for simulation parameters.

is large enough. It was also shown that an RIS-aided network is capable of substantially increasing the capacity as well as the EE. Table V provides a comparison between the RIS-aided and several relay aided networks, as well as random phase shifter networks, where both the advantages and limitations are listed.

Table V: Comparison of the RIS-aided and Benchmarks. The “Power” Implies That the Additional Power Supply at the RISs or at the Relay. The “CT” Denotes Concurrent Transmission

Mode	Pros	Cons	Delay	Power	Interference	CT
RIS-aided	High EE, simple device	CSI must be perfect known	✗	✗	✗	✓
HD relaying under AF protocol	No decoding at relay	Noise is amplified	✓	✓	✗	✗
HD relaying under DF protocol	No self-interference	Latency is high	✓	✓	✗	✗
FD relaying under AF protocol	No decoding at relay	Noise and interference are amplified	✗	✓	Self-interference	✓
FD relaying under DF protocol	No latency	Rate ceiling occurs	✗	✓	Self-interference	✓
MIMO relay	High SE	High cost, difficult to realize at mmWave	✗	✓	✓	✓

D. Discussions and Outlook

Although previous research contributions have been analysed the approximated network’s performance of the RIS-aided networks, there are still some major open research problems. Two scaling laws that have recently been reported for the path loss modeling of RISs that operate as anomalous reflectors and as a focusing lens. However, is there any scenario between electrically

small and electrically large RISs? The realistic propagation models of the signals reflected by RISs constitute promising research directions for modeling the path loss of RIS networks.

Furthermore, most of the previous contributions adopted the approximated distribution for modeling the fading channels, the exact distribution of RIS networks is still in their fancy. Further research directions are expected to model the exact fading channel of the reflected links in both the near-field and far-field regimes.

IV. RIS BEAMFORMING AND RESOURCE ALLOCATION

As described in the previous section, deploying the RIS enables higher performance gains. Motivated by this, how to design the transmit and passive beamforming as well as the optimal allocation of the radio resources have become a non-trivial task. In this section, we first discuss the information-theoretical performance gain of RISs. Then, we review recent research contributions on the joint design of beamforming and resource allocation.

A. Information-Theoretic Perspective

In order to unveil the fundamental performance limits of RISs, several research works [69]–[71] have been devoted to investigating the performance gains from an information-theoretic perspective

- **Capacity-achieving design:** In [69], Karasik *et al.* derived the capacity for an RIS-aided single-input and multiple-output (SIMO) system. With finite input signal constellations, it was proved that a joint information encoding scheme in the transmitted signal and the RIS configuration is required for achieving the channel capacity [69]. Based on this, the authors further proposed a practical strategy by utilizing layered encoding and successive cancellation decoding techniques. Numerical examples showed that the proposed joint encoding scheme outperforms the max-SNR scheme.
- **Capacity region characterization:** The capacity regions of fading broadcast channels (BCs) were proved to be achieved by invoking the superposition coding (SC) at the transmitter and successive interference cancellation (SIC) at the receiver [72]. Inspired by these results, Mu *et al.* [70] investigated the capacity and rate regions of RIS-enhanced multi-user wireless communication systems with NOMA and OMA transmissions. The Pareto boundary of

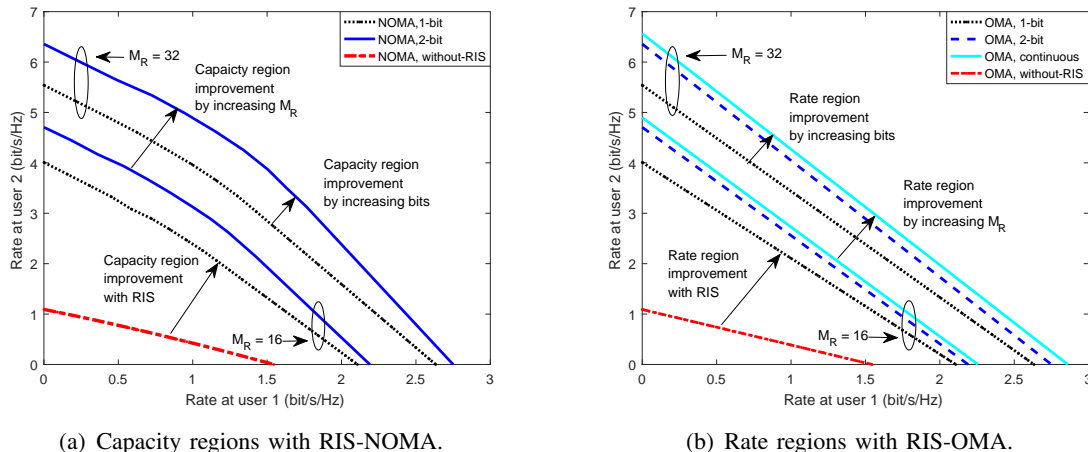


Figure 12: Illustration of the capacity and rate regions for a random channel realization with different RIS phase resolutions. The full parameter settings can be found in [70].

those regions were characterized by solving a series of sum rate maximization problems with the rate-profile technique. As shown in Fig. 12(a) and Fig. 12(b), the RIS is capable of significantly improving both the capacity and rate regions. The capacity/rate regions are further enlarged with more precise phase resolutions and larger size of RIS. Furthermore, Zhang *et al.* [71] investigated the capacity region of multiple access channel (MAC) with two users in both centralized and distributed RIS deployment strategies. The results demonstrated that the centralized RIS deployment achieves a higher capacity gain.

B. Joint Transmit and Passive Beamforming Design

1) *Optimization objectives:* As shown in Fig. 13, an RIS is deployed to assist the transmission between the BS and users by passively reflecting the signals. The RIS phase shifts can be adjusted by the BS through an RIS controller. Hence, the transmit beamforming at the BS and the reflecting beamforming at the RIS can be jointly designed to improve the system performance. In the following, we review the related contributions in terms of the optimization objectives.

- **Transmit power minimization or EE maximization:** In [73], Wu *et al.* minimized the transmit power for an RIS-enhanced MISO system in both single-user and multi-user scenarios. Alternating optimization (AO) based algorithms were developed to find locally-optimal solutions. The passive beamforming was designed by invoking the semidefinite

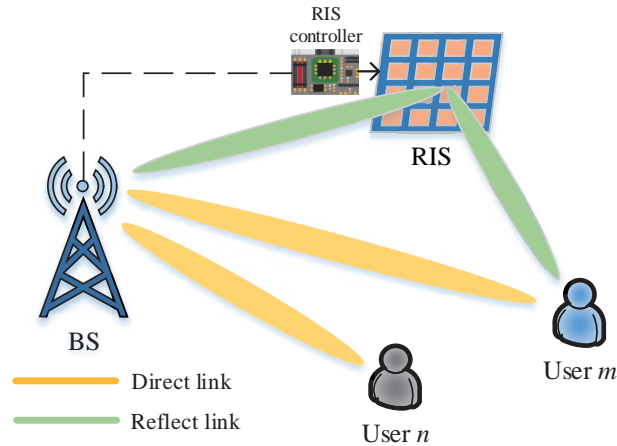


Figure 13: Illustration of joint transmit and passive beamforming design.

relaxation (SDR) approach. It revealed that an RIS can enhance the desired signal and simultaneously decreasing the interference. The same problem was further investigated in [74] by taking discrete RIS phase shifts into consideration. The optimal solutions were derived by applying the branch-and-bound method and exhaustive search for single-user and multi-user scenarios, respectively. To reduce the computational complexity, efficient successive refinement algorithms were further designed. It was shown that the proposed low complexity algorithms are capable of achieving near-optimal performance. Han *et al.* [75] investigated physical-layer broadcasting in an RIS-aided network, where the total transmit power for satisfying quality-of-service QoS requirements of all users was minimized. Furthermore, Fu *et al.* [76] focused on an RIS-enhanced MISO downlink NOMA system, where the transmit power was minimized by jointly optimizing the transmit and reflected beamforming vectors as well as the user decoding order. In order to overcome the drawbacks of the SDR approach, an alternating difference-of-convex (DC) method was proposed for handling the non-convex rank-one constraint. Zhu *et al.* [77] proposed an improved quasi-degradation condition for the RIS-enhanced MISO NOMA system to minimize the transmit power. Under this condition, NOMA is shown to outperform the zero-forcing beamforming. Zheng *et al.* [78] compared the minimum transmit power performance between OMA and NOMA in a discrete phase shift RIS-enhanced SISO system. A near-optimal solution

was obtained by applying the linear approximation initialization and the AO method. The results showed that NOMA may perform worse than TDMA when users have symmetric deployments and rate requirements, which revealed the importance of user pairing in the RIS-assisted NOMA system. Huang *et al.* [79] solved the EE maximization problem in an RIS-enhanced multi-user MISO system, where a realistic RIS power consumption model was proposed in terms of the number of reflected units and phase resolution. An AO-based algorithm was designed, where the RIS phase shifts and transmit power allocation were computed with the gradient descent method and the fractional programming method. The results demonstrated that the RIS achieves significantly better EE performance than the traditional relay-assisted communication. In contrast to the aforementioned works based on the perfect CSI assumption, Zhou *et al.* [80] investigated the robust beamforming design for an RIS-enhanced multi-user MISO system with imperfect CSI. The transmit power was minimized while satisfying QoS requirements of all users under all possible channel error realizations. The formulated non-convex problem was transformed into a sequence of semidefinite programming subproblems, where the CSI uncertainties and the non-convex unit-modulus constraints are handled by applying approximation transformations and convex-concave procedure, respectively [81]. In [82], the robust transmission design was further studied under two channel error models, namely bounded CSI error model and the statistical CSI error model. The S-procedure and the Bernstein-Type inequality were applied in each model. The results unveiled that the RIS may degrade the system performance when the channel error is large. Zappone *et al.* [83] modeled the overhead for channel estimation and RIS configuration. Based on the proposed model, the EE of an RIS-empowered MIMO communication network was maximized by jointly optimizing the RIS phase shifts as well as the transmit and receive filters.

- **SE or capacity maximization:** Yu *et al.* [84] considered the SE maximization problem in an RIS-enhanced MISO system. Since the SDR approach only provides an approximate solution [73], two efficient algorithms were proposed by invoking fixed-point iteration and manifold optimization methods for the passive beamforming design. It was demonstrated that the proposed algorithms can achieve a higher performance with a lower complexity, as compared with the SDR approach. To solve the same problem, a branch and bound

algorithm was further proposed by Yu *et al.* [85], which is capable of obtaining a globally optimal solution. Though suffering from relatively high complexity, the proposed branch and bound algorithm serves as a performance benchmark to verify the effectiveness of existing suboptimal algorithms. In [86], Ning *et al.* focused on an RIS-enhanced downlink MIMO system to maximize the spectrum efficiency. The passive beamforming was designed by using the sum of gains maximization principle and by utilizing the alternating direction method of multipliers. The transmit beamforming was designed using classic singular value decomposition and water-filling solutions. In [87], Ying *et al.* considered an RIS-enhanced mmWave hybrid MIMO systems, where the phase shifts at the RIS were designed by leveraging the angle information of the LoS BS-RIS channel. Moreover, Perović *et al.* [9] investigated RIS-assisted indoor mmWave communications, where two schemes were developed to maximize the channel capacity. Zhang *et al.* [88] characterized the fundamental capacity limit of RIS-aided point-to-point MIMO communication systems, by jointly optimizing the RIS reflection coefficients and the MIMO transmit covariance matrix. The capacity was maximized in both narrowband transmission with frequency-flat fading channels and broadband orthogonal frequency division multiplexing (OFDM) transmission over frequency-selective fading channels. Yang *et al.* [8] proposed a practical transmission protocol by considering channel estimation for an RIS-enhanced OFDM system under frequency-selective channels. To reduce the required training overhead, the RIS elements are divided into multiple groups and estimate the combined channel of each group. Based on this scheme, the achievable rate was maximized by jointly optimizing the power allocation at the transmitter and the phase shifts at the RIS with the AO method. In [89], You *et al.* designed a transmission protocol by considering channel estimation with discrete phase shifts at the RIS. To reduce the channel estimation errors, a low complexity DFT-Hadamard based reflection pattern scheme was developed. The achievable data rate was further maximized with the estimated channel by designing the RIS phase shifts with a successive refinement algorithm.

- **Sum rate maximization:** In [90], Huang *et al.* maximized the sum rate in RIS-enhanced multi-user MISO downlink communications. By employing zero-forcing transmission at the BS, the RIS matrix and the power allocation were alternately optimized with the aid

of the majorization-minimization approach. Similarly, the weighted sum-rate maximization problem was investigated by Guo *et al.* [91]. With the aid of the AO framework, the transmit beamforming was obtained using the fractional programming method. Three iterative algorithms were designed for optimizing the reflection phase shifts in terms of different types of RIS elements. In [92], the asymptotic optimal discrete passive beamforming solution was derived and a modulation scheme was proposed to maximize the achievable sum rate for the RIS-enhanced multi-user MISO transmission. To further enhance the performance, Jung *et al.* [92] designed the user scheduling and power control scheme, which can control the tradeoff between fairness and maximum performance. Mu *et al.* [93] focused their attention on the sum rate maximization problem in an RIS-enhanced MISO NOMA system with both ideal and non-ideal assumptions. The non-convex rank-one constraint was handled by invoking the sequential rank-one constraint relaxation approach. Based on this, the discrete phase shifts were obtained with the quantization-based scheme. Instead of optimizing the passive beamforming with the instantaneous CSI, Zhao *et al.* proposed a two-timescale transmission protocol for maximizing the achievable average sum rate in an RIS-enhanced multiuser system [94]. To reduce the channel training overhead and complexity, the RIS phase shifts were firstly optimized with the statistical CSI. Then, the transmit beamforming was designed with the instantaneous CSI and optimized RIS phase shifts.

- **User fairness:** Nadeem *et al.* [95] maximized the minimum SINR of an RIS-enhanced MISO system, where the BS-RIS-user link was assumed to be a LoS channel. A deterministic approximations was developed for the minimum SINR under the optimal linear precoder by employing random matrix theory. As a result, the RIS phase shifts can be optimized using the channel's large-scale statistics, which can significantly reduce the signal exchange overhead [95]. Yang *et al.* [96] investigated the max-min rate problem in an RIS-enhanced NOMA system in both single-antenna and multi-antenna cases. A combined-channel-strength based user ordering scheme was proposed, which achieved a near-optimal performance.

All the aforementioned research contributions on the joint transmit and passive beamforming design are summarized in Table VI. "SU" and "MU" represent single-user and multi-user, respectively. "DL" and "UL" represent downlink and uplink, respectively.

Table VI: Contributions on Joint Transmit and Passive Beamforming Design

Ref.	Scenarios	Phase shifts	CSI	Main Objectives	Techniques/Characteristics
[73]	SU/MU-DL-MISO	Continuous	Perfect	Transmit power	AO-SDR-based algorithm and two stage algorithm
[74]	SU/MU-DL-MISO	Discrete	Perfect	Transmit power	Near-optimal ZF-based successive refinement method
[75]	MU-DL-MISO	Continuous	Perfect	Transmit power	Physical-Layer Broadcasting
[76]	MU-DL-MISO NOMA	Continuous	Perfect	Transmit power	Alternating DC method
[77]	MU-DL-MISO NOMA	Continuous	Perfect	Transmit power	Improved quasi-degradation condition
[78]	MU-DL-SISO NOMA	Discrete	Perfect	Transmit power	Asymmetric user pairing
[79]	MU-DL-MISO	Continuous	Perfect	EE	A realistic RIS power consumption model
[80]	MU-DL-MISO	Continuous	Imperfect	Transmit power	The worst-case robust beamforming design
[82]	MU-DL-MISO	Continuous	Imperfect	Transmit power	Imperfect cascaded channels at the transmitter
[83]	SU-DL-MIMO	Continuous	Estimated	EE	Overhead model for channel estimation and RIS configuration
[84]	SU-DL-MISO	Continuous	Perfect	SE	Fixed point iteration and manifold optimization
[85]	SU-DL-MISO	Continuous	Perfect	SE	Branch and bound algorithm
[86]	SU-DL-MIMO	Continuous	Perfect	SE	Sum of gains principle
[87]	SU-DL-MIMO mmWave	Continuous	Perfect	SE	Broadband hybrid beamforming
[9]	SU-DL-MIMO mmWave	Continuous	Perfect	Channel capacity	RIS-assisted indoor mmWave environments
[88]	SU-DL-MIMO	Continuous	Perfect	Channel capacity	Frequency-flat fading and frequency-flat selective channels
[8]	SU-DL-SISO OFDMA	Continuous	Estimated	Achievable rate	Reducing channel training and estimation overhead
[89]	SU-UL-SISO	Discrete	Estimated	Achievable rate	Near-orthogonal DFT-Hadamard based reflection patterns
[90]	MU-DL-MISO	Continuous	Perfect	Sum rate	Zero-forcing transmission
[91]	MU-DL-MISO	Continuous/Discrete	Perfect	Weighted sum rate	Iterative algorithms with closed-form expressions
[92]	MU-DL-MISO	Discrete	Perfect	Sum rate	Interference-free modulation scheme
[93]	MU-DL-MISO NOMA	Continuous/Discrete	Perfect	Sum rate	SIC decoding order constraints
[94]	MU-DL-MISO	Discrete	Statistical CSI	Sum rate	Low channel training overhead
[95]	MU-DL-MISO	Continuous	Statistical CSI	Max-min SINR	Signal exchange overhead reduction
[96]	MU-DL-SISO/MISO NOMA	Continuous	Perfect	Max-min rate	Near-optimal user ordering scheme

2) *Approaches for passive beamforming design*: The existing methods for solving the non-convex joint optimizations are mainly based on the AO method. Given the passive beamforming vector, the transmit beamforming design becomes a conventional problem, which has been extensively investigated. However, the passive beamforming design under given transmit beamforming vectors is still a non-trivial task. The main difficulties include: i) passive phase shifters impose non-convex unit-modulus constraints on the elements of the passive beamforming vector; ii) for practical finite resolution passive phase shifters, the passive beamforming design further becomes a nondeterministic polynomial-time (NP)-hard integer programming problem. We list the approaches invoked in the current research contributions as follows. Table VII summarizes the characteristics of those approaches.

Table VII: Summary of Approaches to Passive Beamforming Design

Approaches	Phase shifts	Advantages	Disadvantages	Ref.
SDR	Continuous	Relax to convex problem	Require rank-one solution construction	[73], [77], etc.
Quantization method	Discrete	Easy to implement	Substantial performance loss	[96]
Branch and bound	Continuous/Discrete	Optimal solution	Relatively high complexity	[74], [85]
Iterative algorithms	Continuous/Discrete	Good complexity-performance tradeoff	Performance depends on initialization	[74], [76], etc.

- **SDR**: A common method of handling the non-convex unit-modulus constraint is to transform the passive beamforming vector into a rank-one and positive semi-definite matrix. By

applying the SDR approach which ignores the non-convex rank-one constraint, the original non-convex problem becomes a semidefinite programming (SDP) problem that can be solved by many efficient convex optimization tools. Additional steps with the Gaussian randomization technique are required if the obtained solution is not rank-one. However, the constructed rank-one solution is generally suboptimal and even infeasible for the original problem, which results in performance degradation and cannot guarantee the convergence of the AO-based algorithm.

- **Quantization method:** For the finite resolution phase shifters, one method is to relax the discrete phase shift variables $\theta \in \{0, \frac{2\pi}{N}, \dots, (N-1) \frac{2\pi}{N}\}$ into continuous variables $\theta \in [0, 2\pi)$. After solving the relaxed problem, the obtained continuous solutions are quantized to their nearest discrete values. However, the quantization method may lead to substantial performance loss, which is more pronounced for low-resolution phase shifts. On the other hand, the non-convex unit-modulus constraints still exist after such relaxations.
- **Branch and bound:** Due to the non-convex nature of the passive beamforming design problem, it is challenging to obtain the optimal solution with standard convex optimization techniques. Note that the branch and bound approach has been applied for solving NP-hard discrete and combinatorial optimization problems and some specific continuous optimization problems. In the aforementioned works, the branch and bound approach was adopted for deriving the optimal solution in discrete passive beamforming design [74] and continuous passive beamforming design [85].
- **Iterative algorithms:** The main idea of iterative algorithms is to obtain a locally optimal or high-quality suboptimal solution for the original problem at an acceptable computational complexity. The obtained solution in each iteration is used as the input of the next iteration until convergence. Inspired by this, some iterative algorithms were developed for the passive beamforming design, such as the successive refinement algorithm [74], [88], [89], [91], alternating DC algorithm [76], conjugate gradient search [79], fixed point iteration and manifold optimization methods [84], and the sequential rank-one constraint relaxation approach [93]. It showed that the proposed iterative algorithms can achieve a good tradeoff between performance and complexity.

C. Resource Management in RIS-enhanced Networks

1) *Resource allocation problems:* As shown in Fig. 14, a large-scale RIS-assisted transmission scenario is considered, where multiple BS serve multiple users with the aid of multiple RISs. Next we highlight several issues and review related research contributions.

- **Subchannel assignment:** The bandwidth efficiency can be improved by properly allocating users to different subchannels. Note that the RIS elements are generally not frequency-selective. One common RIS reflection matrix should be shared among all subchannels, which makes the optimization problems more challenging to be solved. To address this difficulty, Yang *et al.* [97] proposed a dynamic passive beamforming scheme, where the resource blocks are dynamically allocated to different user groups with varied RIS phase shifts over different time slots. In [98], Zuo *et al.* investigated the joint subchannel assignment, power allocation and reflection coefficients design problem in a multi-channel downlink RIS-NOMA network.
- **User-RIS association:** In multi-RIS enhanced multi-user communications, how to associate users to RISs is an interesting problem. The user-RIS association schemes in general determine the overall network performance. Considering a multiple RIS-enhanced massive MIMO system, Li *et al.* [99] found that the automatic interference cancelation property holds with infinitely large RISs. Then, the considered max-min SINR problem can be transformed into a user-RIS association problem, which was solved by the proposed greedy search algorithm.
- **Multi-cell RIS association:** In multi-cell scenarios, the optimization problem becomes more sophisticated by jointly considering the user-BS association, user-RIS association and subchannel assignment. In some initial works [18], [100], the RIS was deployed to enhance the performance of cell-edge users. It showed that the RIS can significantly improve cell-edge performance.

2) *Approaches to resource allocation problems:* Note that scheduling different users with different subchannels/RISs/BSs is an NP-hard problem. Though the optimal solution can be obtained by exhaustively searching over all possible association combinations, it requires a prohibitive computation complexity, especially in large-scale networks. Therefore, some low

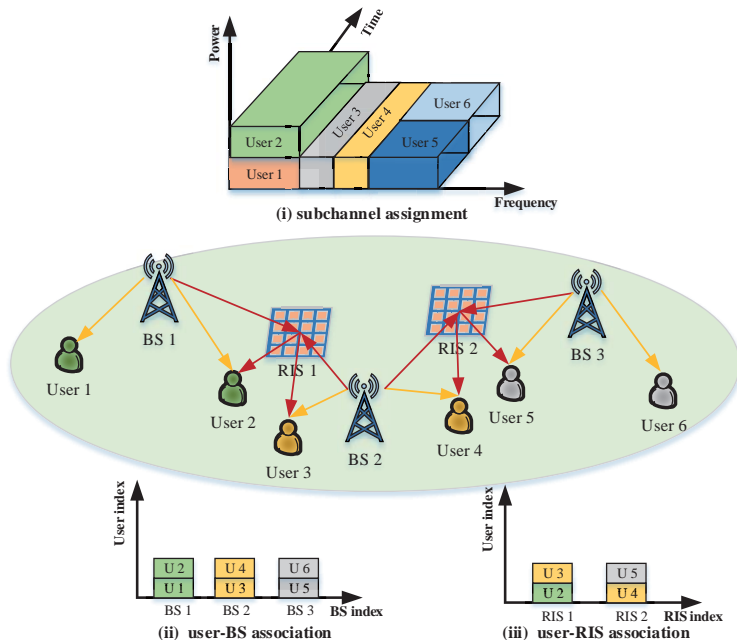


Figure 14: Illustration of resource management in large-scale RIS-enhanced networks.

complexity and efficient algorithms need to be developed for striking a performance-versus-complexity tradeoff. Next we present some promising approaches with their advantages. Table VIII summarizes the characteristics of those approaches.

Table VIII: Summary of Approaches to Resource Allocation Problems

Approaches	Advantages	Disadvantages	Ref.
Binary relaxation	Relax to convex feasible set	Existence of performance gap	-
Matching theory	Achieve near-optimal performance	Require predefined preference list	[98]
Heuristic algorithms	Flexible complexity-performance tradeoff	Unstable performance	[99]

- Binary relaxation:** One idea is to relax the binary variables $\alpha \in \{0, 1\}$ into continuous variables $\alpha \in [0, 1]$, where α represents the user association state. By doing so, the non-convex integer constraint is relaxed to be convex and conventional convex optimization techniques can be applied for solving the relaxed problem. It is worth pointing out that the relaxed problem might still be non-convex especially when the optimization variables are highly-coupled. Additional efforts, such as utilizing the successive convex approximation (SCA) method, are required to obtain an acceptable approximate solution. However, this

kind of relaxation may result in considerable performance loss between the original problem and the relaxed one.

- **Matching theory:** Matching theory is a powerful method developed for solving the combinatorial user association problems. The user association combinational optimization problem in RIS-enhanced networks can be modeled as a high dimensional Users-BSs-RISs-Subchannels matching problem. Though high dimensional matching is NP-hard, it can be decomposed into several 2D matching subproblems, which can be efficiently solved. Particularly, Zuo *et al.* [98] applied many-to-one matching theory for subchannel assignment in an RIS-enhanced NOMA system, which can achieve near-optimal performance. However, leveraging matching theory requires to establish a predefined preference list for both users and resources. Since the channel conditions always fluctuate in RIS-enhanced networks, these preference lists may need to be dynamically updated, which needs further investigations.
- **Heuristic algorithms:** For solving computationally complex problems, one commonly used method is developing heuristic algorithms, where approximate solutions for the original optimization problem can be obtained with an acceptable computational complexity. In the aforementioned works, the greedy search based heuristic algorithm was designed for solving the user-RIS association problem [99]. However, the performance of heuristic algorithms is sensitive to the designed strategies, which is not always stable.

D. Discussions and Outlook

With the growing number of research contributions on RIS-enhanced communications, the advantages of RIS have been verified in terms of SE, EE and user fairness. However, most of the existing treatises solved the non-convex joint optimization problem with the AO method, which decouples the joint transmit and passive beamforming design into two subproblems. Though a high-quality suboptimal solution can be obtained, the optimal performance has not been well understood. Advanced optimization techniques are required for solving this problem. On the other hand, in RIS-enhanced communication systems, obtaining accurate CSI becomes more challenging than that in conventional communications. Developing low complexity channel estimation approaches [8], [89] and robust joint beamforming schemes [80], [82] constitute a

promising research directions for practical RIS implementation.

Additionally, the existing research contributions on resource allocation in RIS-enhanced networks are still in their infancy. Intelligent and dynamical resource allocation schemes should be more deeply investigated, especially for large-scale networks, where subchannel assignment and user-RIS-BS association can be jointly considered.

V. MACHINE LEARNING FOR RIS-ENHANCED COMMUNICATION SYSTEMS

Machine learning (ML) techniques have gained remarkable interests in wireless communications due to their learning capability and large search-space [101]–[103]. We survey existing research contributions, which apply ML techniques for tackling challenges in RIS-enhanced wireless networks. Finally, potential research challenges and opportunities of ML-empowered RIS systems are presented.

A. Motivations and Architecture for Integrating ML in RIS-enhanced Wireless Networks

In this subsection, we first present the limits of the conventional RIS-enhanced wireless networks and the motivations for integrating ML in these networks, followed by the system architecture of ML-empowered RIS-enhanced wireless networks.

To effectively exploit RISs for optimizing wireless networks, preliminary research contributions have studied a number of technical challenges that include channel estimation/modeling, active beamforming for the BS, passive phase shift design of the RIS, as well as resource allocation from the BS to the users. Powerful optimization techniques, such as convex optimization [91], iterative algorithm [73], gradient descent approach [79], and alternating algorithm [104] have been adopted for addressing the aforementioned fundamental challenges. Important insights have been gained by these research contributions. However, the following limits still exist in conventional RIS-enhanced wireless networks:

- The users are generally assumed to be static for simplicity, i.e. the dynamic mobility of users is typically ignored. Another limit in the existing literature is that the communication environment is assumed to be perfectly known, the differentiation of users' demand is always ignored as well.

- The RIS/BS are not capable of learning from the unknown environment or from the limited feedback of the users. In practical applications of RISs in wireless networks, the system parameters are treated as random variables, which naturally leads itself to the derivation of insightful joint probability distributions conditioned on the users' tele-traffic demand and mobility. However, this is a highly dynamic stochastic environment, which is challenging for conventional optimization approaches. Additionally, the feedback from the users is usually resource-hungry and limited, which aggravates the challenges for the conventional RIS-enhanced wireless networks.
- Finally, instantaneous CSI of all the channels are assumed to be available to the BS. However, CSI acquisition in RIS-enhanced wireless networks becomes more challenging than in the conventional relay systems due to the dynamic RIS control, which also aggravates the challenge imposed on the conventional RIS-enhanced wireless networks.

B. Deep Learning for RIS-enhanced Communication Systems

Deep learning (DL) has shown great potentials to revolutionize communication systems. It can be applied in diverse areas of the RIS-enhanced wireless networks due to its powerful learning capabilities [105]–[107].

The acquisition of timely and accurate CSI plays a pivotal role in wireless systems, especially in MIMO networks. However, CSI acquisition becomes more challenging due to the large number of antenna elements in massive MIMO systems [108]. In order to tackle this challenge, a number of research contributions have adopted DL for estimating the channel information, especially for exploiting CSI structures beyond linear correlations.

In contrast to the conventional AF relay-aided wireless networks, in RIS-enhanced wireless networks, the RIS is a passive device, which is not capable of performing active transmission/reception and signal processing [109]. In an effort to estimate a large number of unknown parameters at the BS or users, Taha *et al.* [110] exploited the DL method for learning the RIS reflection matrices directly from the sampled channel knowledge without any knowledge of the RIS array geometry. Liu *et al.* [111] proposed a deep denoising neural network assisted compressive channel estimation for mmWave IRS systems with a low training overhead. Elbir *et al.* [112] presented a DL framework for channel estimation in the RIS-enhanced MIMO system.

It was shown that the proposed CNN-based approach enjoys lower normalized mean-square-error (NMSE) and more robust performance than the benchmarks.

The data-driven DL approach has the advantage of model-free representation or function learning such that no explicit models of the complicated wireless channels are needed, at the expense of requiring large amounts of training data and corresponding computational power. Thus, the DL method can be adopted for estimating the channel information of RIS-enhanced wireless networks.

Apart from the aforementioned application of DL in RIS-enhanced wireless networks, Huang *et al.* [113] leveraged a deep neural network (DNN)-based approach in the indoor communication environment for estimating the mapping between a user's position and the configuration of the RISs unit cells to maximize the received SNR. Additionally, DL can also be applied for learning the optimal RIS phase shift. Gao *et al.* [114] proposed a DL-based algorithm for optimally designing the phase shift of the RIS by training the DL offline. It can be observed that the proposed unsupervised learning mechanism outperformed the conventional optimization approach in terms of computational complexity. Khan *et al.* [115] investigated signal estimation and detection in the RIS-enhanced wireless networks. A DL-based approach was proposed for estimating channels and phase angles from a reflected signal received through an RIS. With the aid of DL, the bit-error-rate performance of the system was improved.

C. Reinforcement Learning for RIS-enhanced Communication Systems

RL is a powerful AI paradigm that can be used to empower agents by interacting with the environment. More explicitly, by exploiting the learning capability (learning from the environment, learning from the feedback of users, learning from its mistakes) of the RL model, the challenges encountered in the conventional RIS-enhanced wireless networks may be mitigated, leading to improved networking performance.

The core idea of the RL-assisted techniques adopted in the RIS-enhanced wireless networks is that they allow the BS/RIS to improve their service quality by learning from the environment, from their historical experience and from the feedback of the users [116]. More explicitly, RL models can be used for supporting the BS/RIS (agents) in their interactions with the environment (states), whilst finding the optimal behavior (actions) of the BS/RIS. Furthermore, the RL model

can incorporate farsighted system evolution (long-term benefits) instead of only focusing on current states. Thus, it is applied for solving challenging problems in the RIS-enhanced wireless networks.

As illustrated in Fig. 15, the RL algorithms can be divided into three categories, namely, value-based algorithms, policy-based algorithms, and actor-critic algorithms. Both advantages and disadvantages exist in the RL algorithms. Since RISs enjoys discrete phase shifts, the DQN algorithm is more suitable for tackling the phase shift design problem.

To fully reap the benefits of the RIS in wireless networks, the joint active and passive design of the RIS-enhanced system has been considered in MISO system [127], [128], OFDM-based system [129], wireless security system [130] and millimeter wave system [131] with the aid of reinforcement learning algorithms. In contrast to the AO techniques, which alternately optimize the transmit beamforming of the BS and the passive phase shift of the RIS, the RL-based solution is capable of jointly designing the beamforming matrix and phase shift matrix. More explicitly, Huang *et al.* [127] applied a deep deterministic policy gradient (DDPG) based algorithm for maximizing the throughput by utilizing the sum rate as instant rewards for training the DDPG model. In the proposed model, the continuous transmit beamforming and phase shift were jointly optimized with low complexity. Taha *et al.* [129] proposed a deep reinforcement learning (DRL) based algorithm for maximizing the achievable transmit rate by directly optimizing interaction matrices from the sampled channel knowledge. In the proposed DRL model, only one beam was utilized for each training episode. Thus, the training overhead was avoided, while the dataset collection phase was not required. Zhang *et al.* [131] presented a DRL based algorithm for maximizing the throughput with both perfect and imperfect CSI. A quantile regression method was applied for modeling a return distribution for each state-action pair, which modeled the intrinsic randomness in the MDP interaction between the RIS and communication environment. Helin *et al.* [130] considered the application of RIS to physical layer security. The system secrecy rate was maximized with the aid of the DRL model by jointly optimizing the beamforming and phase shift matrices under different users' QoS requirements and time-varying channel conditions. Additionally, post-decision state and prioritized experience replay schemes were utilized to enhance the learning efficiency and secrecy performance.

		Reinforcement Learning			
		RL algorithm	Key features	Pros	Cons
Value-based (only be invoked in scenarios with discrete state space and action space)	Q-learning	Utilize the Q-table to train Q-value offline	Can find the optimal policy without requiring knowledge about the environment	Only suitable for scenarios with small state space and action space	
	SARSA	Allows the agent to approach the optimal policy online	Allow the agent to choose optimal actions at each time step in a real-time fashion	Only suitable for scenarios with small state space and action space	
	DQN	Invoke NN as an approximator of Q-function	Can be invoked in scenarios with large state space and action space	Over estimation on action values	
	Double DQN	Invoke two Q-function to select and evaluate Q-values, respectively	Can solve the problem of over estimation	Only discrete state space and action space	
	Dueling DQN	Invoke two NNs to estimate the action value and state value	Have a faster convergence rate than DQN model	High complexity	
	Noisy DQN	Adding Gaussian noise layer in the DQN model	Enhance the exploring performance	Only discrete state space and action space	
	Distributional DQN	Invoke a distribution function instead of Expectation to update Q-function	Higher accuracy than DQN in terms of evaluating Q-function	Require the distribution information of reward function	
	Asynchronous DQN	Multi-agent can train parallelly	Have a faster learning speed than DQN	High complexity	
	Retrace	Return-based off-policy algorithm	More efficient than Q-learning	Only suitable for scenarios with small state space and action space	
Policy-based (can be invoked in scenarios with continuous state space and action space)	PG	Approximate a stochastic policy directly using an independent function approximator with its own parameters	Easy for application;	Sensitive to the parameter setting	
	TRPO	Invoke a loss function to find the optimized parameters	Have a faster convergence rate than value-based approaches	Can only be invoked in special limiting cases; Have a low data efficiency	
	PPO	Alternate between sampling data through interaction with the environment	Easier and more general than TRPO	Have a tradeoff between sample complexity, simplicity and wall-time	
Actor-critic (can be invoked in scenarios with continuous state space and action space)	AC	Utilize critic to update the value function parameters, while utilize actor to update the policy parameters	Have the advantages of both value-based algorithm and policy-based algorithm	Have a lower convergence rate	
	A3C	Multi-agent can train parallelly	Changes in the approximated function get propagated much more quickly	Have a higher variance	
	DDPG	Combination of AC and DQN	Have the advantages of both policy gradient and DQN	Higher complexity; Can not be invoked in a random scenario	
	TD3	Invoke two critics to update the value function parameters	Overcome the problem of over estimation	Higher complexity	
	SAC	Based on maximum entropy	More stable; Enhance the exploring performance	Higher complexity	

Figure 15: Key features, pros and cons of reinforcement learning algorithms [116]–[126]. (PG represents Policy Gradient, TRPO denotes Trust Region Policy Optimization, PPO represents Proximal Policy Optimization, AC denotes Actor-Critic, A3C represents Asynchronous Advantage Actor-Critic, DDPG denotes Deep Deterministic Policy Gradient, TD3 represents Twin Delayed DDPG, SAC denotes Soft Actor-Critic)

D. A Novel Architecture of ML-empowered RIS-enhanced Wireless Networks

As a benefit of the ML-based framework, many challenges in conventional wireless communication networks have been circumvented, leading to enhanced network performance, improved reliability and agile adaptivity [102]. Fig. 16 illustrates the proposed ML-empowered architecture,

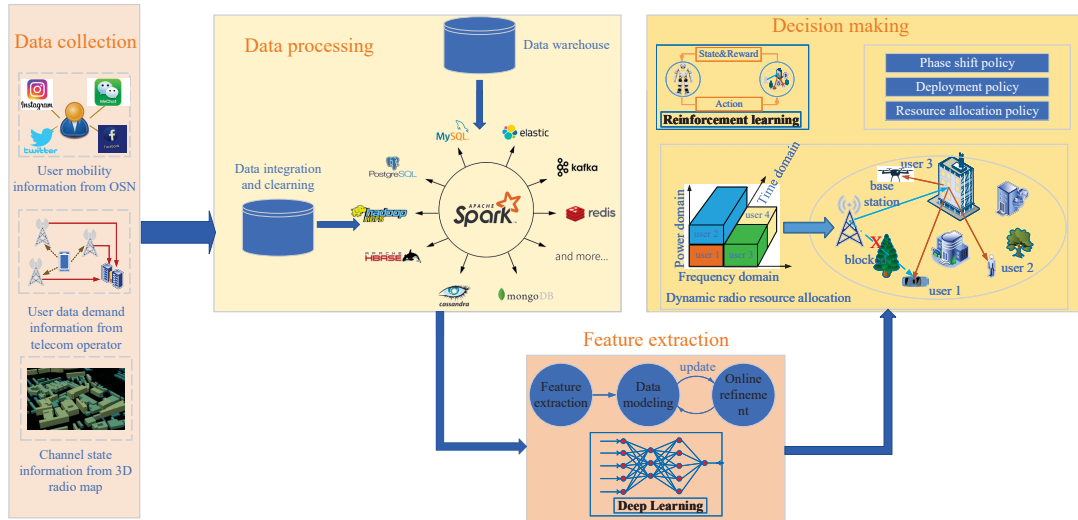


Figure 16: Architecture of ML-empowered RIS-enhanced wireless networks.

where the downlink communications between a BS and a group of users in a particular area are considered. RIS is installed on the facade of a building for enhancing the wireless services [3], [132]. The RIS is linked with a controller, which controls the reflecting elements for hosting the functionality of phase-shifting and amplitude absorption. A two-step approach is applied in the ML-empowered RIS-enhanced wireless networks.

- In the first step, feature extraction is applied before optimizing the network design. The associated user information (e.g., device type, position, data rate demand, mobility, caching demand, computing ability) is collected, stored and processed. Thus, the users' behaviors and requirements can be predicted for efficiently deploying and operating the RISs. Meanwhile, the predicted information can be modified online with the currently collected data as the input.
- Given the extracted features, adaptive schemes are leveraged for controlling the RIS, designing the phase shifts, resource allocation, and interference cancellation.

In ML-empowered RIS-enhanced wireless networks, the RIS is capable of rapidly adapting to the dynamic environment by learning both from the environment and from the feedback of the users.

Research on the RIS deployment is fundamental and essential. However, there is a paucity of

research on the problem of RIS position determination. Additionally, current research contributions mainly consider the performance optimization for both single-user and multi-user scenarios by optimizing the phase shift and/or pre-coding solutions of the RIS-enhanced system [6], [18], [95], [133], [134].

Considering the RIS deployments based on the users' mobility information and particular data demand implicitly assumes that the long-term movement information and tele-traffic requirement of users are capable of being learned/predicted. With this proviso, the deployment and control method of RISs may be designed periodically for maximizing the long-term benefits and hence reducing the additional control. By considering the long-term mobility and data demand of users, RIS-enhanced wireless networks become highly dynamic systems. Meanwhile, in an effort to maximize the service quality in an unknown environment, RISs are supposed to learn by interacting with the environment and adapting the control/deployment policy based on the limited feedback of the users to overcome the uncertainty of the environment.

In [135], an RL-based model is presented to jointly design the deployment policy and phase shift policy of RISs while considering the time-varying data demand of users. As illustrated in Fig. 17, in the RL-based model, the BS acts as an agent. Since a controller is installed, the BS can control both resource allocation policy for users and the RIS's position and phase shift. At each timeslot, the BS periodically observes the state of the RIS-enhanced system. The state space consists of the RIS phase shifts, the allocated power to each user, as well as coordinates of both the RIS and users. An action is carried out by the BS for selecting the optimal control policy. The actions contain changing positions and varying phase shifts of the RIS, as well as varying the allocated power. The key underlying principle of the decision policy is carrying out an action that makes the DQN model obtain the maximum Q-value at each time slot. Following each action, the BS receives a penalty/reward, r_t , determined by the formulated objective function.

- **State of the RL model.** The state space consists of four parts: 1) the current phase shift of each reflecting element in the RIS; 2) the current 3D position of the RIS; 3) the current 2D position of each user; 4) the current power allocated from the BS to each user.
- **Action of the RL model.** The action space consists of three parts: 1) the variable quantity of the n -th reflecting element's phase shift; 2) the moving direction and distance of the RIS; 3) the variable quantity of the k -th user's transmit power.

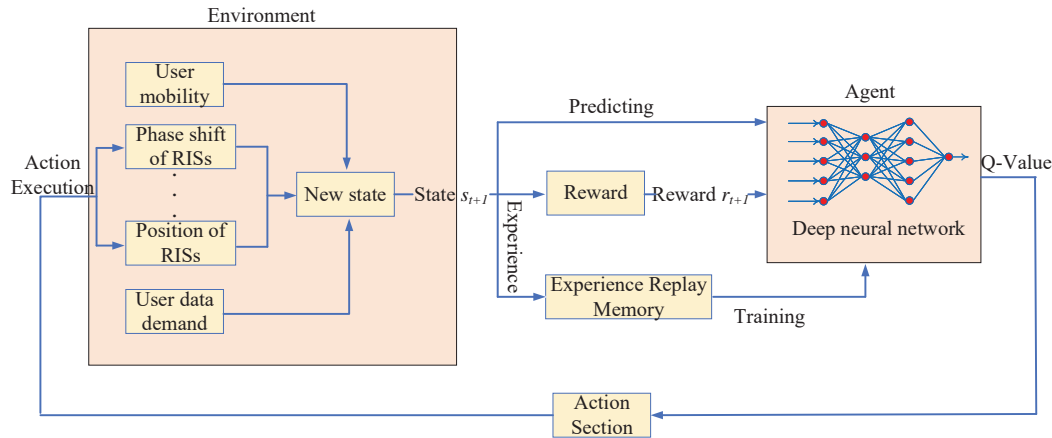


Figure 17: Deep reinforcement learning model for RIS networks.

- **Reward of the RL model.** The reward function is decided by the energy efficiency of the system. When action taken by the BS improves energy efficiency, the BS obtains a reward. Otherwise, when a reduction occurs in energy efficiency, the BS receives a penalty.

Fig. 18 characterizes the energy efficiency of the system in networks both with and without the assistance of an RIS. The energy efficiency is defined as the ratio between the system achievable sum mean opinion score (MOS) and the sum energy dissipation in Joule. It was shown that the energy efficiency of the system is enhanced by employing an RIS. The NOMA-RIS-barycenter line indicates that the RIS is placed at the barycenter of all users. The NOMA-RIS-random line indicates that the RIS is randomly deployed, while the NOMA-RIS-optimal line indicates that the RIS is deployed at the optimal position derived from the proposed decaying double deep Q-network (D³QN) algorithm. The results of Fig. 18 confirm that there exists an optimal position for the RIS as far as the energy efficiency of the RIS-enhanced system is concerned. The performance of the RIS-enhanced system is improved by deploying the RIS at the optimal position compared to random deployment and placing it at the barycenter.

E. Other Machine Learning Techniques for RIS-enhanced Communication Systems

In addition to DL and RL techniques, a range of supervised learning and unsupervised learning algorithms have been applied in the current generation wireless networks. Thus, these approaches can also be adopted for tackling challenges in the RIS-enhanced wireless networks.

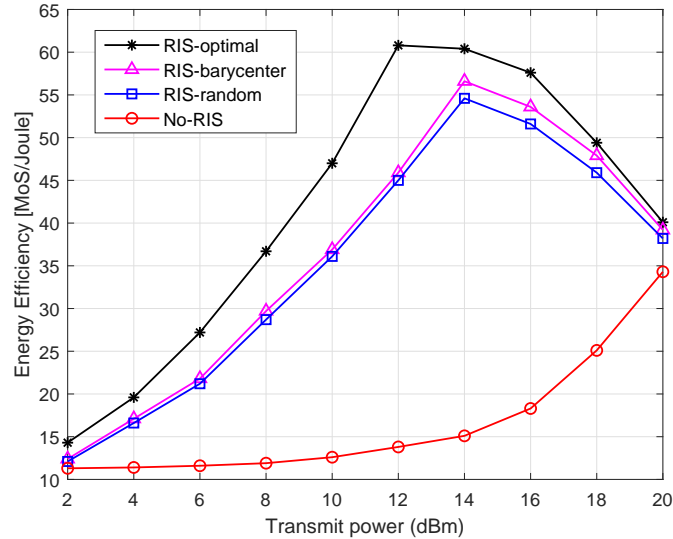


Figure 18: Energy efficiency with and without RIS.

1) *Supervised Learning techniques for RIS-enhanced Communication Systems:* As one of the key branches of machine learning, powerful supervised learning techniques, such as regression, decision tree and random forest, K-nearest neighbors (KNN), support vector machines (SVM) and Bayes classification, have been adopted in diverse scenarios for tackling challenges such as spectrum sensing [136], traffic/QoE prediction [137], channel/antenna selection [138], and networking association [139]. In the RIS-enhanced wireless networks, supervised learning algorithms can also be applied for solving the related problems with sufficient training data due to their advantages of low complexity and fast convergence speed.

2) *Unsupervised Learning techniques for RIS-enhanced Communication Systems:* In contrast to the supervised learning techniques, unsupervised learning methods do not rely on prior knowledge, which is not data-hungry. Thus, the unsupervised learning algorithms [140] such as K-means clustering, expectation-maximization, principal component analysis (PCA) and independent component analysis (ICA) can be applied in the RIS-enhanced wireless networks for tackling challenges such as BS deployment, user clustering/association [141], channel/network state detection [142], data aggregation [143], and interference cancellation [144].

3) *Federated Learning techniques for RIS-enhanced Communication Systems:* Federated learning, which explores training statistical models directly on remote devices, has become a focal

point in the area of large-scale machine learning and distributed optimization [145]. Since the federated learning algorithm is trained at the edge in distributed networks, the inaccessibility of private data is no longer a problem. Due to its privacy-preserving nature, federated learning algorithms can be applied for the deployment and design of multiple RISs, where each RIS can act as a distributed learner, trains its generated data and transfers its local model parameters instead of the raw training dataset to an aggregating unit. Thus, the deployment and design policy can be learned in a decentralized manner.

F. Discussions and Outlook

By exploiting ML learning capabilities, the aforementioned challenges encountered in the RIS-enhanced wireless networks may be mitigated, but they will also pose some new challenges. Examples of these new challenges include the layer design for the DL model, the state-action construction and the reward function design for the RL model. Additionally, simultaneously employing multiple RIS becomes more challenging due to the cooperation amongst RISs. Hence, intelligent deployment and design for multi-RIS enhanced wireless networks are desired.

Apart from the aforementioned application scenarios, RISs can also be successfully applied in wireless power transfer scenarios and security communication scenarios, where the joint deployment and phase shift design of the RISs remain unsolved.

VI. INTEGRATING RIS WITH OTHER TECHNOLOGIES TOWARDS 6G

Current research contributions have proved that RIS-enhanced wireless networks are capable of obtaining tuned channel gains, improved QoS, enhanced coverage range, and reduced energy dissipation. These significant performance enhancements can be applied to diverse wireless communication networks. In this section, we identify the major issues and research opportunities on the path to 6G associated with the integration of RIS and other emerging technologies, such as NOMA networks, PLS, SWIPT, UAV-enabled wireless networks, and autonomous driving networks.

A. NOMA and RIS

In an effort to improve the spectrum efficiency and user connectivity of RIS-enhanced wireless networks, power-domain NOMA technology is adopted, whose key idea is to superimpose

the signals of two users at different powers for exploiting the spectrum more efficiently by opportunistically exploring the users' different channel conditions [48], [146]. Li *et al.* [147] considered a MISO-NOMA downlink communication network for minimizing the total transmit power by jointly designing the transmit precoding vectors and the reflecting coefficient vector. In [8], Yang *et al.* jointly optimized the phase shifts matrix of the RIS, as well as the power allocation from the BS to the users. Thus, the minimum decoding SINR of all users was maximized for optimizing the throughput of the system by considering user fairness. Ding *et al.* [57] proposed a novel design of RIS assisted NOMA networks. It can be observed in [57] that, the directions of users' channel vectors can be aligned with the aid of the RIS, which emphasizes the importance of implementing NOMA technology. For a NOMA-assisted RIS system, the core challenge is that the decoding order is dynamically changed due to the phase shift of the RIS. Mu *et al.* [93] proposed a NOMA-RIS-MISO framework to maximize the throughput of the system by considering the dynamic decoding order condition. The SCA technique and sequential rank-one constraint relaxation (SROCR)-based algorithm were applied to obtain a locally optimal solution. Ni *et al.* [148] proposed a resource allocation framework in multi-cell RIS-NOMA networks, where the achievable sum rate was maximized by solving the joint problem of user association, sub-channel assignment, power allocation, phase shifts design, and decoding order determination.

In contrast to the conventional MIMO-NOMA systems, RIS-NOMA technology can overcome the challenges of the dynamic environment such as random fluctuation of wireless channels, blocking, and user mobility in an energy-efficient manner. The NOMA system can obtain tuned channel gains, improved fair resource allocation, enhanced coverage range, and high energy efficiency with the aid of RISs [149]. However, NOMA also give rise to new challenges when integrated with RIS. For multi-antenna NOMA transmission, the decoding order is not determined by the users' channel gains order, since additional decoding rate conditions need to be satisfied to guarantee successful SIC. Additionally, both the active beamforming and passive phase shift design affect the decoding order among users and user clustering, which makes the decoding order design, user clustering and beamforming design highly coupled.

B. PLS and RIS

It has been shown that RISs are capable of simultaneously enhancing the desired signal power at the intended user and decreasing the interference power at other unintended users [73]. Inspired by this result, several researchers explored the potential performance gain in the context of physical layer security by applying the RIS [104], [150]–[156]. Yu *et al.* [150] considered an RIS-enhanced multiple-input single-output single eavesdropper (MISOSE) channel, where the eavesdropper is equipped with a single antenna. The secrecy rate was maximized by jointly optimizing the transmit beamforming and the RIS phase shift matrix by using an AO-based algorithm. It was demonstrated that the secrecy performance can be further improved by deploying the RIS. Cui *et al.* [151] focused on the scenario where the eavesdropper has a better channel condition than that of the legitimate receiver and both are also highly correlated in space, where the achievable secrecy rate is rather limited in conventional communications. However, it was shown that the direct signal and reflected signal can be destructively added at the eavesdropper with the aid of RIS, thus, significantly improving the secrecy rate. The same problem was further investigated in [104], [153] by considering a multiple-antennas eavesdropper or legitimate receiver. Chu *et al.* [152] minimized the transmit power while satisfying the secrecy rate requirement in the RIS-enhanced MISOSE system. Chen *et al.* [154] studied the minimum-secrecy-rate maximization problem in the RIS-enhanced multi-user multiple-input single-output multiple eavesdropper (MISOME) system by considering both the continuous and discrete reflecting coefficients. Injecting artificial noise (AN) is an effective technique to enhance the secrecy rate [157]. Motivated by this result, Guan *et al.* [155] examined the effectiveness of AN in an RIS-enhanced MISOME system. The achievable secrecy rate was maximized by jointly optimizing the transmit beamforming, AN and the passive beamforming. The results verified the necessity of using AN, especially with a large number of eavesdroppers. Yu *et al.* [156] considered an RIS-enhanced multi-user MISOME system under imperfect CSI to maximize the sum-rate, subject to the maximum information leakage constraint. An efficient AO-based algorithm was developed to optimize the transmit beamforming, the AN covariance matrix, and the RIS phase shifts. Numerical results showed that significant secrecy performance gains can be achieved by the RIS.

C. SWIPT and RIS

SWIPT is an attractive technique for future IoT networks. However, the low energy efficiency at the energy receivers is the main bottleneck in practical SWIPT systems. Equipped with massive low-cost passive reflecting units, RIS is a promising solution for SWIPT systems. Driven by this, RIS-assisted SWIPT has been investigated in [19]–[22]. In [19], Wu *et al.* investigated an RIS-assisted SWIPT system, under individual SINR requirements of information receivers. The weighted sum-power received by energy receivers was maximized by jointly optimizing the transmit and passive beamforming with the proposed AO-based algorithm. Similarly, Tang *et al.* [20] maximized the minimum received power among energy receivers. The results in [19] and [20] showed that an RIS improves the energy harvesting. Pan *et al.* [21] studied the weighted sum rate maximization problem in the RIS-assisted SWIPT MIMO system, subject to the energy harvesting requirement of energy receivers. The block coordinate descent algorithm was designed to find a Karush-Kuhn-Tucker (KKT) stationary point of the original problem. Wu *et al.* [22] extended the RIS-assisted SWIPT system with multiple RISs, where the transmit power was minimized while satisfying the different QoS constraints at information users and energy users. It was shown that the RIS enlarges the wireless power transfer range and reduces the number of required energy beams.

D. UAV and RIS

RISs can be applied in UAV-enabled wireless networks, where UAVs are employed to complement and/or support the existing terrestrial cellular networks [158], [159]. An RIS enhances the UAV coverage and service quality by compensating for the power loss over long distances, as well as forming virtual LoS links between UAVs and mobile users via passively reflecting their received signals. Li *et al.* [24] jointly optimized the UAV trajectory and the RIS phase shift in an iterative manner. It was shown in [24] that, the average achievable rates of the users were significantly improved with the aid of RIS. On the other hand, RISs can also be applied in UAV-aided wireless relay networks for enhancing performance. Zhang *et al.* [160] considered the effective placement of a single UAV, which was equipped with an RIS to assist mmWave downlink transmission while considering user mobility. By jointly designing the UAV trajectory and the RIS reflection parameters, the virtual LoS connection between the BS and users was

guaranteed. Thus, both the average data rate and the achievable downlink LoS probability were improved. Yang *et al.* [161] derived the analytical expressions of outage probability, bit error ratio (BER), and average capacity by approximating the PDF of the instantaneous SNR in RIS-assisted UAV relaying system.

Due to the fact that UAVs are battery-powered, their energy consumption is one of the key challenges. The limited flight-time of UAVs (usually under 30 minutes) hampers the wide commercial roll-out of UAV-aided networking. By deploying RISs, one can adjust the RIS phase shift instead of controlling the UAV movement for forming virtual LoS links between the UAV and the users. Therefore, the UAV can maintain hovering status only when the virtual LoS links can not be formed even with the aid of the RIS. By invoking the aforementioned protocol, the total energy consumption of the UAV is minimized, which in turn, maximizes the UAV endurance. Additionally, by mounting a compact distributed laser charging (DLC) receiver or wireless power transmission (WPT) receiver antenna inside the UAVs, while a DLC/WPT transmitter is deployed on the ground or the building roof, the UAVs can be charged as long as they are flying within the coverage range of the DLC/WPT transmitter [116], [162]. However, the LoS connection between UAVs and the charging stations/vehicles have to be guaranteed, which is challenging in the urban scenario when the LoS link between UAVs and charging stations/vehicles are blocked by high-rise buildings with high probability. RISs are capable of smartly reconfiguring the wireless propagation environment by forming virtual LoS links between UAVs and the charging stations/vehicles via passively reflecting their received signals. Thus, the charging service quality is enhanced with the aid of the RIS.

E. Autonomous Driving/Connected Vehicles and RIS

RISs can also be deployed in Vehicle-to-infrastructure (V2I) assisted autonomous driving systems, where V2I components are employed to complement the costly onboard units (OBUs). V2I networks enable autonomous vehicles (AVs) or connected vehicles (CVs) to receive reliable real-time traffic information from BS, the information is collected by roadside base stations (RBSs) and transmitted from RBSs to BSs, which facilitates the interaction among AVs/CVs and road users, hence enhancing their safety and traffic efficiency [163]–[165]. Since AV/CVs quality and reliability are non-negotiable, the AV/CVs system must be real-time, while the transmission

is supposed to be 100% reliable. However, the service quality of current V2I communication systems cannot be guaranteed due to complex channel terrain in the urban environment and the complexity of road conditions, such as bad weather. Makarfi *et al.* [166] and Wang [167] proved that the performance of vehicular networks can be significantly improved with the aid of RISs. Since the RISs are made of electromagnetic material, which can be installed on key surfaces, such as building facades, highway polls, advertising panels, vehicle windows, and even pedestrians' clothes. With the massive deployment of the RISs, the virtual LoS connection between the BSs and AVs, as well as between the RSUs and BSs will be guaranteed, which enhances the reliability of V2I communications.

F. Discussions and Outlook

RIS studies have unveiled promising research opportunities, such as NOMA networks, PLS, SWIPT, UAV-enabled wireless networks, and autonomous driving networks. Recent research contributions have proved that RIS-enhanced wireless networks can achieve tuned channel gains, improved QoS, enhanced coverage range, and reduced energy dissipation. However, the network and beamforming designs are highly coupled due to dynamic control of the RIS phase, which brings challenges to these new research directions.

VII. CONCLUSIONS

In this paper, recent research works on RIS-enhanced wireless networks proposed for application to next-generation networks have been surveyed with an emphasis on the following aspects: operating principles of RISs, performance evaluation of multi-antenna assisted RIS systems, beamforming and resource allocation for RISs, machine learning in RIS-enhanced wireless networks, and their integration with other key 6G technologies. We have highlighted the advantages and limitations of RISs for communication applications. Further research efforts are needed to bridge the complex physical models of the different RISs implementations with widely used communication models. We have considered the performance evaluation of multi-antenna assisted RISs systems by systematically surveying existing designs for RIS-enhanced wireless networks from the views of performance analysis, information theory and optimization. The majority of current research contributions assume perfect CSI at both the BS and RISs

controller, as well as the users. However, obtaining CSI in RIS-enhanced wireless networks is a non-trivial challenge, which requires a non-negligible training overhead. In addition, we have discussed existing research contributions that apply machine learning for tackling the dynamic essence of the wireless environment such as random fluctuations of wireless channels and user mobility. Design guidelines for ML-empowered RIS-enhanced wireless networks have also been discussed. The benefits of integrating RISs with NOMA, UAV-terrestrial networks, PLS, SWIPT, have been discussed. Indeed, RIS-enhanced wireless networks research is still in its infancy and there are ample opportunities for important contributions and advances in this field.

REFERENCES

- [1] K. B. Letaief, W. Chen, Y. Shi, J. Zhang, and Y.-J. A. Zhang, "The roadmap to 6G: AI empowered wireless networks," *IEEE Commun. Mag.*, vol. 57, no. 8, pp. 84–90, 2019.
- [2] W. Saad, M. Bennis, and M. Chen, "A vision of 6G wireless systems: Applications, trends, technologies, and open research problems," *IEEE network*, vol. 34, no. 3, pp. 134–142, 2020.
- [3] Q. Wu and R. Zhang, "Towards smart and reconfigurable environment: Intelligent reflecting surface aided wireless network," *IEEE Commun. Mag.*, vol. 58, no. 1, pp. 106–112, 2020.
- [4] Y. Cheng, K. H. Li, Y. Liu, K. C. Teh, and H. V. Poor, "Downlink and uplink intelligent reflecting surface aided networks: NOMA and OMA," *arXiv:2005.00996*, 2020.
- [5] T. Hou, Y. Liu, Z. Song, X. Sun, Y. Chen, and L. Hanzo, "MIMO assisted networks relying on large intelligent surfaces: A stochastic geometry model," *arXiv:1910.00959*, 2019.
- [6] Y.-C. Liang, R. Long, Q. Zhang, J. Chen, H. V. Cheng, and H. Guo, "Large intelligent surface/antennas (LISA): Making reflective radios smart," *J. Commun. Inf. Netw.*, vol. 4, no. 2, pp. 40–50, 2019.
- [7] M. Di Renzo, A. Zappone, M. Debbah, M.-S. Alouini, C. Yuen, J. de Rosny, and S. Tretyakov, "Smart radio environments empowered by reconfigurable intelligent surfaces: How it works, state of research, and road ahead," *arXiv:2004.09352*, 2020.
- [8] Y. Yang, B. Zheng, S. Zhang, and R. Zhang, "Intelligent reflecting surface meets OFDM: Protocol design and rate maximization," *IEEE Trans. Commun.*, doi: 10.1109/TCOMM.2020.2981458.
- [9] N. S. Perović, M. Di Renzo, and M. F. Flanagan, "Channel capacity optimization using reconfigurable intelligent surfaces in indoor mmWave environments," *arXiv:1910.14310*, 2019.
- [10] C. Huang, S. Hu, G. C. Alexandropoulos, A. Zappone, C. Yuen, R. Zhang, M. Di Renzo, and M. Debbah, "Holographic MIMO surfaces for 6G wireless networks: Opportunities, challenges, and trends," *arXiv:1911.12296*, 2019.
- [11] M. Di Renzo, K. Ntontin, J. Song, F. H. Danufane, X. Qian, F. Lazarakis, J. de Rosny, D. . Phan-Huy, O. Simeone, R. Zhang, M. Debbah, G. Lerosey, M. Fink, S. Tretyakov, and S. Shamai, "Reconfigurable intelligent surfaces vs. relaying: Differences, similarities, and performance comparison," *IEEE Open J. Commun. Soc.*, doi: 10.1109/OJ-COMS.2020.3002955.
- [12] E. Björnson, Ö. Özdogan, and E. G. Larsson, "Intelligent reflecting surface versus decode-and-forward: How large surfaces are needed to beat relaying?" *IEEE Wireless Commun. Lett.*, vol. 9, no. 2, pp. 244–248, 2020.
- [13] S. Zhou, W. Xu, K. Wang, M. Di Renzo, and M.-S. Alouini, "Spectral and energy efficiency of IRS-assisted MISO communication with hardware impairments," *IEEE Wireless Commun. Lett.*, 2020.
- [14] Y. Cao and T. Lv, "Intelligent reflecting surface enhanced resilient design for MEC offloading over millimeter wave links," *arXiv:1912.06361*, 2019.

- [15] T. Bai, C. Pan, Y. Deng, M. ElKashlan, and A. Nallanathan, "Latency minimization for intelligent reflecting surface aided mobile edge computing," *arXiv:1910.07990*, 2019.
- [16] Y. Cao and T. Lv, "Sum rate maximization for reconfigurable intelligent surface assisted device-to-device communications," *arXiv:2001.03344*, 2020.
- [17] L. Yang, J. Yang, W. Xie, M. O. Hasna, T. Tsiftsis, and M. Di Renzo, "Secrecy performance analysis of RIS-aided wireless communication systems," *IEEE Trans. Veh. Technol.*, accept to appear, 2020.
- [18] C. Pan, H. Ren, K. Wang, W. Xu, M. ElKashlan, A. Nallanathan, and L. Hanzo, "Multicell MIMO communications relying on intelligent reflecting surfaces," *IEEE Trans. Wireless Commun.*, doi: 10.1109/TWC.2020.2990766.
- [19] Q. Wu and R. Zhang, "Weighted sum power maximization for intelligent reflecting surface aided SWIPT," *IEEE Wireless Commun. Lett.*, vol. 9, no. 5, pp. 586–590, 2019.
- [20] Y. Tang, G. Ma, H. Xie, J. Xu, and X. Han, "Joint transmit and reflective beamforming design for IRS-assisted multiuser MISO SWIPT systems," *arXiv:1910.07156*, 2019.
- [21] C. Pan, H. Ren, K. Wang, M. ElKashlan, A. Nallanathan, J. Wang, and L. Hanzo, "Intelligent reflecting surface enhanced MIMO broadcasting for simultaneous wireless information and power transfer," *IEEE J. Sel. Areas Commun.*, doi: 10.1109/JSAC.2020.3000802.
- [22] Q. Wu and R. Zhang, "Joint active and passive beamforming optimization for intelligent reflecting surface assisted SWIPT under QoS constraints," *arXiv:1910.06220*, 2019.
- [23] H. Wang, Z. Zhang, B. Zhu, J. Dang, L. Wu, L. Wang, K. Zhang, and Y. Zhang, "Performance of wireless optical communication with reconfigurable intelligent surfaces and random obstacles," *arXiv:2001.05715*, 2020.
- [24] S. Li, B. Duo, X. Yuan, Y.-C. Liang, M. Di Renzo *et al.*, "Reconfigurable intelligent surface assisted UAV communication: Joint trajectory design and passive beamforming," *IEEE Wireless Commun. Lett.*, vol. 9, no. 5, pp. 716–720, 2020.
- [25] D. Ma, M. Ding, and M. Hassan, "Enhancing cellular communications for UAVs via intelligent reflective surface," in *Proc. IEEE Wireless Commun. Netw. Conf. (WCNC)*, 2020, pp. 1–6.
- [26] A. U. Makarfi, K. M. Rabie, O. Kaiwartya, O. S. Badarneh, X. Li, and R. Kharel, "Reconfigurable intelligent surface enabled IoT networks in generalized fading channels," *arXiv:1912.06250*, 2019.
- [27] D. R. Smith, O. Yurduseven, L. P. Mancera, P. Bowen, and N. B. Kundtz, "Analysis of a waveguide-fed metasurface antenna," *Physical Review Applied*, vol. 8, no. 5, p. 054048, 2017.
- [28] B. O. Zhu, K. Chen, N. Jia, L. Sun, J. Zhao, T. Jiang, and Y. Feng, "Dynamic control of electromagnetic wave propagation with the equivalent principle inspired tunable metasurface," *Scientific reports*, vol. 4, no. 1, pp. 1–7, 2014.
- [29] J. Y. Dai, J. Zhao, Q. Cheng, and T. J. Cui, "Independent control of harmonic amplitudes and phases via a time-domain digital coding metasurface," *Light: Science & Applications*, vol. 7, no. 1, p. 90, 2018.
- [30] S. R. Rengarajan and Y. Rahmat-Samii, "The field equivalence principle: Illustration of the establishment of the non-intuitive null fields," vol. 42, no. 4, pp. 122–128, 2000.
- [31] V. S. Asadchy, M. Albooyeh, S. N. Tcvetkova, A. Díaz-Rubio, Y. Ra'idi, and S. Tretyakov, "Perfect control of reflection and refraction using spatially dispersive metasurfaces," *Physical Review B*, vol. 94, no. 7, p. 075142, 2016.
- [32] B. H. Fong, J. S. Colburn, J. J. Ottusch, J. L. Visher, and D. F. Sievenpiper, "Scalar and tensor holographic artificial impedance surfaces," vol. 58, no. 10, pp. 3212–3221, 2010.
- [33] N. M. Estakhri and A. Alù, "Wave-front transformation with gradient metasurfaces," *Physical Review X*, vol. 6, no. 4, p. 041008, 2016.
- [34] B. O. Zhu, J. Zhao, and Y. Feng, "Active impedance metasurface with full 360 reflection phase tuning," *Scientific reports*, vol. 3, p. 3059, 2013.
- [35] N. K. Emani, A. V. Kildishev, V. M. Shalaev, and A. Boltasseva, "Graphene: a dynamic platform for electrical control of plasmonic resonance," *Nanophotonics*, vol. 4, no. 1, pp. 214–223, 2015.
- [36] S. Abeywickrama, R. Zhang, Q. Wu, and C. Yuen, "Intelligent reflecting surface: Practical phase shift model and beamforming optimization," *IEEE Trans. Commun.*, doi: 10.1109/TCOMM.2020.3001125.
- [37] V. Arun and H. Balakrishnan, "Rfocus: Beamforming using thousands of passive antennas," in *17th USENIX Symposium on Networked Systems Design and Implementation (NSDI 20)*, 2020, pp. 1047–1061.

- [38] A. Welkie, L. Shangguan, J. Gummesson, W. Hu, and K. Jamieson, "Programmable radio environments for smart spaces," in *Proceedings of the 16th ACM Workshop on Hot Topics in Networks*, 2017, pp. 36–42.
- [39] M. Dunna, C. Zhang, D. Sievenpiper, and D. Bharadia, "ScatterMIMO: enabling virtual MIMO with smart surfaces," in *Proceedings of the 26th Annual International Conference on Mobile Computing and Networking*, 2020, pp. 1–14.
- [40] R. J. Bell, K. R. Armstrong, C. S. Nichols, and R. W. Bradley, "Generalized laws of refraction and reflection," *JOSA*, vol. 59, no. 2, pp. 187–189, 1969.
- [41] J. Huang and J. A. Encinar, "Reflectarray antennas, a john wiley & sons," *Inc., Publication*, 2008.
- [42] E. Basar, M. Di Renzo, J. De Rosny, M. Debbah, M.-S. Alouini, and R. Zhang, "Wireless communications through reconfigurable intelligent surfaces," *IEEE Access*, vol. 7, pp. 116 753–116 773, 2019.
- [43] W. Tang, M. Z. Chen, X. Chen, J. Y. Dai, Y. Han, M. Di Renzo, Y. Zeng, S. Jin, Q. Cheng, and T. J. Cui, "Wireless communications with reconfigurable intelligent surface: Path loss modeling and experimental measurement," *arXiv:1911.05326*, 2019.
- [44] H.-T. Chen, A. J. Taylor, and N. Yu, "A review of metasurfaces: physics and applications," *Reports on progress in physics*, vol. 79, no. 7, p. 076401, 2016.
- [45] J. Huang and R. J. Pogorzelski, "A ka-band microstrip reflectarray with elements having variable rotation angles," *IEEE Trans. Antennas Propagat.*, vol. 46, no. 5, pp. 650–656, 1998.
- [46] M. Di Renzo, F. H. Danufane, X. Xi, J. de Rosny, and S. Tretyakov, "Analytical modeling of the path-loss for reconfigurable intelligent surfaces—anomalous mirror or scatterer?" *arXiv:2001.10862*, 2020.
- [47] Y. Liu, Z. Ding, M. ElKashlan, and H. V. Poor, "Cooperative non-orthogonal multiple access with simultaneous wireless information and power transfer," *IEEE J. Sel. Areas Commun.*, vol. 34, no. 4, pp. 938–953, 2016.
- [48] Y. Liu, Z. Qin, M. ElKashlan, Y. Gao, and L. Hanzo, "Enhancing the physical layer security of non-orthogonal multiple access in large-scale networks," *IEEE Trans. Wireless Commun.*, vol. 16, no. 3, pp. 1656–1672, 2017.
- [49] W. Yi, Y. Liu, and A. Nallanathan, "Modeling and analysis of D2D millimeter-wave networks with poisson cluster processes," *IEEE Trans. Commun.*, vol. 65, no. 12, pp. 5574–5588, 2017.
- [50] T. Hou, Y. Liu, Z. Song, X. Sun, and Y. Chen, "Exploiting NOMA for UAV communications in large-scale cellular networks," *IEEE Trans. Commun.*, vol. 67, no. 10, pp. 6897–6911, 2019.
- [51] H. ElSawy, E. Hossain, and M. Haenggi, "Stochastic geometry for modeling, analysis, and design of multi-tier and cognitive cellular wireless networks: A survey," *IEEE Communications Surveys Tutorials*, vol. 15, no. 3, pp. 996–1019, 2013.
- [52] M. A. Kishk and M.-S. Alouini, "Exploiting randomly-located blockages for large-scale deployment of intelligent surfaces," *arXiv:2001.10766*, 2020.
- [53] M. Di Renzo and J. Song, "Reflection probability in wireless networks with metasurface-coated environmental objects: An approach based on random spatial processes," *EURASIP J. Wireless Commun.*, no. 99, Apr. 2019.
- [54] K. S. Ali, M. Haenggi, H. ElSawy, A. Chaaban, and M.-S. Alouini, "Downlink non-orthogonal multiple access (NOMA) in poisson networks," *IEEE Trans. Commun.*, vol. 67, no. 2, pp. 1613–1628, 2018.
- [55] Z. Ding, R. Schober, and H. V. Poor, "On the impact of phase shifting designs on IRS-NOMA," *IEEE Wireless Commun. Lett.*, doi: 10.1109/LWC.2020.2991116.
- [56] Z. Zhang, Y. Cui, F. Yang, and L. Ding, "Analysis and optimization of outage probability in multi-intelligent reflecting surface-assisted systems," *arXiv:1909.02193*, 2019.
- [57] Z. Ding and H. Vincent Poor, "A simple design of IRS-NOMA transmission," *IEEE Commun. Lett.*, vol. 24, no. 5, pp. 1119–1123, 2020.
- [58] X. Qian, M. Di Renzo, J. Liu, A. Kammoun, and M.-S. Alouini, "Beamforming through reconfigurable intelligent surfaces in single-user MIMO systems: SNR distribution and scaling laws in the presence of channel fading and phase noise," *arXiv:2005.07472v1*, 2020.
- [59] T. Hou, Y. Liu, Z. Song, X. Sun, Y. Chen, L. Hanzo *et al.*, "Reconfigurable intelligent surface aided NOMA networks," *arXiv:1912.10044*, 2019.

- [60] J. Lyu and R. Zhang, "Spatial throughput characterization for intelligent reflecting surface aided multiuser system," *IEEE Wireless Commun. Lett.*, vol. 9, no. 6, pp. 834–838, 2020.
- [61] L. Dai, B. Wang, M. Wang, X. Yang, J. Tan, S. Bi, S. Xu, F. Yang, Z. Chen, M. Di Renzo *et al.*, "Reconfigurable intelligent surface-based wireless communications: Antenna design, prototyping, and experimental results," *IEEE Access*, vol. 8, pp. 45 913–45 923, 2020.
- [62] T. Hou, Y. Liu, Z. Song, X. Sun, and Y. Chen, "MIMO-NOMA networks relying on reconfigurable intelligent surface: A signal cancellation based design," *arXiv:2003.02117*, 2020.
- [63] K. Ntontin, J. Song, and M. Di Renzo, "Multi-antenna relaying and reconfigurable intelligent surfaces: End-to-end SNR and achievable rate," *arXiv:1908.07967*, 2019.
- [64] H. Zhang, B. Di, L. Song, and Z. Han, "Reconfigurable intelligent surfaces assisted communications with limited phase shifts: How many phase shifts are enough?" *IEEE Trans. Veh. Technol.*, vol. 69, no. 4, pp. 4498–4502, 2020.
- [65] J. Yuan, Y.-C. Liang, J. Joung, G. Feng, and E. G. Larsson, "Intelligent reflecting surface-assisted cognitive radio system," *arXiv:1912.10678*, 2019.
- [66] C. You, B. Zheng, and R. Zhang, "Channel estimation and passive beamforming for intelligent reflecting surface: Discrete phase shift and progressive refinement," *arXiv:1912.10646*, 2019.
- [67] W. Shi, X. Zhou, L. Jia, Y. Wu, F. Shu, and J. Wang, "Enhanced secure wireless information and power transfer via intelligent reflecting surface," *arXiv:1911.01001*, 2019.
- [68] B. Lyu, D. T. Hoang, S. Gong, D. Niyato, and D. I. Kim, "IRS-based wireless jamming attacks: When jammers can attack without power," *arXiv:2001.01887*, 2020.
- [69] R. Karasik, O. Simeone, M. Di Renzo, and S. Shamai, "Beyond max-SNR: Joint encoding for reconfigurable intelligent surfaces," *arXiv:1911.09443*, 2019.
- [70] X. Mu, Y. Liu, L. Guo, J. Lin, and N. Al-Dhahir, "Capacity and optimal resource allocation for IRS-assisted multi-user communication systems," *arXiv:2001.03913*, 2020.
- [71] S. Zhang and R. Zhang, "Intelligent reflecting surface aided multiple access: Capacity region and deployment strategy," *arXiv:2002.07091*, 2020.
- [72] L. Li and A. J. Goldsmith, "Capacity and optimal resource allocation for fading broadcast channels .I. ergodic capacity," *IEEE Trans. Inf. Theory*, vol. 47, no. 3, pp. 1083–1102, 2001.
- [73] 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, 2019.
- [74] Q. Wu and R. Zhang, "Beamforming optimization for wireless network aided by intelligent reflecting surface with discrete phase shifts," *IEEE Trans. Commun.*, vol. 68, no. 3, pp. 1838–1851, 2020.
- [75] H. Han, J. Zhao, D. Niyato, M. Di Renzo, and Q.-V. Pham, "Intelligent reflecting surface aided network: Power control for physical-layer broadcasting," *arXiv:1910.14383*, 2019.
- [76] M. Fu, Y. Zhou, and Y. Shi, "Reconfigurable intelligent surface empowered downlink non-orthogonal multiple access," *arXiv:1910.07361*, 2019.
- [77] J. Zhu, Y. Huang, J. Wang, K. Navaie, and Z. Ding, "Power efficient IRS-assisted NOMA," *arXiv:1912.11768*, 2019.
- [78] B. Zheng, Q. Wu, and R. Zhang, "Intelligent reflecting surface-assisted multiple access with user pairing: NOMA or OMA?" *IEEE Commun. Lett.*, vol. 24, no. 4, pp. 753–757, 2020.
- [79] C. Huang, A. Zappone, G. C. Alexandropoulos, M. Debbah, and C. Yuen, "Reconfigurable intelligent surfaces for energy efficiency in wireless communication," *IEEE Trans. Wireless Commun.*, vol. 18, no. 8, pp. 4157–4170, 2019.
- [80] G. Zhou, C. Pan, H. Ren, K. Wang, M. Di Renzo, and A. Nallanathan, "Robust beamforming design for intelligent reflecting surface aided miso communication systems," *IEEE Wireless Commun. Lett.*, doi: 10.1109/LWC.2020.3000490.
- [81] T. Lipp and S. Boyd, "Variations and extension of the convex–concave procedure," *Optimization and Engineering*, vol. 17, no. 2, pp. 263–287, 2016.
- [82] G. Zhou, C. Pan, H. Ren, K. Wang, and A. Nallanathan, "A framework of robust transmission design for IRS-aided MISO communications with imperfect cascaded channels," *arXiv:2001.07054*, 2020.

- [83] A. Zappone, M. Di Renzo, F. Shams, X. Qian, and M. Debbah, "Overhead-aware design of reconfigurable intelligent surfaces in smart radio environments," *arXiv:2003.02538*, 2020.
- [84] X. Yu, D. Xu, and R. Schober, "MISO wireless communication systems via intelligent reflecting surfaces," in *Proc. IEEE/CIC Int. Conf. Commun. China (ICCC)*, 2019, pp. 735–740.
- [85] X. Yu, D. Xu, and R. Schober, "Optimal beamforming for MISO communications via intelligent reflecting surfaces," *arXiv:2001.11429*, 2020.
- [86] B. Ning, Z. Chen, W. Chen, and J. Fang, "Beamforming optimization for intelligent reflecting surface assisted mimo: A sum-path-gain maximization approach," *IEEE Wireless Commun. Lett.*, doi: 10.1109/LWC.2020.2982140.
- [87] K. Ying, Z. Gao, S. Lyu, Y. Wu, H. Wang, and M. Alouini, "GMD-based hybrid beamforming for large reconfigurable intelligent surface assisted millimeter-wave massive MIMO," *IEEE Access*, vol. 8, pp. 19 530–19 539, 2020.
- [88] S. Zhang and R. Zhang, "Capacity characterization for intelligent reflecting surface aided MIMO communication," *IEEE J. Sel. Areas Commun.*, doi: 10.1109/JSAC.2020.3000814.
- [89] C. You, B. Zheng, and R. Zhang, "Intelligent reflecting surface with discrete phase shifts: Channel estimation and passive beamforming," *arXiv:1911.03916*, 2019.
- [90] C. Huang, A. Zappone, M. Debbah, and C. Yuen, "Achievable rate maximization by passive intelligent mirrors," in *Proc. IEEE Int. Conf. Acoust., Speech Signal Process. (ICASSP)*, 2018, pp. 3714–3718.
- [91] H. Guo, Y.-C. Liang, J. Chen, and E. G. Larsson, "Weighted sum-rate optimization for intelligent reflecting surface enhanced wireless networks," *arXiv:1905.07920*, 2019.
- [92] M. Jung, W. Saad, M. Debbah, and C. S. Hong, "On the optimality of reconfigurable intelligent surfaces (RISs): Passive beamforming, modulation, and resource allocation," *arXiv:1910.00968*, 2019.
- [93] X. Mu, Y. Liu, L. Guo, J. Lin, and N. Al-Dhahir, "Exploiting intelligent reflecting surfaces in NOMA networks: Joint beamforming optimization," *IEEE Trans. Wireless Commun.*, accept to appear, 2020.
- [94] M.-M. Zhao, Q. Wu, M.-J. Zhao, and R. Zhang, "Intelligent reflecting surface enhanced wireless network: Two-timescale beamforming optimization," *arXiv:1912.01818*, 2019.
- [95] Q. Nadeem, A. Kammoun, A. Chaaban, M. Debbah, and M. Alouini, "Asymptotic max-min SINR analysis of reconfigurable intelligent surface assisted MISO systems," *IEEE Trans. Wireless Commun.*, doi: 10.1109/TWC.2020.2986438.
- [96] G. Yang, X. Xu, and Y.-C. Liang, "Intelligent reflecting surface assisted non-orthogonal multiple access," *arXiv:1907.03133*, 2019.
- [97] Y. Yang, S. Zhang, and R. Zhang, "IRS-enhanced OFDMA: Joint resource allocation and passive beamforming optimization," *IEEE Wireless Commun. Lett.*, vol. 9, no. 6, pp. 760–764, 2020.
- [98] J. Zuo, Y. Liu, Z. Qin, and N. Al-Dhahir, "Resource allocation in intelligent reflecting surface assisted NOMA systems," *arXiv:2002.01765*, 2020.
- [99] X. Li, J. Fang, F. Gao, and H. Li, "Joint active and passive beamforming for intelligent reflecting surface-assisted massive MIMO systems," *arXiv:1912.00728*, 2019.
- [100] H. Xie, J. Xu, and Y.-F. Liu, "Max-min fairness in IRS-aided multi-cell MISO systems with joint transmit and reflective beamforming," *arXiv:2003.00906*, 2020.
- [101] H. Gacanin and M. Di Renzo, "Wireless 2.0: Towards an intelligent radio environment empowered by reconfigurable meta-surfaces and artificial intelligence," *arXiv:2002.11040*, 2020.
- [102] X. Liu, M. Chen, Y. Liu, Y. Chen, S. Cui, and L. Hanzo, "Artificial intelligence aided next-generation networks relying on UAVs," *arXiv:2001.11958*, 2020.
- [103] C.-X. Wang, M. Di Renzo, S. Stanczak, S. Wang, and E. G. Larsson, "Artificial intelligence enabled wireless networking for 5G and beyond: Recent advances and future challenges," *IEEE Wireless Commun.*, vol. 27, no. 1, pp. 16–23, 2020.
- [104] H. Shen, W. Xu, S. Gong, Z. He, and C. Zhao, "Secrecy rate maximization for intelligent reflecting surface assisted multi-antenna communications," *IEEE Commun. Lett.*, vol. 23, no. 9, pp. 1488–1492, 2019.
- [105] A. Zappone, M. Di Renzo, M. Debbah, T. T. Lam, and X. Qian, "Model-aided wireless artificial intelligence: Embedding expert knowledge in deep neural networks for wireless system optimization," *IEEE Veh. Technol. Mag.*, vol. 14, no. 3, pp. 60–69, 2019.

- [106] Z. Qin, H. Ye, G. Y. Li, and B. F. Juang, "Deep learning in physical layer communications," *IEEE Wireless Commun.*, vol. 26, no. 2, pp. 93–99, 2019.
- [107] A. Zappone, M. Di Renzo, and M. Debbah, "Wireless networks design in the era of deep learning: Model-based, AI-based, or both?" *IEEE Trans. Commun.*, vol. 67, no. 10, pp. 7331–7376, 2019.
- [108] C.-K. Wen, W.-T. Shih, and S. Jin, "Deep learning for massive MIMO CSI feedback," *IEEE Wireless Commun. Lett.*, vol. 7, no. 5, pp. 748–751, 2018.
- [109] J. Chen, Y.-C. Liang, H. V. Cheng, and W. Yu, "Channel estimation for reconfigurable intelligent surface aided multi-user MIMO systems," *arXiv:1912.03619*, 2019.
- [110] A. Taha, M. Alrabeiah, and A. Alkhateeb, "Enabling large intelligent surfaces with compressive sensing and deep learning," *arXiv:1904.10136*, 2019.
- [111] S. Liu, Z. Gao, J. Zhang, M. Di Renzo, and M.-S. Alouini, "Deep denoising neural network assisted compressive channel estimation for mmWave intelligent reflecting surfaces," *arXiv:2006.02201*, 2020.
- [112] A. M. Elbir, A. Papazafeiropoulos, P. Kourtessis, and S. Chatzinotas, "Deep channel learning for large intelligent surfaces aided mm-Wave massive MIMO systems," *IEEE Wireless Commun. Lett.*, doi: 10.1109/LWC.2020.2993699.
- [113] C. Huang, G. C. Alexandropoulos, C. Yuen, and M. Debbah, "Indoor signal focusing with deep learning designed reconfigurable intelligent surfaces," in *2019 IEEE 20th International Workshop on Signal Processing Advances in Wireless Communications (SPAWC)*, 2019, pp. 1–5.
- [114] J. Gao, C. Zhong, X. Chen, H. Lin, and Z. Zhang, "Unsupervised learning for passive beamforming," *IEEE Commun. Lett.*, vol. 24, no. 5, pp. 1052–1056, 2020.
- [115] S. Khan and S. Y. Shin, "Deep-learning-aided detection for reconfigurable intelligent surfaces," *arXiv:1910.09136*, 2019.
- [116] X. Liu, Y. Liu, Y. Chen, and L. Hanzo, "Trajectory design and power control for multi-UAV assisted wireless networks: A machine learning approach," *IEEE Trans. Veh. Technol.*, vol. 68, no. 8, pp. 7957–7969, 2019.
- [117] H. Van Hasselt, A. Guez, and D. Silver, "Deep reinforcement learning with double Q-learning," in *Thirtieth AAAI Conference on Artificial Intelligence*, 2016.
- [118] Z. Wang, T. Schaul, M. Hessel, H. Van Hasselt, M. Lanctot, and N. De Freitas, "Dueling network architectures for deep reinforcement learning," *arXiv:1511.06581*, 2015.
- [119] M. Fortunato, M. G. Azar, B. Piot, J. Menick, I. Osband, A. Graves, V. Mnih, R. Munos, D. Hassabis, O. Pietquin *et al.*, "Noisy networks for exploration," *arXiv:1706.10295*, 2017.
- [120] W. Dabney, M. Rowland, M. G. Bellemare, and R. Munos, "Distributional reinforcement learning with quantile regression," in *Thirty-Second AAAI Conference on Artificial Intelligence*, 2018.
- [121] V. Mnih, A. P. Badia, M. Mirza, A. Graves, T. Lillicrap, T. Harley, D. Silver, and K. Kavukcuoglu, "Asynchronous methods for deep reinforcement learning," in *International conference on machine learning*, 2016, pp. 1928–1937.
- [122] J. Schulman, F. Wolski, P. Dhariwal, A. Radford, and O. Klimov, "Proximal policy optimization algorithms," *arXiv:1707.06347*, 2017.
- [123] P. Hämäläinen, A. Babadi, X. Ma, and J. Lehtinen, "PPO-CMA: Proximal policy optimization with covariance matrix adaptation," *arXiv:1810.02541*, 2018.
- [124] T. P. Lillicrap, J. J. Hunt, A. Pritzel, N. Heess, T. Erez, Y. Tassa, D. Silver, and D. Wierstra, "Continuous control with deep reinforcement learning," *arXiv:1509.02971*, 2015.
- [125] T. Haarnoja, A. Zhou, P. Abbeel, and S. Levine, "Soft actor-critic: Off-policy maximum entropy deep reinforcement learning with a stochastic actor," *arXiv:1801.01290*, 2018.
- [126] N. C. Luong, D. T. Hoang, S. Gong, D. Niyato, P. Wang, Y.-C. Liang, and D. I. Kim, "Applications of deep reinforcement learning in communications and networking: A survey," *IEEE Commun. Surv. Tut.*, vol. 21, no. 4, pp. 3133–3174, 2019.
- [127] C. Huang, R. Mo, and C. Yuen, "Reconfigurable intelligent surface assisted multiuser MISO systems exploiting deep reinforcement learning," *IEEE J. Sel. Areas Commun.*, doi: 10.1109/JSAC.2020.3000835.
- [128] K. Feng, Q. Wang, X. Li, and C.-K. Wen, "Deep reinforcement learning based intelligent reflecting surface optimization for MISO communication systems," *IEEE Wireless Commun. Lett.*, vol. 9, no. 5, pp. 745–749, 2020.

- [129] A. Taha, Y. Zhang, F. B. Mismar, and A. Alkhateeb, “Deep reinforcement learning for intelligent reflecting surfaces: Towards standalone operation,” *arXiv:2002.11101*, 2020.
- [130] J. Z. D. N. Helin Yang, Zehui Xiong and L. Xiao, “Deep reinforcement learning based intelligent reflecting surface for secure wireless communications,” *arXiv:2002.12271*, 2020.
- [131] Q. Zhang, W. Saad, and M. Bennis, “Millimeter wave communications with an intelligent reflector: Performance optimization and distributional reinforcement learning,” *arXiv:2002.10572*, 2020.
- [132] M. Di Renzo, M. Debbah, D.-T. Phan-Huy, A. Zappone, M.-S. Alouini, C. Yuen, V. Sciancalepore, G. C. Alexandropoulos, J. Hoydis, H. Gacanin *et al.*, “Smart radio environments empowered by AI reconfigurable meta-surfaces: An idea whose time has come,” *arXiv:1903.08925*, 2019.
- [133] J. Ye, S. Guo, and M. Alouini, “Joint reflecting and precoding designs for SER minimization in reconfigurable intelligent surfaces assisted MIMO systems,” *IEEE Trans. Wireless Commun.*, doi: 10.1109/TWC.2020.2994455.
- [134] M. Jung, W. Saad, and G. Kong, “Performance analysis of large intelligent surfaces (LISs): Uplink spectral efficiency and pilot training,” *arXiv:1904.00453*, 2019.
- [135] X. Liu, Y. Liu, Y. Chen, and H. V. Poor, “RIS enhanced massive non-orthogonal multiple access networks: Deployment and passive beamforming design,” *arXiv:2001.10363*, 2020.
- [136] K. Umebayashi, M. Kobayashi, and M. López-Benítez, “Efficient time domain deterministic-stochastic model of spectrum usage,” *IEEE Trans. Wireless Commun.*, vol. 17, no. 3, pp. 1518–1527, 2017.
- [137] Z. Feng, X. Li, Q. Zhang, and W. Li, “Proactive radio resource optimization with margin prediction: A data mining approach,” *IEEE Trans. Veh. Technol.*, vol. 66, no. 10, pp. 9050–9060, 2017.
- [138] K. G. M. Thilina, E. Hossain, and D. I. Kim, “DCCC-MAC: A dynamic common-control-channel-based MAC protocol for cellular cognitive radio networks,” *IEEE Trans. Veh. Technol.*, vol. 65, no. 5, pp. 3597–3613, 2015.
- [139] P. Abouzar, K. Shafiee, D. G. Michelson, and V. C. Leung, “Action-based scheduling technique for 802.15. 4/zigbee wireless body area networks,” in *IEEE International Symposium on Personal, Indoor and Mobile Radio Communications*, 2011, pp. 2188–2192.
- [140] J. Wang, C. Jiang, H. Zhang, Y. Ren, K.-C. Chen, and L. Hanzo, “Thirty years of machine learning: the road to pareto-optimal wireless networks,” *IEEE Commun. Surv. Tut.*, doi: 10.1109/COMST.2020.2965856.
- [141] X. Liu, Y. Liu, and Y. Chen, “Reinforcement learning in multiple-UAV networks: Deployment and movement design,” *IEEE Trans. Veh. Technol.*, vol. 68, no. 8, pp. 8036–8049, 2019.
- [142] A. Assra, J. Yang, and B. Champagne, “An EM approach for cooperative spectrum sensing in multiantenna CR networks,” *IEEE Trans. Veh. Technol.*, vol. 65, no. 3, pp. 1229–1243, 2015.
- [143] A. Morell, A. Correa, M. Barceló, and J. L. Vicario, “Data aggregation and principal component analysis in WSNs,” *IEEE Trans. Wireless Commun.*, vol. 15, no. 6, pp. 3908–3919, 2016.
- [144] J. Li, H. Zhang, and M. Fan, “Digital self-interference cancellation based on independent component analysis for co-time co-frequency full-duplex communication systems,” *IEEE Access*, vol. 5, pp. 10222–10231, 2017.
- [145] S. Niknam, H. S. Dhillon, and J. H. Reed, “Federated learning for wireless communications: Motivation, opportunities and challenges,” *arXiv:1908.06847*, 2019.
- [146] Y. Liu, Z. Qin, M. Elkashlan, Z. Ding, A. Nallanathan, and L. Hanzo, “Non-orthogonal multiple access for 5G and beyond,” *Proc. IEEE*, vol. 105, no. 12, pp. 2347–2381, 2017.
- [147] Y. Li, M. Jiang, Q. Zhang, and J. Qin, “Joint beamforming design in multi-cluster MISO NOMA intelligent reflecting surface-aided downlink communication networks,” *arXiv:1909.06972*, 2019.
- [148] W. Ni, X. Liu, Y. Liu, H. Tian, and Y. Chen, “Resource allocation for multi-cell IRS-aided NOMA networks,” *arXiv:2006.11811*, 2020.
- [149] A. Sousa de Sena and P. Nardelli, “What role do intelligent reflecting surfaces play in non-orthogonal multiple access?” *TechRxiv*, 2020.
- [150] X. Yu, D. Xu, and R. Schober, “Enabling secure wireless communications via intelligent reflecting surfaces,” in *IEEE Proc. of Global Commun. Conf. (GLOBECOM)*, 2019, pp. 1–6.

- [151] M. Cui, G. Zhang, and R. Zhang, "Secure wireless communication via intelligent reflecting surface," *IEEE Wireless Commun. Lett.*, vol. 8, no. 5, pp. 1410–1414, 2019.
- [152] Z. Chu, W. Hao, P. Xiao, and J. Shi, "Intelligent reflecting surface aided multi-antenna secure transmission," *IEEE Wireless Commun. Lett.*, vol. 9, no. 1, pp. 108–112, 2020.
- [153] L. Dong and H. Wang, "Secure MIMO transmission via intelligent reflecting surface," *IEEE Wireless Commun. Lett.*, vol. 9, no. 6, pp. 787–790, 2020.
- [154] J. Chen, Y. Liang, Y. Pei, and H. Guo, "Intelligent reflecting surface: A programmable wireless environment for physical layer security," *IEEE Access*, vol. 7, pp. 82 599–82 612, 2019.
- [155] X. Guan, Q. Wu, and R. Zhang, "Intelligent reflecting surface assisted secrecy communication: Is artificial noise helpful or not?" *IEEE Wireless Commun. Lett.*, vol. 9, no. 6, pp. 778–782, 2020.
- [156] X. Yu, D. Xu, Y. Sun, D. W. K. Ng, and R. Schober, "Robust and secure wireless communications via intelligent reflecting surfaces," *arXiv:1912.01497*, 2019.
- [157] S. Goel and R. Negi, "Guaranteeing secrecy using artificial noise," *IEEE Trans. Wireless Commun.*, vol. 7, no. 6, pp. 2180–2189, 2008.
- [158] Q. Wang, Z. Chen, H. Li, and S. Li, "Joint power and trajectory design for physical-layer secrecy in the UAV-aided mobile relaying system," *IEEE Access*, vol. 6, pp. 62 849–62 855, 2018.
- [159] A. Osseiran, F. Boccardi, V. Braun, Kusume *et al.*, "Scenarios for 5G mobile and wireless communications: the vision of the METIS project," *IEEE Commun. Mag.*, vol. 52, no. 5, pp. 26–35, 2014.
- [160] Q. Zhang, W. Saad, and M. Bennis, "Reflections in the sky: Millimeter wave communication with UAV-carried intelligent reflectors," in *IEEE Proc. of Global Commun. Conf. (GLOBECOM)*, 2019, pp. 1–6.
- [161] L. Yang, F. Meng, J. Zhang, M. O. Hasna, and M. Di Renzo, "On the performance of RIS-assisted dual-hop UAV communication systems," *IEEE Trans. Veh. Technol.*, doi: 10.1109/TVT.2020.3004598.
- [162] Q. Liu, J. Wu, P. Xia, S. Zhao, W. Chen, Y. Yang, and L. Hanzo, "Charging unplugged: Will distributed laser charging for mobile wireless power transfer work?" *IEEE Veh. Technol. Mag.*, vol. 11, no. 4, pp. 36–45, 2016.
- [163] L. Yao, J. Wang, X. Wang, A. Chen, and Y. Wang, "V2X routing in a VANET based on the hidden Markov model," *IEEE Trans. Intell. Transport. Syst.*, vol. 19, no. 3, pp. 889–899, 2018.
- [164] R. P. D. Vivacqua, M. Bertozzi, P. Cerri, F. N. Martins, and R. F. Vassallo, "Self-localization based on visual lane marking maps: An accurate low-cost approach for autonomous driving," *IEEE Trans. Intell. Transport. Syst.*, vol. 19, no. 2, pp. 582–597, 2018.
- [165] G. Williams, P. Drews, B. Goldfain, J. M. Rehg, and E. A. Theodorou, "Information-theoretic model predictive control: Theory and applications to autonomous driving," *IEEE Trans. Robot.*, vol. 34, no. 6, pp. 1603–1622, 2018.
- [166] A. Makarf, K. M. Rabie, O. Kaiwartya, K. Adhikari, X. Li, M. Quiroz-Castellanos, and R. Kharel, "Reconfigurable intelligent surfaces-enabled vehicular networks: A physical layer security perspective," *arXiv:2004.11288*, 2020.
- [167] J. Wang, W. H. Zhang, X. Bao, T. Song, and C. Pan, "Outage analysis for intelligent reflecting surface assisted vehicular communication networks," *arXiv:2005.00996*, 2020.