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Reconfigurable Intelligent Surfaces (RIS) and Their Role in Next-Generation Wireless Networks: An Overview

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ABSTRACT

Extensive research is now peering into the next generation of wireless technology. The significant talking points are how to effectively manage scarce wireless resources with the spiraling amount of wireless data traffic and the exponential growth of the number of nodes occupying the wireless communication ecosystem. Giant performance strides are offered by promising state-of-the-art technologies, such as Massive MIMO and mm-Wave technology, in tackling this resource scarcity problem; however, their application has proven prohibitive. Given its energy-efficient and low-cost characteristics, RIS has emerged as a promising technique for the beyond 5G networks. Furthermore, when deployed in a wireless communication scenario, the passive nature also means it can reliably extend network coverage and enhance spectral efficiency and security in the physical layer. This paper presents an in-depth overview of the background of RIS, its applications, and use cases, especially concerning wireless communications. This paper also touches on the RIS application to wireless communication networks and its combination with other emergent wireless technologies such as NOMA, SWIPT, UAVs and autonomous vehicles. Finally, a comparative case study was presented in which comparisons were drawn out for RIS-aided communication and relay-aided communication, with direct communication as a benchmark.

1 | Introduction

The wireless communication landscape has undergone a dramatic transformation over the past decade, with global data traffic expanding twentyfold compared to the levels attained in 2005. As projected by the International Telecommunication Union (ITU), this surge is expected to reach five (5) zettabytes by 2030 [1, 2]. The emergence of the Internet of Things (IoT), massive machine-type communication (MTC), and resource-intensive applications like virtual and augmented reality (VAR) has created unprecedented capacity demands on wireless networks. These advances, while revolutionary, have introduced significant challenges in power consumption and operational expenses (OPEX), raising important environmental concerns [3].

As 5G networks continue to evolve with groundbreaking technologies like millimeter-wave, massive MIMO, and small cells, the wireless ecosystem faces mounting pressure to meet these escalating traffic demands. Industry forecasts, including the Ericsson mobility report 2020, project global mobile subscribers to reach 8.8 billion by 2026, with 5G accounting for approximately 40%. Looking beyond 5G, the anticipated requirements for 6G are even more demanding, with Samsung Research highlighting three pivotal services: fully immersive extended reality (XR), high-fidelity mobile holograms, and digital replicas. These applications will require staggering performance metrics—peak data rates of 1000 Gbps, user experienced data rates of 1 Gbps, and air latency below 0.1 ms. Consequently, the conundrum for telecommunication operators remains in providing high-capacity networks at a potentially reduced cost; thus, making energy efficient communication an essential metric for 5G and beyond networks. According to the definition of energy efficiency (EE) in [4], it is defined as the number of bits transmitted from source to destination over a power consumption unit in a wireless communications network. Additionally, the general conception is that the power consumption is tied to the OPEX; as a result.

Wireless operators are tasked with utilizing various techniques to limit the OPEX while still ensuring optimal hitch-free end-to-end communications. Thus, due to the burgeoning challenges envisaged with the continuous growth of wireless traffic, researchers in academia and industry have been exploring solutions beyond traditional network optimization at the source or destination, rather casting an additional focus on the transformation of the propagation environment itself. This paradigm shift has led to the emergence of Reconfigurable Intelligent Surfaces (RIS) as a promising technology for next-generation wireless networks. RIS represents a revolutionary approach to wireless communication, comprising meta-surfaces with numerous reconfigurable passive elements that can independently modify the phase of impinging waves. This technology offers a unique solution to controlling the traditionally unpredictable wireless propagation environment through software-based management, similar to how modern networks control their protocol stack [5].

The importance of RIS lies in its potential to fundamentally reshape wireless communication systems. By enabling dynamic adjustment of signal reflections, RIS can enhance communication coverage, improve throughput, and increase energy efficiency—all while maintaining cost-effectiveness through its passive architecture. Its ability to operate noiselessly in full-duplex mode, combined with its energy-efficient design, positions RIS as a key enabling technology for beyond 5G (B5G) networks. The RIS-aided network would become transformational beyond connecting transceivers to become an innovative space with distributed intelligent communications, sensing, and computing platforms [6]. To put it more succinctly, the author in [7] went further to define a RIS-assisted network as an intelligent radio environment where the propagation environment is transformed into a smart reconfigurable space capable of playing an effective role in transferring and processing information.

As wireless networks evolve from network-centric to device-centric architectures, incorporating technologies like Device-to-Device (D2D) communication and local caching, RIS emerges as a crucial component in creating intelligent radio environments. These environments actively participate in information transfer and processing, offering a sustainable solution to the mounting challenges of capacity, coverage, and energy efficiency in next-generation wireless networks.

The composition of the paper is as follows: Section 2 takes a brief review of RIS. It delves concisely into the use-cases and possible effects of RIS technology on wireless communication systems. Section 3 reviews the applications and performance improvements of RIS-assisted wireless communication over non-RIS communications regarding the next-generation wireless communication system. Section 4 comprehensively looks at the theoretical aspects and physics behind the essential operation of the RIS. We take a comprehensive look at the various categorizations of RIS as it pertains to EM propagation. We examine RIS categorization based on structure, location in the wireless ecosystem, and the control mechanism. Section 5 breaks down the analysis of a RIS-assisted wireless communication system. We also look at a comparative study of RIS with other base technologies, such as relay systems. Section 6 analyzes various state-of-the-art optimization techniques of RIS-assisted wireless communication systems. The section examines a typical RIS-assisted wireless communication system model where direct and RIS links exist. We also look at existing works showing how RIS-assisted communication systems improve spectral efficiency, energy efficiency, security, localization, and mapping. Section 7 reviews the integration of RIS with other emergent technologies such as NOMA, SWIPT, UAV, and autonomous driving. Section 8 looks at the application of ML techniques in optimizing RIS-assisted wireless communication. Also, we examine a comparative analysis of the application of various ML algorithms on the RIS-assisted wireless communication system. Section 9 comprehensively spells out the challenges associated with RIS-assisted wireless communication systems and tailors the future research directions and opportunities for the optimal deployment of RIS in wireless communication systems. Section 10 provides a comparative analysis of RIS-aided communication against relay-aided communication while employing direct communication as a benchmark. Finally, Section 11 concludes the paper.

2 | Review of Metasurfaces

As wireless networks evolve beyond the fifth generation (B5G), the number of nodes in the wireless ecosystem continues to grow exponentially with trends like the IoT and machine-to-machine (m2m) type communications [8]. Given the resource-intensive innovative applications such as 3-D media, unmanned mobility, and virtual reality, traffic and data rate demand and transmission reliability have put tremendous pressure on mobile operators due to already scarce wireless resources [8–10]. High costs and their inability to cope with the harsh nature of the propagation environment have been the blight of some advanced technologies (Massive MIMO, millimeter wave, and full duplexing) and have downplayed the possibilities that could otherwise be attainable with their deployment. As a result, intensive research for physical layer technologies that can play a crucial role in B5G networks has begun [11]. The Reconfigurable Intelligent Surfaces (RIS) is a groundbreaking technological option that garnered considerable attention.

Until recently, performance optimization of wireless networks was focused primarily on the network controller side, including components like the base station (BS) and the network operator [12]. However, the electromagnetic propagation medium has remained an uncontrollable feature. Due to the randomness of the electromagnetic propagation medium, the transmitted signal, as a result of reflection, diffraction, and scattering, becomes distorted and attenuated, and delayed copies reach the destination in different paths. This multipath fading has a delimiting effect on the performance of wireless networks. Consequently, researchers within academia and industry are proposing a technique to control electromagnetic propagation by making the environment space somewhat intelligent [13]. The RIS or *intelligent reflective* *surface (IRS)* is simply a surface with real-time reconfigurable and controllable scattering properties (polarization, amplitude, and time delay) to improve the performance of the communication system [14]. In physical terms, a RIS is a two-dimensional, manufactured surface of electromagnetic material composed of reconfigurable scattering elements. The scattering elements are tiny antennas that receive and retransmit signals without amplification but with configurable time delays, corresponding to a phase shift in narrowband signals. These scattered signals from the RIS are subsequently constructively added up at the receiver, depending on the desire of the network designer. With the proper deployment of RIS in the environment, such as in walls of buildings, its elements can be programmed to have a desirable multipath fading effect. This process invariably transforms the previously unpredictable EM propagation environment into an intelligent environment for sensing, analogue computing, and wireless communication [15]. Furthermore, since wireless systems have become device-centric and optimization can occur at both receiver and transmitter, adding a RIS-controlled environment will make the overall system even more controllable to support a more enhanced quality of service.

The concept of *smart wireless communication* provides an added advantage to network operators and designers as it gives them greater freedom when the environment is among the entities to be programmed. A few research works have shown that with proper programming, a smart propagation environment can significantly impact the transmission performance of a wireless communication system [8, 16, 17]. Several works have shown possible use cases of RIS to improve the performance of a wireless communication system by programming the RIS to mitigate the harmful fading effect of the otherwise unpredictable propagation environment. The authors in [18, 19] introduced a novel class of planar metamaterials, which can alter the course of incident electromagnetic waves in a controllable way. The authors in [20] utilized hypersurface tiles in the wireless medium to effectively manipulate the wireless channel. By controlling the current distribution on the hypersurface tiles, they could reconfigure the impinging electromagnetic waves to suit a desirable purpose. The authors in [21] presented another use case of RISs. They employed massive MIMO to realize a smart environment, allowing full-wave control with plasmonic arrays deployed at the transmitter, receiver, and channels. Although ultra-massive MIMO significantly enhances the wireless channel conditions, manipulating the electromagnetic waves can only be performed at the transceivers while the propagation environment remains stochastic. Thus, the channel model cannot be reconfigured using the software. Therefore, it cannot be described as actively having controlled participation in wireless communication [22]. The authors in [23] utilized an artificial neural network (ANN) to explore the optimal setting for manipulating an intelligent wall indoors. This scheme remarkably improved the performance and adaptability of the network. However, the approach in [24] was somewhat different; it utilizes an electronically tunable metasurface known as spatial microwave modulators (SMM) to manipulate the electromagnetic waves. Simulation results show that the appropriate placement of the SMM in an indoor environment, such as an office, enhances the wireless network's performance by manipulating electromagnetic waves. In the next section, we look at the concept of an intelligent radio environment expected in 6G communication networks and shed more light on what features make these reconfigurable surfaces impactful for optimizing the wireless communication process.

3 | Advantages of RIS-Assisted Communications

An intelligent radio environment is a wireless propagation environment whose adaptability is controlled by a controller to improve wireless communication [7]. Thus, control of the wireless medium makes the wireless communication system reconfigurable and adaptable to suit the desired purpose. Currently, the operation of the wireless communication system is elastically optimized and controlled using software to enhance the performance of the network, thereby meeting the quality-of-service (QoS) requirements [25]. Thus, a smart radio environment eliminates the stochastic nature of a propagation medium, replacing it with a more deterministic environment. As a result, optimizing this software-controlled medium improves the performance of the wireless system [26]. Thus, this implies that the integrated intelligent wireless medium into the group of entities to be optimized opens a whole new world of opportunities. Additionally, the technology is anticipated to be a mainstay in future wireless communication [22, 27].

As one of the enabling technologies of 6G wireless communications, it is imperative to understand the constituent elements of the RIS and their effect on its operation in a wireless communication scenario. It is comprised of dielectric or metallic scattering particles with microscopic features that can transform electromagnetic waves differently [28]. These reconfigurable metasurfaces, if properly deployed, provide several benefits to wireless communication systems. Some of the benefits include:

- *Malleability and ease of deployment*:

The RIS comprises metamaterials made of low-cost, dielectric, passive scattering elements. The metamaterials are malleable and easily reshaped into any convention. This unique feature provides it with some flexibility in terms of deployment. Furthermore, as suggested in some works [23, 25, 29], the adaptability of RIS makes it quite easily mounted on surfaces such as walls of buildings and ceilings. Furthermore, it can also fit into tight spaces. Along the same line, these metasurfaces are devoid of active components that perform any signal processing tasks, which can be power draining; as a result, RIS is an exciting candidate for WPT techniques. Figure 1 shows the various use cases of RIS and their integration into wireless networks.

- *The flexibility of control through passive beamforming*:

Another important advantage of RIS-assisted wireless communication networks is their ability to perform passive beamforming by optimizing the phase shifts of the scattering elements. This enables the signal reflections to be directed toward the intended receiver while being nulled in other directions. In many cases, the number of reflecting scattering elements is substantial, depending on the size of the metasurface. Thus, the phase control of the RIS, along with the operational parameters of the transceivers (such as transmit beamforming, power allocation, or resource

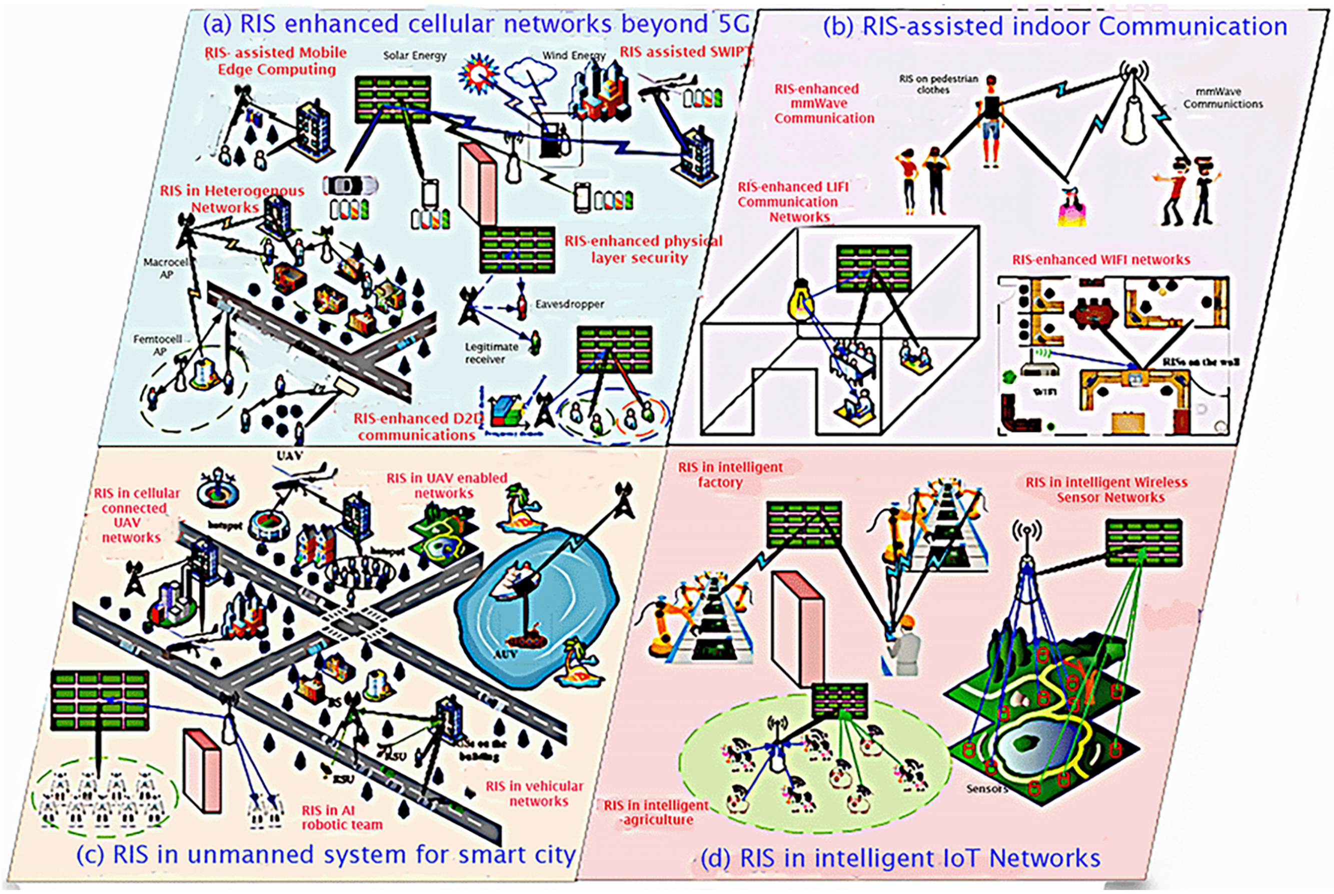

FIGURE 1 | RIS use cases in wireless communication networks [30].

allocation), is jointly optimized to enhance the performance of an IRS-assisted wireless communication system [31].

- *Compatibility with other emerging technologies*:

Since the RIS lacks active components, power consumption is relatively low as the complex signal processing process is non-existent. This factor makes it a good candidate for powering using wireless power transfer (WPT) techniques. WPT is a crucial technology for B5G networks, as recent deployments of the 5G networks have not seen it extensively employed. In 6G, however, the battery-less device regime is expected to soar as communication distances become even shorter, making wireless nodes scavenge even more for ambient RF energy sources for power. With these exciting features of RIS technology, interest within the academia and industry will soar, making it a compelling technology for combination with other emergent technologies/research areas, including unmanned aerial vehicle (UAV) communications, autonomous driving, and mobile edge computing (MEC) [23, 29, 32].

4 | Understanding the Fundamentals and Physics of RIS

Reconfigurable intelligent surfaces (RIS) are 2-D material structures with programmable macroscopic physical characteristics [30]. The most exciting aspect of these surfaces comes from their response to EM waves, particularly their different reconfigurations to meet a desirable user. Applying RIS to a communication network, the channels between the transmitters and receivers can be configured to improve the overall network performance. In addition, the RIS can guarantee improved signal strength at the terminal equipment. This guarantee has made the subject of RIS an exciting prospect when discussing the nascent technologies for the 6G or beyond 5G era. Discussions on other intuitions on the fundamental principles of the RIS operation and exactly how the EM waves trigger its responses are laid bare in subsequent sections. However, before these discussions, it is imperative to understand the different categorizations of RIS.

4.1 | Categorization of RIS

Although several design considerations for reconfigurable surfaces have been in the works now [33], their analysis and application to the wireless communication industry are still in their infancy [34]. As a result, we can define some salient categorizations for RIS in a wireless communication system. Depending on the design objective, we can classify a RIS based on placement in the wireless network. Furthermore, a different RIS classification based on its composite structure is also studied. The following section describes several principles responsible for the different modes of operation of RIS and its associated networks to provide an even more in-depth understanding of how RIS-aided networks can achieve even better performance.

1. *Categorization Based on Placement of RIS*
   RIS can be categorized based on its location of operation. They can be located at the transmitter side, known as *waveguide RIS*, or they can be situated between the transmitter and receiver as *refractive RIS* or *reflective RIS*. In each location type, RIS transforms the impinging EM wave into a desired wave propagating in free space [34]. Based on the Surface equivalence principle (SEP) [35], the reflected and refracted EM wave can be measured using an equivalent time-harmonic radiating source on the surface.
   i. Waveguide RIS: A simple theoretical illustration of the waveguide RIS was presented in [36]. The authors analyzed waveguide RIS with its elements modeled as uncoupled magnetic dipoles. The product of the reference wave and each element's polarizability determines the magnitude of each dipole element. Thus, the metasurface can perform beamforming by adjusting the polarizability of its elements. Each scattering element functions as a micro-antenna. The lightweight nature of the metasurfaces makes them able to fit into tight spaces than the traditional antenna arrays.
   ii. Refractive RIS: In [37], the authors proposed a theoretical design of a perfectly refracting metasurface. It highlighted the role of omega-type Bi-anisotropy (a feature of magnetoelectric coupling) in the design of lossless-component realizations of perfectly refractive surfaces [36].
   iii. Reflective RIS: A digital coding reflective metasurface was designed in [38]. Varactor diodes with a tunable biasing voltage are contained within each scattering element of the metasurface. Each scattering element can apply discrete phase shifts to achieve beamforming by predesigning several digitized biasing voltage levels.
2. *Categorization Based on Structure*

a. Brief description of metasurfaces and metasurface types

RIS can be categorized based on structure as metamaterial-based or patch-array based. For a better understanding of RISs, it is necessary to provide a more profound intuition of their features and characterization in relation to the added value it brings to the wireless performance of networks. As described in [5], a metasurface is a manufactured, two-dimensional material of sub-wavelength thickness that shows unique EM properties depending on its structural parameters. The authors in [8] described metasurfaces as artificial materials re-engineered to exhibit special electromagnetic features absent in naturally occurring materials. From the definitions, we deduce some facts that the metasurfaces are manufactured materials with a near-zero thickness which exhibit unique characteristics that transform the impinging electromagnetic waves. In the metasurfaces, the impinging incident and reflection angles are not necessarily the same as spelled out in the law of reflection. The thickness with aligning array arrangement of the scattering elements is responsible for transforming certain features of the impinging incident EM waves. Characteristics such as the angular direction and amplitude of the reflected or diffracted waves depend on the thickness. Thus, the arrangement of the scattering elements in a metasurface alters the resonance frequency, which invariably leads to a change in the boundary conditions leading to a shift in the phase angles of the reflected and diffracted waves.

Metasurfaces are usually fabricated with a specific purpose so that the structure of the scattering elements remains in place. These scattering elements have fixed EM properties that can be tailored differently. For example, metasurfaces can be perfect absorbers at a given frequency. The authors in [28, 39, 40] provide intrinsic analyses of the EM properties of the metamaterials and their impending applications. Given that the fabrication of metasurfaces is for a specific purpose, a challenge arises when that purpose changes, requiring a redesign of the metasurface to fit this new need. This redesigning process is non-sustainable, and this can lead to a considerable rise in OPEX. Also, the structural parameters of the scattering elements forming the metasurface should be re-assessed according to the specific application requirements. This process can also be computationally expensive [35, 41].

On the other hand, reconfigurable intelligent surfaces (RIS) can be configured to control the phase shifts attained by each scattering element. To put it more intuitively, an external stimulus in the form of an incident EM wave impinges on the scattering elements, causing an alteration of the physical parameters. This change, in turn, alters the EM properties of the metasurface without any need for fabrication [42]. However, two pertinent design issues abound; the first is how to design an effective control mechanism to connect and communicate with an enormous size of scattering elements. Second, how can the reflected or refracted wave be re-engineered with complete and accurate control of the phases? The following subsections provide ample discussion on the *RIS* control mechanism to bolster the first issue and point us in the right direction to meet the second issue.

b. RIS control mechanism

To understand the RIS system's control mechanism, we draw inferences from Love's surface equivalent principle (SEP) and the Huygen-Fresnel principle to present a clearer picture. A wireless signal is an EM wave that propagates in 3-D space. EM waves attenuate as they travel through space and interact with scattering particles. According to SEP, the electric and magnetic currents on the surface will uniquely determine the EM field outside or within a surface. This principle implies an alteration of the boundary conditions of the surface or substrate when impinged upon by incident electromagnetic waves. The SEP provides the basis for RIS analysis, particularly in the case of reflective and refractive RIS. However, it stops short of specifying the analysis of the EM field strength produced by the surface currents.

On the other hand, the Huygen-Fresnel principle is used to determine the wireless signal strength at any given point in the field. It asserts that every unobstructed point on a wavefront acts as a source of secondary spherical waves at a specific moment in time. These secondary waves originating from different points mutually interfere [43]. The sum of these secondary waves makes up the wavefront, and hinging on this principle, a quantifiable analysis of the EM field scattered by RIS can be carried out [30].

Waveguide RIS operates by coupling the three-dimensional free-space EM waves with a two-dimensional surface wave. Metasurfaces are 2-D equivalent metamaterials that guide waves through total internal reflection to the desired destination. Thus, the metasurface can be viewed as a hologram, encoding extra information about the radiated signal as it propagates through 3D space [30, 43, 44].

c. Signal analysis of the RIS technology

To properly understand the RIS operation, we will recall our understanding of wave optics to effectively grasp the effect of EM field strength and a beamwidth of an impinging waveform scattered by a passive, perfectly conducting plate of finite size. This understanding will provide a basic intuition of the ideal operation of a RIS.

Figure 2 depicts a rectangular conducting plate of size $(l \times k)$ with a nominal thickness $(e_z = 0)$ located in the horizontal plane (spanned by e_x and e_y). A linearly polarized electromagnetic wave with magnitude E_i impinges on the plate from a source with LoS distance, d_i away. The assumption is that the plane's center is where the Poynting vector enters the plane at $\theta_i = 0$. Due to the spherical nature of the waveform, the distance traveled from the source to the plate's center is $\sqrt{d_i + \frac{l^2}{4}}$. Thus, the phase discrepancy is by

$$q\left(\sqrt{d_i + \frac{l^2}{4}} - d_i\right) \approx \frac{\pi l^2}{4\lambda d_i} \tag{1}$$

The electric and magnetic field distributions of the incident EM wave are respectively given by

$$\boldsymbol{E}_i = E_i e^{-jk(\sin(\theta_i)y - \cos(\theta_i)z)} e_x \tag{2}$$

$$\boldsymbol{H}_i = \frac{E_i}{\eta}\left(\cos(\theta_i)e_y + \sin(\theta_i)e_z\right)e^{-jk(\sin(\theta_i)y - \cos(\theta_i)z)} \tag{3}$$

where η is the impedance of the propagating medium.

The electrons of the metal plate are excited into motion by the electric field, and they move in the direction of e_x but not in the direction of e_y since the electric field is orthogonal to the e_y. Since the plate is sub-wavelength thick, the e_z direction is negligible. The moving electrons induce EM radiation resulting in a scattered wave [34].

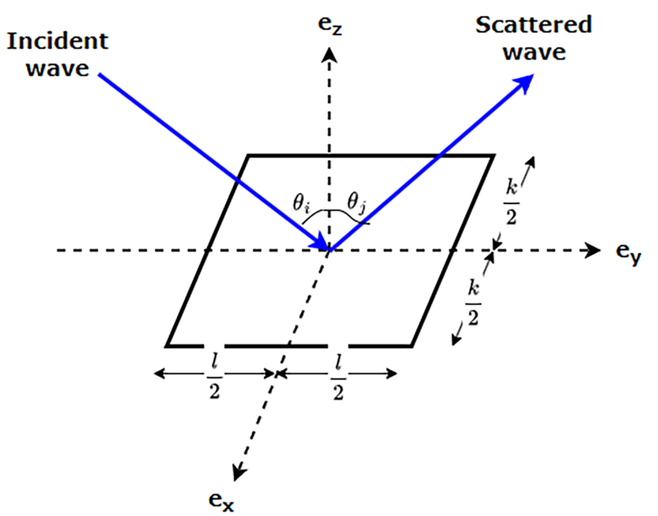

FIGURE 2 | An impinging wave scattered by a $l \times k$ metal plate.

Lemma 1. *The squared magnitude of the scattered field in the e_y, e_z plane and at an arbitrary observation angle, $\theta_j \in \left[0, \frac{\pi}{2}\right]$ (measured in the e_z direction)*

$$\boldsymbol{G}(r, \theta_j) = \left(\frac{lk}{\lambda}\right)^2 \frac{E_i^2}{r^2}\cos^2(\theta_i)\left[\frac{\sin\frac{\pi l}{\lambda}(\sin\theta_j - \sin\theta_i)}{\frac{\pi l}{\lambda}(\sin\theta_j - \sin\theta_i)}\right]^2 \tag{4}$$

At a far-field observation distance,

$$r \geq \frac{2\max(l,k)}{\lambda}$$

The result in (4) neglects edge effects and is drawn from optics techniques in standard physics. For proof of (4), please refer to reference [45] Example 11.

Thus, the magnitude $\boldsymbol{G}(r, \theta_j)$ of the scattered field is directly proportional to the area $(lk)^2$ of the metallic plate and E_i, which is inversely proportional to the square of the distance. From Snell's law, the magnitude $\boldsymbol{G}(r, \theta_j)$ is at a maximum when the observation angle, $\theta_j = \theta_i$. This is the condition for specular reflection for which the term in the parenthesis equals 1.

Figure 3 shows the plot of the normalized squared magnitude $\boldsymbol{G}(r, \theta_j)$ as a function of θ_j for a fixed $\theta_i = 30^\circ$. When l and k are smaller or equal to λ, the magnitude of the scattered field is almost identical in all observation angles. We observed that when l and k are about 10 times larger than λ, the beamwidth gets small, and the magnitude is most prominent when the observation angle is about 30°.

Corollary 1. *A receiving antenna of effective electrical size, $\frac{\lambda}{\mu} \times \frac{\lambda}{\mu}$, located at distance $r \gg \frac{l}{\mu}$ from the plate with an angle θ_j to the antenna's center will receive a signal power given by*

$$\mathrm{G}(r, \theta_j) \times \left(\frac{\lambda}{\mu}\right)^2 \tag{5}$$

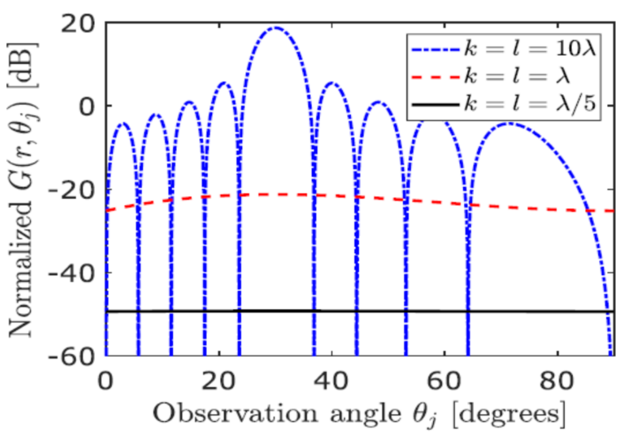

FIGURE 3 | Normalized $\boldsymbol{G}(r, \theta_j)$ versus observation angle θ_j when $\theta_i = 30^\circ$ [34].

Proof. The antenna will see the plate through an angular window of $\frac{\lambda}{\mu r}$ radians. As long as $\frac{\lambda}{\mu r} \ll \frac{\lambda}{l\cos(\theta_i)}$, the field strength will be approximately constant, and the magnitude of the scattered field increases by a scale of the square of $\frac{\lambda}{\mu}$. For line-of-sight propagation, E_i is inversely proportional to d_i^2, the above corollary proves that the received power is proportional to ${}^{(lk)^2}/_{(d_i r)^2}$. The constant of proportionality is dependent on the wavelength and angles. Thus, the received power increases monotonously with l and k when $\theta_j = \theta_i$. As the electron excites, more energy is induced into the radiated plate. □

Furthermore, since the plate is finite, multiple adjacent plates can be deployed together. Moreover, coupling effects are neglected when the plates are sufficiently spaced before applying superposition. Interference (constructive or destructive) develops from the relative phase shift obtained when scattered fields are received at a specific location. Thus, the squared field strength from N plates under constructive interference is given by

$$\left(N\sqrt{\boldsymbol{G}(r,\theta_j)}\right)^2 = N^2\boldsymbol{G}(r,\theta_j) \tag{6}$$

The number of plates N appears in (7) as a joint term Nlk thus $N^2 = (Nlk)^2$.

d. Tunability of RIS: achieving the RIS system model

In wireless communications, RISs, like relays, are mainly used to extend coverage and boost the signal in the receiver's direction. RIS achieves this directivity by performing an anomalous reflection of the incident beam so that the shape of the scattered field is such that it focuses the primary beam on the receiver [46]. However, the ideal case is when $\theta_j = \theta_i$, the passive case discussed earlier suffices.

To put it into better perspective, we consider a similar wave impinging on a RIS of a similar structure as the metal plate in Figure 1. The purpose of the RIS is to focus the reflected beam in the direction of an intended user, denoted by the angle θ_R. The ideal field distributions of the scattered waves are given by:

$$\boldsymbol{E_R} = E_R e^{-jk(\sin(\theta_R)y - \cos(\theta_R)z)} e_x \tag{7}$$

$$\boldsymbol{H_R} = \frac{E_R}{\eta}(\cos(\theta_R)e_y + \sin(\theta_R)e_z)e^{-jk(\sin(\theta_R)y - \cos(\theta_R)z)} \tag{8}$$

The surface impedance transforms the incident wave with distributions $(\boldsymbol{E_i}, \boldsymbol{H_i})$ into $(\boldsymbol{E_R}, \boldsymbol{H_R})$. On the $x-y$ plane, when $z = 0$, the superposition of the incident and reflected electric field can be written as:

$$E_t = E_i e^{-jk(\sin(\theta_i)y)} e_x + E_R e^{-jk(\sin(\theta_R)y)} e_x \tag{9}$$

The desired phase of the reflection coefficient is:

$$\emptyset_R = \angle\left(\frac{E_R e^{-jk(\sin(\theta_R)y)}}{E_i e^{-jk(\sin(\theta_i)y)}}\right) = -q\sin(\theta_R)y + q\sin(\theta_i)y \tag{10}$$

Differentiating with respect to y, we obtain the gradient of the reflection coefficient in the generalized Snell's law:

$$q(\sin(\theta_i) - \sin(\theta_R)) = \frac{d\emptyset_R(y)}{dy} \tag{11}$$

This relationship between $\emptyset_R(y)$, θ_i and θ_R are fundamental in the RIS configuration. With control of the surface impedance, the local surface phase, $\emptyset_R(y)$ is obtained at each point on the surface, and the desired phase of the output wave is obtained.

Thus, the application of the surface impedance to tune the local surface phase is done via various mechanisms such as electrical voltage, optical pumping, or thermal excitation. However, the electrical voltage control mechanism remains the most convenient for wireless communication. The voltage can be quantized and controlled via a field programmable array chip (FPGA), as shown in Figure 4.

The composition of a RIS is such that it consists of several small elements (unit cells) to allow for reconfiguration of the local

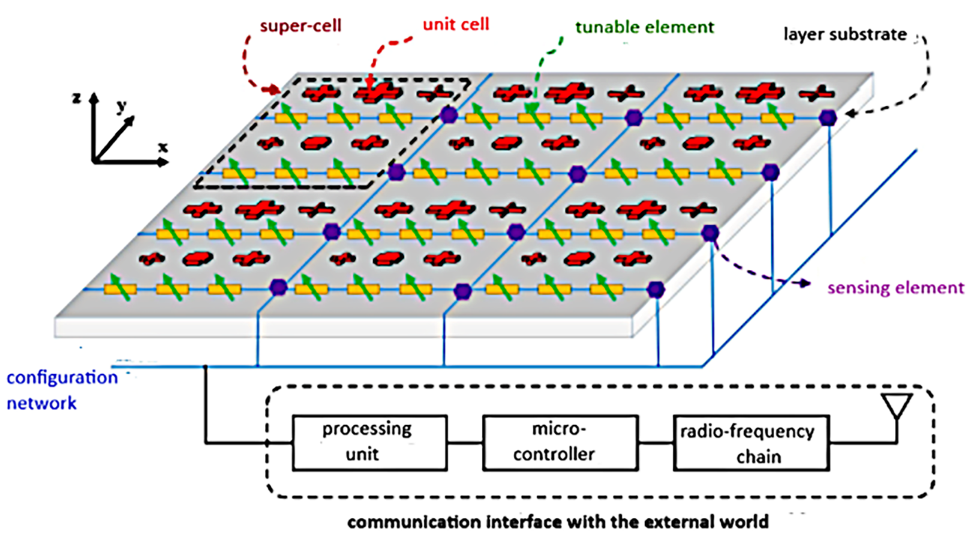

FIGURE 4 | A typical RIS with an extensive array of scattering elements [15].

phases to achieve the main beam with the desired angle, θ_R. As discussed earlier, the electric field of the impinging wave causes the induction of an electric surface current in the e_x direction. This current is manipulated in the RIS by tuning each scattering element's surface impedance to obtain a surface phase profile approximating the generalized Snell's law requirement. This process leads to a scattered wave with maximum amplitude towards θ_R rather than θ_i.

Lemma 2. *The squared magnitude of the scattered field at an arbitrary observation angle $\theta_j \in \left[-\frac{\pi}{2}, \frac{\pi}{2}\right]$ if a RIS is used for the reflection of a signal in the direction, θ_R is given by*

$$\boldsymbol{G_{RIS}}\left(r, \theta_j, E_i^2\right) = \left(\frac{lk}{\lambda}\right)^2 \frac{E_i^2}{r^2} \cos^2(\theta_i) \left[\frac{\sin\frac{\pi l}{\lambda}\left(\sin\theta_j - \sin\theta_R\right)}{\frac{\pi l}{\lambda}\left(\sin\theta_j - \sin\theta_R\right)}\right]^2 \quad (12)$$

At a far-field observation distance,

$$r \geq \frac{2\max(l, k)}{\lambda}$$

The intercepted power is the same in the RIS as in the perfectly conducting plate; however, the maximum magnitude of the scattered field occurs when $\theta_j = \theta_R$. Suppose the transmit power is P_t, and the transmitter has an antenna gain G_t; we can deduce the following relationship:

$$\frac{E_i^2}{2\eta} = \frac{P_t G_t}{4\pi d_i^2} \quad (13)$$

where the effective antenna of the receiver antenna is $\frac{\lambda^2}{4\pi} G_r$ with G_r, the receive antenna gain. Thus, the received signal power for a far-field receiver at a distance r in the direction θ_j is given by:

$$P_r\left(P_t, d_i, r, \theta_j\right) = \frac{1}{2\eta} \boldsymbol{G_{RIS}}\left(r, \theta_j, \frac{P_t G_t \eta}{2\pi d_i^2}\right)\left(\frac{\lambda^2}{4\pi} G_r\right) \quad (14)$$

Corollary 2. *The path loss at the far-field distance r when using a RIS to direct a signal in the direction θ_R is given by*:

$$\beta_{RIS}\left(d_i, r, \theta_j\right) = \frac{P_r\left(P_t, d_i, r, \theta_j\right)}{P_t} = \frac{G_t G_r}{(4\pi)^2}\left(\frac{lk}{d_i r}\right)^2 \cos^2\left(\theta_i\right) \left[\frac{\sin\frac{\pi l}{\lambda}\left(\sin\theta_j - \sin\theta_R\right)}{\frac{\pi l}{\lambda}\left(\sin\theta_j - \sin\theta_R\right)}\right]^2 \quad (15)$$

The ideal case in (16) *occurs when $\theta_j = \theta_R$ making the term in the square parenthesis unity. Thus, the path loss expression becomes*:

$$\beta_{RIS}\left(d_i, r, \theta_j\right) = \frac{G_t G_r}{(4\pi)^2}\left(\frac{lk}{d_i r}\right)^2 \cos^2\left(\theta_i\right) \quad (16)$$

Observation 1. *From inception, our analysis has been generalized to waves having electric fields parallel in the x-direction. However, upon extension to a more general basis, we observe that the resultant path loss expression will still be dependent upon the total effective area $lk \cos\left(\theta_i\right)$ of the RIS*. From the above discussions, let us assume that the RIS of area ($l \times k$) is composed of $N_l \times N_k$ sub-wavelength surface elements, each of size $\frac{l}{N_l} \times \frac{k}{N_k}$ where $\frac{l}{N_l}, \frac{k}{N_k} \leq \lambda$; the path loss between the transmitter and receiver through the *nth* surface element (in the absence of other surface elements) is given by

$$\beta_{RIS}^s\left(d_i, r, \theta_j\right) = \frac{G_t G_r}{(4\pi)^2}\left(\frac{lk}{N_l N_k d_i r}\right)^2 \cos^2\left(\theta_i\right) \quad (17)$$

It is imperative to note that $\beta_{RIS}^s\left(d_i, r, \theta_j\right)$ is the same for all n since it is assumed that

$$r \geq \frac{2\max(l, k)}{\lambda}$$

If $\emptyset_n$ is the local surface phase of the nth element, and constructive interference is adopted for a combined reflection with all other N surface elements to an intending receiver. The path loss between the transmitter and receiver through the RIS is given by

$$\left(N\sqrt{\beta_{RIS}^s\left(d_i, r, \theta_j\right)}\right)^2 = \beta_{RIS}\left(d_i, r, \theta_j\right) \quad (18)$$

Hence, we can think of a RIS as an array of sub-wavelength-sized scattering elements/unit cells that achieve anomalous reflection/refocusing by aligning the phases of their reflected signals at the receiver.

5 | Analysis of RIS in Wireless Communication System

The idea of a smart radio environment is becoming more realizable as the stochastic entity of the wireless network can now be reconfigured to suit the desired purpose by mounting RIS on facades of physical objects within the environment such as walls of buildings, ceilings, signposts as well as other moving objects such as UAVs, trucks, and even floating balloons [8, 47–49]. Using RIS to enhance the wireless communication channel between a source and a given destination entails an even distribution of RIS scattering elements on the physical objects within the channel. Therefore, several factors must be considered when modeling a RIS-assisted wireless communication network. The first consideration is the location or placement of the RIS unit. Next are the electromagnetic properties of the RIS elements. Finally, as seen from Huygens' principle, the manipulation adopted by other waveguides RIS operating within the same environment is also hugely important. As much as discussions on the physics of the RIS elements are essential, their effect on the wireless communication network remains an open issue. To fully comprehend the advantages of RIS-assisted communication networks, we will explore some works that evaluate their performance compared to other technologies like relay networks.

5.1 | Performance Analysis of RIS

This section provides a concise summary of the current works that comprehensively analyze RIS to realize an optimized state-of-the-art C-SWAP (Cost, Size, Weight, and Power) design. These analyses also compare the performance of RIS with other modern technologies. A significant feature of RIS is the large

TABLE 1 | Research contributions on RIS-assisted MIMO networks.

References	Scenario	Design objective	Technique	Users	Direction
[8]	SISO	Outage probability, SER, SINR, ergodic capacity	Comparison with AF relay	Single user	Downlink
[51]	MIMO	Outage probability, ergodic capacity, SE, and EE	Stochastic geometry	Multiple users	Downlink
[50]	SISO	Sum-rate gain	Comparison with DF relay	Single user	Downlink
[52]	MIMO	Outage probability, ergodic capacity, SE, and EE	Signal enhancement using Passive beamforming weights	Multiple users	Downlink
[53]	SISO	Effective channel gain	Comparison with random phase shifting	Single user	Downlink
[54]	MIMO	Effective channel gain	Random matrix theory	Single user	Downlink
[55]	MIMO	Sum-rate gain	Sum-rate gain	Multiple users	Downlink
[56]	SISO	Outage probability	Signal enhancement techniques	Single user	Downlink
[57]	SISO	Outage probability and throughput	Channel gain	Single user	Uplink
[58]	SISO	Effective channel gain	Signal enhancement techniques	Single user	Downlink
[59]	MISO	Sum-rate	Discrete phase shift	Multiple users	Downlink

arrays of minute, inexpensive scattering elements (antenna), which can be optimized to meet design conditions. This extra diversity in the spatial has made RIS an attractive proposition as it continues to garner interest in academia [50] and industry [51]. These studies have repeatedly shown that RIS outperforms other technologies in terms of spectral efficiency (SE) and energy efficiency (EE), although some challenges persist. The first challenge is analyzing and obtaining the exact number of channels between the source and destination on either side of an intermediate RIS. Along the same line, estimating the effective channel gain after passive beamforming at the RIS is another big challenge. Table 1 summarizes some of the designs of RIS-enhanced networks.

5.2 | RIS Against Other Base Technologies

To accurately measure the performance advantage of RIS-enhanced networks, it is imperative to conduct a comparative analysis with other key technologies, such as relays.

a. *Relay Systems*

A relay is generally a cooperative scheme that extends wireless coverage while improving throughput, spectral, and energy efficiency. Relaying can be classified based on protocols can be classified as amplify-and-forward (AF) or decode-and-forward (DF) or based on transmission modes as full-duplex (FD) or half-duplex (HD) modes. The authors in [1] provided a theoretical basis for comparing RIS-assisted networks' efficiency and AF-relay wireless systems. First, they characterized the end-to-end (e2e) wireless channel coefficient of the RIS-assisted wireless system using the probability density function (PDF) and cumulative density function (CDF). They then derived closed-form expressions for both the instantaneous and average e2e signal-to-noise ratio (SNR) for the RIS-assisted and AF-relaying wireless systems. They then calculated the diversity gain, outage probability (OP), and symbol error rate (SER) for various modulation schemes of both systems under consideration. Simulation results show that the RIS-assisted networks outperform the relay networks in terms of SER, OP, and ergodic capacity. A different approach was considered in [60], where an evaluation of the achievable data rate of the RIS-assisted wireless network to a DF relaying SISO network where the direct link between the BS and the user is poor. The observation in [60] is that when the RIS metasurfaces are extremely large, they can outperform DF relaying in terms of the total transmit power and energy efficiency, including the dissipation in the transceiver hardware. The authors in [52, 53] used the principle of maximum ratio transmission (MRT) and maximum ratio combination (MRC) to perform a comparative analysis on the e2e signal-to-noise ratio and the ergodic capacity of the relay-aided network in full-duplex (FD) mode, then half-duplex (HD) mode using the amplify-and-forward (AF) relaying protocol and then the DF relaying protocol. The authors extended this comparison to the RIS. Thus, an established fundamental basis for comparing wireless communications assisted by HD relays, FD relays (with different relaying protocols), and RIS. Related works have been carried out in [61] to analyze the performance of RIS in terms of SNR and ergodic capacity. A hybrid approach was considered in [53] to extend coverage using the RIS-empowered reflection and DF relaying. The two schemes were proposed by drawing on the crucial features of the two technologies. Simulation results showed that a combination of the two technologies presents a better performance in terms of signal-to-interference ratio than when considering a RIS-only system or a relay-only system. They showed that these two exciting technologies could coexist harmoniously under the right transmission conditions through extensive numerical studies and theoretical derivations. Simulation results demonstrated that the relay serves as an additional component that enhances performance in the RIS-assisted transmission scenario, particularly where the channel rapidly

TABLE 2 | Comparison table of RIS and benchmark relay technology.

Scheme	Ad-P	D	RT	Interference	Advantage	Disadvantage
HD with AF relaying	Yes	Yes	No	No	No complexities of decoding at the relay	Amplification of the noise alongside the signal
HD with DF relaying	Yes	Yes	No	No	No self-interference at the relay	High latency
FD with AF relaying	Yes	No	Yes	Self-interference	No complexities of decoding at the relay	Amplification of noise and interference
FD with DF relaying	Yes	No	Yes	Self-interference	No latency	Rate ceiling exists
MIMO relay	Yes	No	Yes	Yes	High spectral efficiency	High cost of deployment Difficult to realize at mm-wave
RIS-assisted	Yes	No	Yes	No	Low-cost materials, capable of high EE and SE, simplistic design	CSI has to be perfectly known

Note: The additional power implies that a different power supply at the relay and RIS. Ad-P, D, and RT stand for additional power, delay, and retransmission, respectively, at the relay/RIS.

deteriorates. Table 2 provides a summarized comparison between the HD relay, FD relay, and RIS-assisted network with characteristics and drawbacks listed therein.

To present a more comparative performance analysis of a RIS-aided systems with a conventional relay-aided systems (AF/DF relay system), we compare key performance objectives of the two systems in terms of power consumption, spectral efficiency, coverage, hardware complexity, cost of production, latency, interference management, and implementation.

- *Signal processing and power consumption*: Although RIS can operate actively or passively in wireless communication networks, the passive RIS are particularly engaged in wireless networks without any signal processing. Its primary function is to alter the phase and amplitude of the incoming electromagnetic waves to enhance signal quality at the receiver [1]. This passive nature allows for extremely low power consumption, with power mainly required for controlling the reflection elements [2]. In configurations where some reflecting elements are active, they are readily low-powered and can utilize energy harvesting or low-power supplies. The requisite active signal processing and amplification in relays makes them more power-consuming and often require dedicated power supplies. Thus, in terms of energy efficiency and/or power consumption, RIS offer significant advantages over traditional relays and given the precincts of the United Nations Sustainable Development goals (SDGs) [62], more precisely with goal number 7, which is more concerned with affordable, sustainable, and clean energy for the environment.
- *Hardware Complexity and cost of production/maintenance*: The simplicity of the RIS infrastructure and its relatively low manufacturing and overall operational cost make RIS more suited to modern wireless communication standards. Furthermore, the potential for easy scalability to larger sizes is very appealing, with its passive nature well suited to dense deployments, as it does not significantly increase interference or power consumption [60]. Relays, on the other hand, have more complex hardware circuitry, including RF chains, amplifiers, and processing units. As a result, relay-aided wireless networks tend to involve higher manufacturing and operational costs, and scaling as the networks get denser incurs significant cost increments and complexity.
- *Spectral Efficiency and Coverage*: Although both can improve spectral efficiency and coverage, RIS provides greater control over the propagation environment, and given the greater degrees of freedom (DoF) [63], it can be tailored to provide better gains in differing channel conditions.
- *Latency*: Achieving real-time communication is crucial for modern wireless applications, including autonomous driving, industrial automation, and virtual reality. A seamless integration of RIS with these emergent applications requires real-time communication with very limited latency for optimal operation. The passive nature of RIS is advantageous for its seamless integration/operation with these trending applications. Furthermore, even lower latency can be achieved by applying some "state-of-the-art" strategies. These strategies include applying faster reconfiguration algorithms [24, 64–67], low latency protocol design [68–70], low complexity reflective elements [67, 68], hybrid RIS design, and channel estimation and feedback reduction [59, 69, 70]. With the relays, there are inherent processing delays, especially associated with the conventional half duplex AF/DF relays.
- *Implementation and deployment*: The adaptability of RIS makes it suitable for integration in existing infrastructure, such as walls, ceilings, and other surfaces, allowing it to be more seamlessly deployed in urban environments or smart buildings [31]. Nevertheless, the performance of RIS systems is vastly determined by careful environmental planning, as the placement of RIS panels and the surrounding physical environment can significantly affect their performance. Moreover, RIS is still an emergent technology, and ongoing standardization efforts are needed to define how RIS will be integrated into future networks. On the other hand, relays are a well-established technology, with standardized deployment and mature strategies for implementation [71]. However, they require dedicated installation sites and regular maintenance, such as ensuring sufficient power supply and managing the active components. Furthermore, relays offer more straightforward network planning since they have a well-understood performance profile in most environments.

Table 3 tabulates this comparative analysis in terms of various performance metrics and presents takeaways pointing in the direction to take for future wireless communication systems.

TABLE 3 | Table showing a comparative analysis of traditional RIS and relay technology.

	Design objective	RIS	Relays	Takeaways
1	Signal Processing and Power Consumption	• Passive reflection with no signal processing [15, 31]. • Extremely low power consumption, mainly for controlling reflection elements. • Can operate without an external power source in some configurations.	• Active signal processing (amplify-and-forward or decode-and-forward). • Higher power consumption due to active components [71–73]. • May require dedicated power supply [74].	RIS offers significant energy efficiency advantages over traditional relays. This makes them more suitable for green communications and IoT applications.
2	Hardware Complexity and Cost	• Simple hardware structure consisting of passive reflecting elements. • Lower manufacturing and deployment costs [6]. • Potentially easier to scale to larger sizes [60].	• More complex hardware including RF chains, amplifiers, and processing units [75]. • Higher manufacturing and operational costs. • Scaling to larger sizes increases complexity and cost significantly.	RIS presents a more cost-effective and scalable solution, especially for large-scale deployments.
3	Spectral Efficiency and Coverage	• Can enhance spectral efficiency by optimizing the propagation environment. • Provides flexible coverage enhancement through intelligent reflection [63]. • Performance heavily dependent on optimization algorithms.	• Improves coverage through active retransmission [76]. • Can provide high spectral efficiency, especially with advanced relaying techniques [50, 77, 78]. • Performance more predictable and less dependent on environmental factors [75].	While both can enhance coverage and spectral efficiency, RIS offers more flexibility in shaping the propagation environment, potentially leading to higher gains in favorable conditions.
4	Latency	• Near-instantaneous reflection with minimal processing delay [60]. • Latency mainly from control and optimization algorithms [79].	• Inherent processing delay, especially in decode-and-forward relays [80]. • Additional latency due to buffering and signal processing [81].	RIS can potentially offer lower latency, particularly beneficial in applications requiring real-time communication.
5	Implementation and Deployment	• Can be integrated into existing structures (walls, ceilings) [24]. • Requires careful environmental planning for optimal performance [20]. • Still an emergent technology with several ongoing standardization efforts [26].	• Well-established technology with mature standards and deployment strategies. • Requires dedicated installation sites and maintenance. • More straightforward network planning and integration [28].	While relays offer a more mature and well-understood solution, RIS presents new opportunities for seamless integration into the environment, potentially leading to more ubiquitous coverage enhancement [24, 26].

From Table 3, we can see that RIS and traditional relays each have their strengths and are suited to different scenarios. RIS excels in energy efficiency, cost-effectiveness, and flexibility, making it promising for future green and massive IoT deployments. Traditional relays offer reliable performance and are well-integrated into existing networks. The choice between them depends on specific application requirements, deployment scenarios, and technological maturity. However, despite RIS being an emergent technology, it demonstrates significant advantages in meeting several key Sustainable Development Goals (SDGs). Its energy efficiency, innovative nature, sustainability, and potential for cost-effective wide deployment make it a more aligned technology with the UN's SDGs.

b. *Surfaces with random phase shifts*:

One significant property of RIS is that it can shift the phase of the impinging incident signal, thereby controlling the amplitude and phase of the resulting reflected signal at the receiver side. The authors in [48] considered two designs of IRS-NOMA, one with coherent phase shifting where the reflected signal matched the incident signals while the other had random phase shifts. Simulation results show that the two designs accomplish different trade-offs between reliability and complexity.

6 | Optimization of RIS-Assisted Wireless Communication Networks

6.1 | System Model for RIS-Assisted Communications

Like any other cooperative communication, the most accurate system model to ascertain the veracity of any assisting link is to measure it against the direct link. In this context, we examine a line-of-sight (LoS) configuration with a direct link between a single antenna source and destination. However, there is also an indirect link between the source and destination through the RIS. The signal received at the receiver is expressed as:

$$y_d = \left(\underbrace{\sqrt{\beta_{RIS}^{s}}\boldsymbol{h}_{sr}^{T}\boldsymbol{\Phi}\boldsymbol{h}_{rd}}_{RIS\ channel} + \underbrace{\sqrt{\beta_{sd}}e^{j\phi_{sd}}}_{Direct\ channel} \right) x + n_d \tag{19}$$

where $\boldsymbol{h}_{sr} = \left[e^{j\psi_1^{sr}}, \ldots, e^{j\psi_n^{sr}}, \ldots, e^{j\psi_N^{sr}} \right]^{\boldsymbol{T}}$ and $\boldsymbol{h}_{rd} = \left[e^{j\psi_1^{rd}}, \ldots, e^{j\psi_n^{rd}}, \ldots, e^{j\psi_N^{rd}} \right]^{\boldsymbol{T}}$ is the normalized LoS from the source to RIS and the RIS to the intended receiver. Let the signal x has power P_t and $n_d \tilde{} \mathcal{N}_c(0,\ \sigma^2)$ is the additive white Gaussian noise with zero mean and variance, σ^2. A diagonal matrix, $\boldsymbol{\Phi}$

with the diagonal elements representing the surface phases of each scattering element. Mathematically

$$\mathbf{\Phi} = diag\left(e^{j\phi_1}, \ldots, e^{j\phi_n}, \ldots, e^{j\phi_N}\right)$$

From the above definition for $\mathbf{\Phi}$, we transform Equation (19) to

$$y_d = \left(\sqrt{\beta_{RIS}^s}\sum_{n=1}^{N} e^{j\left(\psi_n^{sr}+\psi_n^{rd}+\phi_n\right)}\right)x + \sqrt{\beta_{sd}}e^{j\phi_{sd}}x + n_d \tag{20}$$

The RIS can be configured such that $\mathbf{\Phi}$ is selected to maximize the received signal power. Thus, selecting $\phi_n = \phi_{sd} - \psi_n^{sr} - \psi_n^{rd}$ to align all phases in the signal terms in (21), the equation is simplified to

$$y_d = \left(N\sqrt{\beta_{RIS}^s} + \sqrt{\beta_{sd}}\right)e^{j\phi_{sd}}x + n_d \tag{21}$$

Hence, the SNR is given by

$$\text{SNR} = \frac{\left(N\sqrt{\beta_{RIS}^s} + \sqrt{\beta_{sd}}\right)^2 P_t}{\sigma^2} = \frac{\left(\sqrt{\beta_{RIS}} + \sqrt{\beta_{sd}}\right)^2 P_t}{\sigma^2} \tag{22}$$

The second equality term stems from (18). As we have seen from our discussions in the previous sections, an exciting feature of RIS-assisted communication is the transformation of the impinging incident signals by combining constructively with the intended receiver. This combination enhances the signal strength of the reflected signals at the intended receiver. A reverse process can be done for unintended receivers by destructive combination. In [82], proper experimentation of this process formed the basis for further theoretical and practical analyses to improve and optimize the performance of the overall RIS system. The following subsections present an intrinsic review of some state-of-the-art optimized designs for RIS-assisted communication systems. SE maximization, EE maximization, and minimization of transmit powers are some design objectives discussed in these novel works.

6.2 | Spectral-Efficiency Maximization

Most often than not, the wireless communication designer aims to optimize the wireless channel's end-to-end capacity. Emerging technologies continue to churn out regularly to improve the capacity or SNR of wireless networks. RIS is no different and has brought tremendous advantages in terms of SNR enhancements. Several works have aimed at showing how their designs can maximize the SNR. The authors in [82] concentrate on a RIS-enhanced multiple-input single-output (MISO), where multiple passive scattering elements in a RIS are used to support the downlink transmission. The goal of the design is to simultaneously optimize the transmit beamforming of the AP and the continuous phase shift of each scattering unit. To achieve this, a joint beamforming problem was formulated to maximize the received signal power at the receiver. Initially, an approximate solution, serving as an upper bound, was derived using semi-definite relaxation (SDR). The active and passive beamforming strategies are then iteratively modified using alternating optimization. Given the fixed passive beamforming, the maximum-ratio transmission strategy is a simple way to get the AP's optimum beamforming. The RIS's optimal passive beamforming may be aligned with the direct channel to increase the signal strength, provided the AP's beamforming. An increase in the number of scattering elements of the RIS leads to an increase in the SNR of the RIS-assisted MISO system compared to the non-RIS-assisted MISO system. A different RIS design was considered in [83], where a double-faced active (DFA) RIS was deployed to improve the SE of a MIMO network. This novel double-faced structural design enables the RIS to enhance its service coverage which has become restrictive in the half-space design of the conventional RIS. The authors formulated a SE maximization by the joint optimization of the transmit beamforming and the DFA-RIS configuration constrained by the per-element power in the RIS. Due to the large number of constraints, a parallelizable analytic algorithm was proposed, which was guaranteed to converge. Another significant result posted in [31] is that the receiver's SNR increases by a factor of the square of the number of scattering elements. This result was so huge that it was corroborated by recent research, which led to the notion that RIS has better power-scaling laws than massive MIMO (m-MIMO) [84, 85]. The authors in [67] did a comparative numerical analysis of two emerging technologies, RIS-aided networks and massive MIMO networks. This analogy is for a better intuition on why the SNR achieved by the m-MIMO networks was significantly larger than that achieved by the RIS-assisted network while stating that for RIS to achieve a high enough SNR as the m-MIMO, the surface must be substantially large. Similar work was carried out in [58], where a RIS-assisted MISO wireless system was considered. The authors addressed the design challenge of jointly optimizing the beamformer at the access point (AP) and the phase shifts at the RIS. Two algorithms were proposed to solve the resultant non-convex optimization problem, utilizing manifold algorithm and fixed-point iteration techniques. Their simulation results showed that the two algorithms achieved higher spectral efficiency and enjoyed reduced complexities.

Another scenario to consider in designing RIS-assisted wireless networks is multi-user coordinated communications. Our review has only considered single-user cases where SNR maximization was the design objective. An extension to the multi-user case will make the review realistic as the design consideration slightly shifts towards system-wide sum-rate maximization. The authors in [86] considered a multiuser system using multiple RISs. The spatial throughput of the RIS-assisted system can be better than that of the FD-facilitated method, assuming the ideal self-interference cancellation (SIC). It is also demonstrated that the active relays and passive RISs should be used in the network with different strategies to maximize their respective throughputs. In contrast, passive RISs are used to support local rate enhancement. Another interesting observation is that, while the IRS should be placed as close to the BS or user for maximum throughput in the single-user scenario, the multi-user system allows for distributed placement of the RIS to maximize throughput. Furthermore, an intriguing throughput-fairness tradeoff results in equipping the few RISs with more scattering elements to boost throughput and incurs uneven spatial rate distribution of the users.

The authors in [87] considered a RIS-aided MISO system to enhance the overall system's spectral efficiency (SE). They aimed to maximize the SE with user proportional fairness by optimizing the power allocation at the BS and the phase shifters at the RIS. The resulting non-convex optimization problems were solved using iterative alternating optimization techniques for the transmit powers and the phase shifters. Simulation results show improved performance gain in SE over the random phase shift method and the convention zero-forcing transmission method. A similar design was investigated in [70], where the authors utilized a Passive Intelligent Mirror (PIM) for multi-user MISO downlink operation. The transmit powers and the reflection coefficients were optimized to ensure that the sum rate is maximized subject to QoS constraints at the users. The resultant non-convex problem is solved by alternating maximization using the majorization-minimization method. Numerical results show some enhancement in the overall system throughput. However, it is worth noting that the perfect channel information (CSI) was assumed to be known. This assumption will not hold quite accurately with exceptionally large RISs. In [88], the authors considered a MISO downlink system with the design objective of maximizing the weighted sum rate across all the users by jointly optimizing the beamforming at the AP as well as the phase vector of the RIS scattering elements by assuming the first perfect CSI and then imperfect CSI. The simulation results showed that the proposed algorithm performed better when channel uncertainties were below 10%. In [89], the authors investigated a RIS-enhanced MISO downlink communication system to maximize the sum rate. A passive beamformer was developed to achieve near-optimal performance asymptotically, along with a modulation scheme aimed at improving the system's sum rate without causing interference to users. Additionally, a resource allocation algorithm was designed that jointly optimizes user scheduling and transmit power control, balancing the tradeoff between rate fairness among users and the system's overall maximum sum rate.

One general consideration in a sum-rate maximization problem is the difficulty in guaranteeing the individual rate requirement for users in the MISO downlink setting. However, although individual rate constraints can be assigned as in [54, 55], incorrectly setting the minimum rate requirement may not achieve the design objective. This may drastically affect the sum-rate performance. User fairness is essential in multi-user networks to resolve the sum-rate maximization problem. The authors in [90] focused on the downlink of a RIS-assisted multi-user MISO system where the BS communicates with the end users via the RIS with no direct link between the BS and the users. It is assumed that both the BS-to-RIS and RIS-to-user links are line-of-sight (LoS). They developed deterministic approximations for the minimum SINR achieved by the optimal linear precoder (OLP), subject to a power constraint, for any given RIS phase matrix. Simulation results show that the RIS-enhanced network outperforms a half-duplex system with few passive reflecting elements. In contrast, a larger RIS with more reflecting elements can outperform a full-duplex system. In [91], the authors considered a different approach; their goal was to maximize the rate performance while ensuring user fairness by maximizing the minimum decoding SINR of the users in a RIS-assisted MISO downlink network. They jointly optimized the transmit beamforming at the BS and the phase shifter at the RIS. A user ordering scheme based on combined channel strength was proposed to separate the user ordering and collaborative beamforming designs. Additionally, to address the non-convex problem, they developed an algorithm utilizing block coordinate descent (BCD) and semi-definite relaxation (SDR) techniques.

6.3 | Energy Efficiency (EE) Maximization

Another vital consideration in RIS-assisted networks is their ability to minimize the transmit power at the BS, thereby improving the energy efficiency of the entire system. Furthermore, the reconfigurable feature of the RIS makes it flexible enough to be modified to improve the channel conditions between the wireless transceivers, making the BS require less power for transmission. This characteristic has made the RIS a key candidate for green communications. The authors in [72] considered a wideband multi-RIS-aided cell-free network that employed low-powered RISs in place of power-hungry BSs to enhance the EE of the network. To accomplish this, they employed a zero-forcing (ZF) beamforming approach to optimize the active beamforming, while using sequential programming to enhance the passive beamforming at the RISs. The authors finalized by providing a reliable and efficient energy consumption model backed by simulation results. Considering a RIS-assisted NOMA downlink network, the authors in [73] formulated a power minimization problem while optimizing the joint beamformer at the AP and the phase-shifting matrix at the RIS. SDR was first applied to the resulting non-convex problem due to its challenging nature. Then a difference-of-convex (DC) algorithm was used to solve the relaxed optimization problem. Simulation results show a transmission power reduction of at least 8 dB when using a RIS with 50 scattering elements.

Similarly, in [76], the authors considered a RIS-assisted MISO downlink scenario to minimize the total transmit power at the access point (AP) under individual users' SINR constraints. Employing the SDR technique followed by alternating optimization, second-order cone programming (SOCP) was used to optimize the active transmit beamformer at the antenna array at the AP, while the RIS passive beamformer was reduced to a standard relay optimization problem. Furthermore, an asymptotic analysis carried out on the system with an infinitely enormous number of scattering elements on the RIS showed that a factor of the reciprocal of the square of the number of scattering elements on the RIS scales down the transmit power. Numerical results verify a reduced transmit power for the users farthest from the AP.

An entirely different approach was considered in [74, 75, 77], in which the design objective was to minimize the total power in a multi-user MISO downlink system. The users were divided into clusters, and NOMA was used in each group to improve information transmission. Thus, to minimize the total power in the network by optimizing both the BS transmit beamformer and the RIS's passive beamforming, an efficient SOCP-based alternating direction method of multipliers (ADMM) was proposed. Furthermore, a ZF-based sub-optimal algorithm was introduced to minimize computational complexity. The simulation results show a significant performance improvement over traditional SDR-based algorithms, as obtained in [75]. The authors in [76] considered a rather simplistic network where a power amplifier is utilized for reflection amplification between a set of RISs to combat the multiplicative path losses somewhat introduced in the standalone RIS. The authors formulated a capacity maximization problem and analyzed theoretical bit error rate (BER) performance via computer simulations. Results showed that the EE of the system was enhanced while eliminating the multiplicative path losses introduced by the standalone systems.

6.4 | Physical Layer Security Enhancement

Physical layer security (PLS) is an essential aspect of any modern wireless communication system and has received considerable attention from academia and industry in recent years [77, 78]. A few state-of-the-art approaches have been proposed to enhance security at the physical layer [81]. However, these approaches have significant drawbacks in deployment and maintenance costs (or, for short, CAPEX). These drawbacks have led to an even more intensive search for a new energy-efficient and cost-effective paradigm for the next-generation wireless system. The RIS's low cost and wave-manipulating features make it an exciting candidate for the modern physical layer security approach in B5G systems. The wave-manipulating feature makes it flexible enough to simultaneously focus enhanced beams in the direction of the intended receiver while suppressing the beam in other directions (Figure 5). PLS was shown in [82], where a RIS was used to enhance the communication between a legitimate multi-antenna transmitter and an intending receiver in the presence of a single antenna eavesdropper. In the scenario shown in fig. 5 from [79], a transmitter, TX with N_t antennas serves a single antenna legitimate receiver via an IRS (with M phase shifters) in the presence of a single antenna eavesdropper with the TX-IRS, IRS-legitimate receiver, IRS-eavesdropper channel are denoted as $\boldsymbol{G} \in \mathbb{C}^{M \times N_t}$, $\boldsymbol{h}_I \in \mathbb{C}^{M \times 1}$, and $\boldsymbol{h}_e \in \mathbb{C}^{M \times 1}$ respectively. The goal is to prevent the eavesdropper from intercepting the information by placing the RIS close to the legitimate receiver, thereby controlling the reflected signals to the receiver and maximizing the secrecy rate at the receiver. The authors developed an algorithm based on blocked coordinate descent (BCD) and majorization minimization (MM) to solve the secrecy rate maximization problem. Simulation results showed that the secrecy rate is enhanced when a RIS is deployed within the communication system. For more intuition, the secrecy rate is a measure of information that can be sent securely over a communication channel at a given time [78–80]. Other works posting similar designs on RIS-assisted PLS can be found in [84].

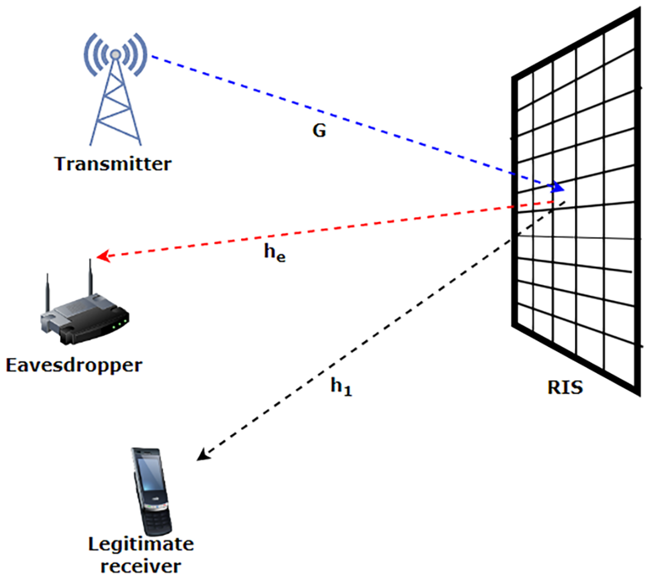

FIGURE 5 | A RIS-assisted secure communication system [79].

The authors in [85] considered a challenging scenario where the eavesdropping channel has better channel conditions than the intended communication link, with both links highly correlated in space. The design objective of maximizing the secrecy communication rate was enhanced by jointly optimizing the transmitting beamformer at the AP and the phase shifter at the RIS. The authors devised a sub-optimal solution using SDR and alternative optimization to solve the resulting optimization problem. Results show significant improvement in the secrecy rate in the RIS-assisted system over one with no RIS in its setup. The authors in [86] considered a multi-channel scenario for improving the PLS of a wireless communication system consisting of a BS transmitting to multiple users in the presence of numerous eavesdroppers. Various RISs assist the communication with the assumption that line of sight (LoS) exists only between the BS, the users, and the RISs due to the propagation in the terahertz spectrum, which the 6G standard may adopt. Each RIS randomly generates reflection coefficient matrices and employs them for pilot signal in the uplink and data transmission in the downlink. The BS selects the links to the user with the best secrecy for each reflection matrix generated. Numerical results in [89] show that the secrecy rate of the proposed scheduling scheme exceeds other conventional systems. Another fascinating work on PLS was done in [90], where the authors developed a simple scheduling scheme exploiting information jamming to improve the secrecy rate of a 2-way communication via RIS. There is an eavesdropper amid the two-way communication where the signal of one user is exploited as a source of helpful information jamming to degrade the eavesdropping link. The lower bound of the average secrecy rate and its scaling laws were derived to assess secrecy performance. Simulation results confirm the validity of the theoretical analysis and demonstrate an enhancement in secrecy performance compared to other benchmark schemes.

Other physical layer security techniques to mitigate potential vulnerabilities in RIS-aided systems include secure beamforming techniques [92], artificial noise injection [93] interference management techniques such as adaptive nulling for hostile jammers [94, 95] and application of redundant control paths [96]. Table 4 lists some of the potential physical layer vulnerabilities of RIS-aided wireless communications and their mitigation measures.

TABLE 4 | Physical layer vulnerabilities of RIS-aided networks and possible mitigation measures.

	Physical layer vulnerability	Mitigation measure
1	Eavesdropping Attacks: This refers to the unauthorized interception of reflected signal	• Secure beamforming optimization [92, 97–100] • Artificial noise generation [93, 101] • Physical layer encryption [102] • Random phase shifting [103] • Directional Modulation [104]
2	Jamming Attacks: This refers to the deliberate of RIS operation	• Adaptive nulling [95] • Anti-jamming techniques [105] • Frequency hopping [106] • Power allocation optimization [107, 108]

6.5 | RIS Performance in Dynamic (Rapidly Changing) Environment

RIS offer significant potential for wireless communication in environments with rapidly changing propagation conditions [109, 110]. However, their performance in these dynamic scenarios presents both opportunities and challenges worth examining.

a. *Adaptive Capabilities in Fluctuating Environments*

RIS technology demonstrates remarkable adaptability to environmental changes, though implementing this adaptability requires sophisticated control systems:

Deep Reinforcement Learning (DRL) frameworks have emerged as effective solutions for dynamic RIS configuration in Non-Orthogonal Multiple Access (NOMA) systems. These approaches enable real-time adjustments without relying on offline training models [111].

Contemporary DRL implementations can rapidly respond to environmental fluctuations while maintaining equitable service distribution among users across changing conditions [111].

b. *Real-Time Channel Estimation Challenges*

The effectiveness of RIS in dynamic environments heavily depends on accurate channel state information, which becomes increasingly difficult to obtain as conditions change:

Mobile deployment scenarios, particularly those involving unmanned aerial vehicles (UAVs) [112], can introduce additional complexity to channel estimation due to the compound mobility of both the RIS platform and communication endpoints [111].

Research is advancing in predictive channel modeling using machine learning techniques that can anticipate channel states in highly variable environments, potentially overcoming the latency limitations of traditional estimation methods.

c. *Environmental Context and Performance Variation*

The performance profile of RIS technology varies substantially depending on the deployment context:

Indoor implementations consistently demonstrate superior performance metrics compared to outdoor deployments, likely due to more predictable multipath characteristics and controlled interference patterns [113].

Effective indoor deployment requires RIS installations to exceed certain dimensional thresholds to meaningfully influence propagation characteristics beyond ambient multipath effects [114].

d. *Fading Conditions Response*

Dynamic environments present diverse fading scenarios that significantly impact RIS performance:

Recent studies have conducted thorough analyses of RIS-enabled communication systems under various fading models, including the crucial effects of phase noise on signal quality [110].

This research provides essential insights for optimizing RIS phase configurations to counteract specific fading patterns in changing environments.

e. *Computational Resource Requirements*

Managing RIS functionality in dynamic settings presents substantial computational challenges:

Large-scale deployments featuring numerous RIS elements require significant processing capability to calculate optimal configurations in response to environmental changes [115].

Current research focuses on developing computationally efficient algorithms that can determine near-optimal RIS configurations with reduced processing requirements, making real-time adaptation more feasible [116].

While RIS technology demonstrates considerable promise for enhancing wireless communications in dynamic environments with rapidly changing propagation conditions, realizing this potential is dependent upon addressing several key challenges. Ongoing advancements in deep reinforcement learning, predictive channel modeling, and computationally efficient optimization algorithms continue to improve RIS performance in these challenging scenarios, pointing towards increasingly robust implementations in the future.

f. *Adoption of RIS in Wireless Communications Design (Single vs. Multi-RIS-Aided Strategies)*

Adopting RIS technology in wireless networks has enhanced performance metrics such as spectral efficiency, energy efficiency, and coverage. However, most existing works have considered adopting a single RIS, which has seen the emergence of channel-rank deficiency computation problems [117]. In addition, this design considerably limits the system capacity in multi-user systems. A multi-RIS assisted network where the RISs are deployed in a distributed manner can eliminate this channel rank problem given that the base station to RISs channels can be generated as a sum of multiple rank-one channels, guaranteeing higher rank channels. Table 5 highlights some works that have employed multiple RIS to enhance system performance compared to the conventional single RIS designs.

7 | Integration of RIS With Other Emergent Technologies

The sections above show that RIS-assisted networks can achieve tuned channel gains and provide better QoS and increased coverage. Also, they improve the energy efficiency of the wireless communication network they serve.

Figure 6 depicts a diagrammatic representation of a combination of RIS with some emergent technologies. The combination

TABLE 5 | Multi-RIS-aided communication networks.

References	Design objective	Direction	Scenario	Technique
[118]	Secrecy rate maximization	Downlink	Single user	SDR
[63]	Energy efficiency maximization	Downlink	Multi-user	SDR, SCA
[119]	Weighted sum rate maximization	Downlink	Multicell multi-user	MM, CCM
[120]	Mean square error minimization	Uplink	NOMA	Federated learning
[121]	Ergodic capacity & Outage probability	Downlink	Single user	Method of moments

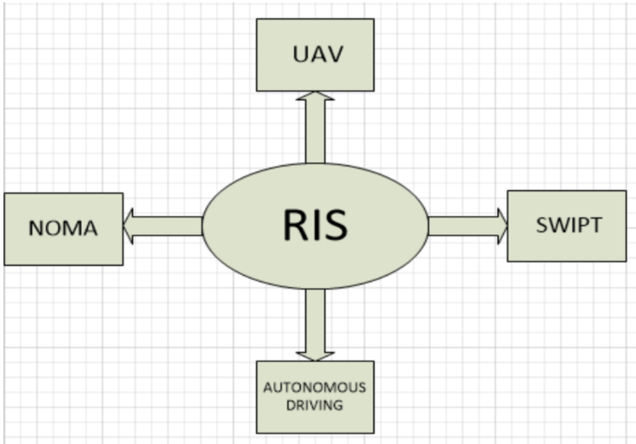

FIGURE 6 | RIS with some identified emergent technologies.

of RIS's enhancement features with other emergent technologies as shown in Figure 6 will further boost network-wide performance. This section identifies some emergent technologies and reviews the state-of-the-art when combined with RIS. The following subsections discuss some of these research works and identify some research opportunities for further exploration of the next-generation networks. The recognized emergent technologies include NOMA, SWIPT, autonomous driving networks, and unmanned aerial vehicles (UAV).

7.1 | RIS-Assisted NOMA

With the proliferation of advanced multimedia applications (such as ultra-high-definition video and virtual reality), the capacity requirements for wireless communications have surged to an unprecedented, all-time high. The challenge for 5G communications networks is dealing with large-scale heterogeneous data traffic due to the ever-increasing demands for user access brought about by introducing common trends such as IoT and smart cities [63]. The authors adopted non-orthogonal multiple access (NOMA) to mitigate the challenges and accommodate several users in one orthogonal resource block. The process improves the spectral efficiency of the entire network. This same can be said for the RIS-assisted network in [122]. The spatial directions of the channels of the near users are used at the BS to obtain orthogonal beams using SDMA. Then the cell-edge users are served on these beams by aligning their channel vectors to the beams with the aid of the RIS, emphasizing the advantages of NOMA [123]. The work in [89] considered a RIS-aided multi-cluster MISO downlink communication system. The design-objective is to minimize the total transmit power by optimizing the transmit-precoding vectors and the reflecting coefficient vectors.

A low-complexity SOCP-ADMM algorithm was developed to provide the locally optimal solution as the conventional SDR approach exhibited high computational complexity and deteriorating performance. Similarly, the authors proposed a resource allocation framework in a multi-cell RIS-NOMA network [124], where they deployed a RIS to improve the wireless service. The design objective is to maximize the achievable sum rate by jointly formulating the power allocation, sub-channel assignment, and phase shift. A challenging mixed integer non-linear programming (MINLP) results decomposed into two sub-problems solved using successive convex approximations and swap-matching. From the numerical results, the authors make three essential deductions: the first observation shows that incorporating RIS in the network enhances the sum rate of multi-cell NOMA networks. The second observation is that the proposed algorithms for RIS-assisted multi-cell networks can have higher energy efficiency than conventional NOMA counterparts. Finally, the third observation shows that the trade-off between spectrum efficiency and coverage area can be tuned by judiciously selecting the number of cells in the network [73].

The combination of massive MIMO and NOMA technologies in wireless networks will give rise to networks with unprecedented spectral efficiency and shallow latency levels. However, the harsh wireless channel environment remains a challenge that undermines the advantage of such a network. Including RIS in such a network mitigates the environmental challenge; thus, the network can obtain high energy efficiency, enhanced network coverage, and improved fair resource allocation [125]. Despite the significant performance gains of the RIS-enhanced multi-antenna NOMA systems, several lingering drawbacks still abound. One such challenge lies in the determination of the optimal user orderings. Dynamic optimization of the RIS relies on instantaneous realizations of the direct link from BS to users and the indirect link from BS to RIS to the user. This optimization is also contingent on the current state of scattering elements, which relate to the RIS coefficients and the users' successful channel gains (and thus the users' orderings). Therefore, having many users with an extremely large RIS with an enormous number of scattering elements increases the complexity of the optimization problem, making it realistically almost unrealizable.

7.2 | RIS-Aided SWIPT Networks

SWIPT wireless networks have the added advantage of improved SE and EE, making them attractive proposition for the internet

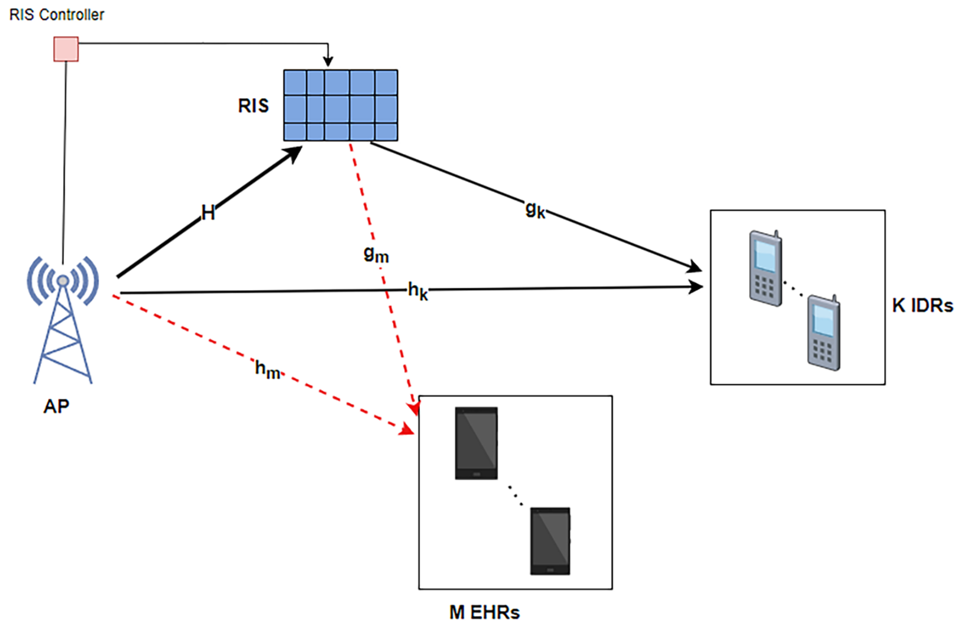

FIGURE 7 | A SWIPT system supported by a RIS [99].

of intelligent things (IoITs). However, due to the different power sensitivity of the energy-harvesting receivers (EHRs) and the information-decoding receivers (IDRs), co-locating the receivers has become impracticable as the EHR with higher power sensitivity can have a debilitating effect on the information content of the signal [126]. Thus, a typical practice is to place the EHRs closer to the BS while the IDRs are further off. Incorporating a RIS can be advantageous in this design as its passive beamforming feature can boost the signal strength at the IDRs while improving the energy efficiency of the wireless power transfer at the EHRs. Recall from [127] that the RIS can generate a "signal hot spot" and an interference-free zone in their vicinities via joint active beamforming at the AP and passive beamforming at the RIS. This feature mainly appeals to WPT and, thus, the EHR in SWIPT networks. There is limited state-of-the-art literature on RIS-aided SWIPT networks, but the few available came out with excellent observations. In [128], the authors considered a RIS SWIPT network with multiple antennas BS communicating in the downlink via a RIS with several multi-antenna IDRs while guaranteeing the EH requirements at the EHRs. The design objective is to maximize the weighted sum rate at the IDRs while jointly optimizing the transmit precoding of the BS and the phase shift matrix of the RIS. BCD decouples the resultant optimization problem into several sub-problems while utilizing low-complexity iterative algorithms to find the Karush-Kuhn-Tucker stationary point. Simulation results confirm that combining RIS with SWIPT improves the overall system performance and posts faster convergence times. The authors in [99], captured in Figure 7, considered a scenario where RIS assists a SWIPT system. The SWIPT network consists of an AP with multiple antennas serving multiple IDRs and EHRs. The design objective is to maximize the weighted sum power received by the EHRs by jointly optimizing the transmit precoders at the AP, and the reflect phase shifts at the RIS subject to individual SINR at the IDRs. The authors proposed an efficient AO algorithm to solve the resulting non-convex problem. In [129, 130], the authors designed an energy-efficient secure RIS-aided SWIPT system, as shown below. The design goal is to maximize the overall energy efficiency of the system by jointly optimizing the transmit beamforming vectors at the access point (AP), the artificial noise (AN) covariance vector at the AP, and the phase shifts at the RIS. Initially, they applied semidefinite relaxation (SDR), followed by an efficient algorithm based on alternating optimization to address the non-convex optimization problem. Simulation results indicate that energy efficiency improves with the use of RIS.

7.3 | RIS-Aided UAV

The agility of UAVs has made them a viral adaptation in many fields. The significant feature of the high altitude in which they can operate allows them to mitigate the bottlenecks of several challenging scenarios, such as urban blockages, emergency services, and remote and difficult-to-reach areas. UAVs have become a popular option in applications for security surveillance [131, 132], disaster rescue missions [133, 134], pipeline monitoring, and geographical exploration [131, 135].

The integration of RIS and UAV offers a number of benefits to enhance wireless communication performance. Some of the benefits as a result of RIS-UAV integration include:

- Enhanced Coverage: RIS can be strategically placed to reflect and redirect signals around obstacles, creating virtual line-of-sight (LoS) links between UAVs and ground users.
- Improved Signal Strength: Intelligent configuration of RIS elements can constructively enhance the quality of the signal at the desired receivers, thereby enhancing the quality of the communication.
- Interference Mitigation: RIS can be used to create destructive interference at non-intended receivers, reducing unwanted signal interference.

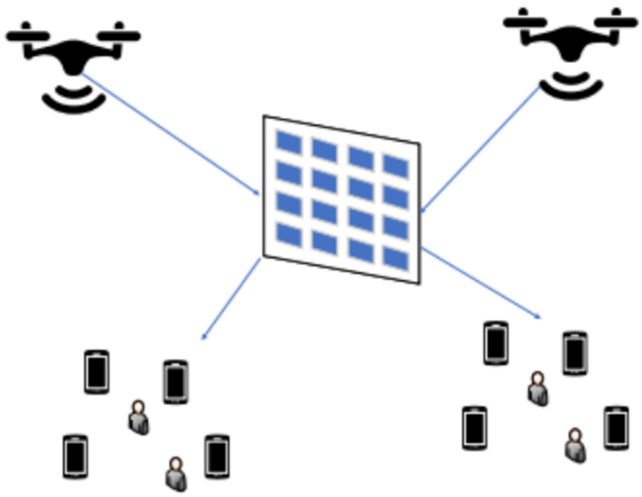

FIGURE 8 | RIS-aided UAV wireless communication system [107].

- Energy efficiency: Unlike traditional MIMO systems or active relays, RIS passively reflects signals without requiring RF chains, significantly reducing power consumption and hardware costs. In recent times, researchers have been exploring various approaches to optimize energy efficiency in RIS-UAV assisted multi-user communication. Several energy efficiency optimization techniques have been studied in the literature ranging from Beamforming and power allocation [136], UAV Trajectory and RIS configuration [137], and SWIPT integration [138]. An intriguing approach, captured in Figure 8, was considered in [139]. The authors proposed a centralized DRL approach for maximizing the energy efficiency (EE) of the RIS-aided UAV networks by jointly optimizing the UAVs' power allocation and the RIS's phase-shift matrix. They also proposed a parallel approach to mitigate the information transfer bottleneck of the centralized process. Simulation results show improved performance of both DRL approaches over the conventional system in terms of EE, flexibility, and processing time. Another interesting novel approach was proposed in [140] using a Stackelberg game formulation. In this work, the UAV acts as leader, determining the optimal RIS phase-shift angles to maximize the overall received signal strength. The users act as followers, participating in a non-cooperative game to maximize their utility by deriving optimal uplink transmission power. This approach aims to achieve power savings and improve overall user satisfaction in smart city environments.

Despite the benefits, the integration of Reconfigurable Intelligent Surfaces (RIS) with Unmanned Aerial Vehicles (UAVs), especially in multiuser environments, presents complex challenges that fundamentally reshape wireless network optimization. A primary challenge lies in the simultaneous management of multiple user requirements while coordinating RIS-equipped UAVs, where the system must balance diverse Quality of Service (QoS) demands, varying user mobility patterns, and dynamic channel conditions. This complexity is further amplified by the need to optimize RIS phase-shifts and UAV positions simultaneously for multiple users, often with conflicting requirements, while managing interuser interference and maintaining fair resource allocation across the network.

The operational dynamics of multiuser UAV-RIS systems introduce unique challenges in resource management and user scheduling. Critical considerations include the development of efficient user grouping strategies, dynamic bandwidth allocation, and adaptive power control mechanisms that can respond to rapid changes in user distribution and demand patterns. The system must also address the challenge of maintaining stable connections for multiple users while managing UAV mobility constraints, energy limitations, and RIS configuration updates. This necessitates sophisticated scheduling algorithms that can prioritize users based on their requirements while ensuring system-wide optimization of resources and maintaining acceptable service levels for all users.

Additionally, the practical deployment of multiuser UAV-RIS systems requires careful consideration of scalability and performance optimization across varying user densities and distribution patterns. Solutions must encompass intelligent beam management strategies that can serve multiple users simultaneously, adaptive UAV positioning algorithms that optimize coverage for user clusters, and efficient channel estimation techniques that can handle multiple user links concurrently. The system also needs to incorporate robust interference management mechanisms and user-specific beam tracking algorithms while maintaining the energy efficiency of the UAV platform. Success in deploying such systems ultimately depends on developing integrated approaches that combine sophisticated multi-user MIMO techniques, efficient resource allocation protocols, and advanced optimization algorithms specifically designed for the challenging dynamics of aerial RIS platforms serving multiple users simultaneously.

7.4 | RIS-Aided Vehicle-to-Infrastructure (V2I) Communication for Autonomous Driving

Autonomous driving or self-driving cars are powered by V2I communications, which provide reliable, secure, and seamless real-time wireless data exchange between vehicles and other road infrastructures such as vehicles, road signs, traffic lights, and other roadside BS. This connectivity is bidirectional, enabled by hardware, software, and firmware systems. Autonomous driving is widely expected to revolutionize road traffic demanding realities, thereby improving mobility/mobility patterns, safety, and traffic efficiency. Over the last few years, intensive research within academia and industry towards improving the prospects of V2I communication for self-driving cars. However, some challenging aspects still need to be navigated for self-driving cars to deploy on the road safely. One of these challenges is the complex channel terrains in the urban environment associated with wireless data transmission and the meandering road network navigating hills and mountains in the not-so-urban areas. RIS can be deployed on these vehicular networks to improve efficiency and performance. The authors in [141] showed that applying a RIS in the vehicular ad-hoc networks (VANETs) significantly reduces the outage probability of vehicles within its vicinity. They also showed that better results are obtained with more RIS elements. In [142], the authors investigated the physical layer security of different RIS-aided vehicular network system models in the presence of eavesdroppers. Results showed that the system's performance in terms of secrecy outage probability and average secrecy capacity mainly depends on the number of RIS elements and the placement distances of the RIS. The authors in [143] considered a RIS-aided VANET consisting of a RIS-enabled beacon vehicle and client vehicles. Using Fox's H-function distribution, the V2V approach modeled the communication links between the beacon and client vehicles caused by multipath fading. Performance evaluation of the generated models showed improvements in outage probability and effective rate.

The overall goal of autonomous driving is safety; this is accomplished if traffic rules are followed. Thus, from a general perspective, reliability and security are top for autonomous driving. Hence, for proper implementation of RIS-enhanced V2I-assisted autonomous driving, the wireless service quality at every time slot is of utmost importance. However, the question of the reliability of RIS-enhanced autonomous driving still abounds and remains a limiting challenge.

8 | Machine Learning for RIS-Assisted Wireless Communication

As wireless standards transitioned from 1G to 5G, researchers in academia and industry have tended to optimize the wireless communication system at either the source (e.g., the BS) or the destination (e.g., the end users). With the recent introduction of RIS, the stochasticity or randomness of the wireless propagation channel can also be tailored and optimized efficiently. From the previous sections, it is fair to say that intensive research carried out over the last years on RIS-assisted networks has shown tremendous improvement in SE and EE. A keen observation from the state-of-the-art on RIS-assisted networks is that many of them formulated their design objective based on the joint optimization of the active beamforming at the APs and passive beamforming at the RIS. This optimization problem is a non-convex problem that is often solved using the alternating optimization framework to find the sub-optimum. However, the resultant algorithmic solution is highly computationally complex for larger RIS with many scattering elements, making its viability difficult in a dynamic radio environment. Therefore, a more generalized approach capable of handling an ample state space with fast learning capabilities is essential due to the growing data size in wireless communication [27]. Therefore, the interest in machine learning techniques for wireless communication has risen remarkably over the last decade [144, 145]. This section surveys existing research contributions that apply ML techniques to tackle challenges in RIS-assisted networks. Several machine-learning techniques exist; however, we will probe into the most common ones related to RIS-assisted wireless networks in the reviewed literature.

8.1 | Deep Learning for RIS-Assisted Communication Networks

Deep learning (DL) is a specialized machine learning technique that conducts the learning process by extracting and refining data features using Artificial Neural Networks (ANNs) [102–104]. This concept of learning has come up in leaps and bounds to revolutionize the wireless communications industry as the amount of traffic and the number of nodes in the wireless communication system continue to surge. Deep learning techniques are well suited to RIS-aided communication networks, not just because of their ability to handle enormous data but also because of their ability to efficiently learn and approximate input features [110].

Acquiring timely and precise channel state information (CSI) is necessary for communication systems, especially MIMO networks. However, obtaining the CSI comes with challenges, such as sacrificing some throughput and dealing with additional computational complexities. Moreover, in m-MIMO, with an enormous number of antenna elements, CSI acquisition becomes even more cumbersome. This challenge becomes even more cumbersome with RIS because of their passive nature (passive beamforming), unlike AF relays or other active devices that can send training sequences for channel estimation. However, with its potent learning capabilities, DL can be adopted to mitigate this drawback.

The authors in [146] considered an unsupervised learning methodology for the RIS's passive beamforming optimization focused on a well-trained DNN making real-time predictions. Simulation findings show that the DL approach achieves near-optimal efficiency in less time than traditional SDR-based techniques. In [147], the authors considered a transmitter-receiver communication aided by a sizeable intelligent surface (LIS) with many reflecting elements. Due to the massive number of reflecting surfaces, CSI estimation and beam training are challenging. Moreover, such a set-up's computational complexity and power consumption are exceptionally high. As a result, the authors proposed a compressive sensing and deep learning approach to directly learn the LIS reflection matrices from the sampled channel information without prior knowledge of the LIS phased array geometry. In [16], the authors considered a passive/active RIS architecture with a few RF chains. They proposed a compressive sensing channel estimation method with a complex value de-noising network for mm-wave RIS communication systems with low training overhead. The authors observed a remarkable reduction of the normalized mean square error (NMSE) with a few elements activated in the training phase. Furthermore, there was an improved performance in fleeting time with the deep learning method.

The authors in [148] followed another interesting approach. The authors considered dual-hop communication through a RIS with no line-of-sight path between the source and destination. A signal detection technique based on deep learning was proposed to estimate channels and phase angles from a signal reflected via the RIS. A significant advantage is that it drops the pilot signaling phase, reducing transmission overhead. The authors in [27] considered a deep neural network (DNN) approach for efficient online wireless configuration of a RIS when deployed in an indoor communication environment. The offline training phase creates a fingerprinting database of the users' coordinates. The effectively trained DNN maps user positions to the configuration of RIS unit cells to optimize SNR. Simulations using ray tracing in a 3D environment demonstrate that this DNN-based configuration method enhances system throughput at the user's location.

8.2 | Reinforcement Learning for RIS-Assisted Communications

Reinforcement learning (RL) is a special kind of learning where an agent aims to maximize its long-term reward by interacting with the environment based on a trial-and-error process. The reinforcement learning approach allows a feedback loop between the agent and the environment, permitting the agent to experience dataset changes over a period due to its interaction with the environment [30]. RL is well suited to RIS-assisted networks as it will enable the agent (BS/RIS) to quickly learn from their interactions with the environment (users' conditioning) to improve the quality and performance of their network. The challenge of computational complexity in larger RIS is wholly overcome with RL-based RIS-assisted networks. Also, scenarios with ample state space can combine RL with deep neural networks to give rise to deep reinforcement learning (DRL). The DRL is an effective technique as it combines the ability to interact with the environment and then utilizes the robust function approximation available in deep learning; it can depict the action. Thus, DRL or RL techniques are prototypical for solving challenging problems in wireless networks.

RL algorithms can be value-based, policy-based, or actor-critic algorithms. Value-based RL is suitable for scenarios with discrete state and action spaces, whereas policy-based RL is applicable in continuous state-action spaces. Also, the classification of the RL algorithm can be online or offline, depending on the training phase. Given the discrete phase shifts in RIS, a DRL is best suited for tackling the phase shift design problem.

Table 6 summarizes a few RL-based solutions for RIS-assisted wireless communications. Several RL-based RIS-assisted communications exist in the literature; the authors in [17] considered a MISO scenario where an AP was transmitting through a RIS in the downlink to a cluster of users. They leveraged a deep deterministic policy gradient (DDPG) neural network to jointly optimize the transmit-beamforming matrix at the AP and the phase shift matrix at the RIS.

The RL design has reduced complexity compared to the iterative, alternating optimization techniques. For example, in [160], the authors utilized DRL tools to devise an algorithm that maximizes the achievable transmission rate by directly predicting the interaction matrices with minimal beam-training overhead, which reduces complexity and time by dropping a chunk of the training phase.

In [159], the authors proposed a novel framework for optimizing a millimeter wave base station's downlink multi-user communication aided by a reconfigurable intelligent reflector (IR). They developed a robust two-phase DRL algorithm to maximize the system throughput while considering perfect and imperfect CSI. The first phase assumed a perfect CSI with the joint optimization of the BS transmit precoder and the RIS's reflection coefficient. In the second imperfect-CSI phase, they utilized a quantum–regression–distributed deep-reinforcement learning (QR-DDRL) algorithm to learn the optimal reflection and, thus, the maximum expected downlink capacity. The flexibility of the DRL technique was shown in [118], where they extended their study to PLS. The design goal was to maximize the secrecy rate by jointly optimizing the transmit beamformer at the BS and the phase shift matrices under time-varying channels.

TABLE 6 | Some RL-based solutions for RIS-assisted wireless communications.

References	System model	Design objective	End-user	RL algorithm	Algorithm type
[149]	Multi-hop Terahertz Communication	Maximization of coverage	Multiple	Deep Deterministic Policy Gradient (DDPG)	Actor-critic
[150]	MISO downlink NOMA	Sum rate maximization	Multiple	DDPG	Actor-critic
[151]	MISO communication	SNR maximization	Single	DDPG	Actor-critic
[152]	MISO communication	Transmit power minimization	Single	DDPG	Actor-critic
[153]	MISO communication	Sum rate maximization	Multiple	DDPG	Actor-critic
[154]	Vehicular communications	Achievable rate	Multiple	DQN	Value-based
[17]	OFDM-based communication network	Achievable rate	Multiple	DQN	Value-based
[155]	Multi-RIS uplink	Sum rate maximization	Multiple	DQN	Value-based
[156]	RIS-assisted UAV communications	Minimization of sum Age-of-information	Multiple	PPO	Policy-based
[157]	MISO downlink	Energy efficiency maximization	Multiple	D3QN	Value-based
[158]	UAV-RIS wireless networks	Optimized beamforming and trajectory of UAV	Multiple	DDQN	Value-based
[159]	MISO downlink	Secrecy rate maximization	Multiple	PDS-PER	Value-based
[160]	MISO	Sum rate maximization	Multiple	QR-DDRL	

9 | Technical Challenges and Future Directions

Although RIS-aided communications offer considerable advantages and performance enhancements, implementing RIS in practice remains challenging. This section highlights and examines the main obstacles that hinder the practical deployment of RIS in wireless communication networks.

9.1 | Channel Estimation in RIS-Aided Communication Networks

Time and accurate channel estimation are essential for reliable transmissions in wireless communication, especially in multi-antenna systems with high data rates. In a typical RIS-aided communication network, the BS performs the channel estimation. The BS communicates the acquired CSI to the RIS from the BS via a RIS controller, and phase shift adjustments are made based on the received information. A practical method for channel estimation with RIS involves estimating each element individually, meaning only one element is activated at a time while the others remain off. This approach enables separate analysis of direct channels from the base station to users and the channels reflected by the RIS. However, for more extensive networks with large RIS consisting of many reflecting elements, the above ON/OFF scheme is not cost-effective due to the excessive training overhead.

Furthermore, there is a significant loss in reflected signal power when only one RIS element is turned on at any given time. This process significantly degrades the received signal quality and impairs the accuracy of the channel estimation process. To ease the training overhead for large-scale RIS networks, the authors in [119] proposed grouping the RIS elements into sub-surfaces; this results in only the RIS reflected channel associated with the sub-surfaces that require estimation. However, for RIS-aided networks with many users and an enormous number of RIS elements, as expected in future networks, the design of a low-overhead channel estimation process remains an open problem.

9.2 | Reconfiguration of RIS for Controllable Reflections

Electrical voltage is the most convenient choice for RIS tuning as it is easy to quantize and control electronic impedances in an electronic chip/surface. However, the reflection coefficient in each element is the most crucial parameter to consider when designing a RIS-aided wireless communication system. This reflection coefficient has two arguments: the reflection amplitude and the phase shifts. The ability to vary the reflection coefficient is advantageous from a wireless communication perspective as it can be configured to improve the system's performance. However, in practice, more extensive networks with large RIS have a significant number of reflecting elements. Therefore, it is appropriate to implement only a finite number of discrete phase shifts and amplitude levels to keep hardware cost and design complexity to a minimum.

Moreover, optimization of the reflection coefficients becomes more cumbersome with discrete variables. As a result, most works in literature assume an ideal phase-shift model where each element of the RIS implements total signal reflection without considering their respective phase shifts. However, this is practically impossible due to the strong coupling between the reflection amplitude and the phase shift. Therefore, for in-depth and accurate performance analysis of RIS, we consider realistic phase-shift models with phase-dependent amplitude responses.

9.3 | Strategies for the Deployment of RIS in Wireless Communications Systems

Another challenging issue is selecting an appropriate deployment strategy in RIS-assisted multi-user networks, with active beamforming at the BS and passive beamforming at the RIS. An effective deployment strategy must guarantee performance enhancements promised by RIS technology while considering practical factors such as propagation conditions, coverage space, deployment costs, and user distribution. In a typical RIS single-user design, the provided number of RIS elements can be combined as a single RIS or partitioned into several cooperative RIS, resulting in even more cooperative passive beamforming gain. The multi-user design can take on two distinct deployment approaches; the first is a centralized deployment approach where the RIS elements are grouped as a single RIS and placed within the premise of the BS. The second is a distributed deployment approach, where the RIS elements are partitioned into multiple RIS and placed near the users' hotspots. The distributed RIS deployment approach is generally more likely to establish line-of-sight (LoS) links with the BS and users than the centralized RIS approach. However, the distributed approach tends to increase the signaling overhead due to the coordination among the multiple RISs as well as their communication with the BS. Subsequently, optimally selecting the number of active RIS elements in centralized and distributed approaches remains an open challenge.

9.4 | Standardization of Reconfigurable Intelligent Surfaces (RIS)

Several standardization initiatives have been going on regarding the standardization of RIS technologies. Although the standardization process is still in its infancy, major telecommunication bodies like the 3rd Generation partnership project (3GPP) have led the way on this alongside the ETSI standardization initiative. The next sub-section briefly describes the ongoing RIS initiatives across the different standardization bodies.

i. *3GPP Initiatives*: The 3GPP has been assessing Reconfigurable Intelligent Surfaces (RIS) technology in its current standardization roadmap, specifically from Release 18 and into the initiatives scheduled for Release 19 and subsequent releases. Discussions on RIS have been highlighted in Release 17 under subsection (10) under the study item "Study of network-controlled repeaters" [161, 162]. More extensive discussions were done in Release 18 and beyond with particular emphasis on channel estimation and measurement procedures, configuration protocols, evaluation methodologies and integration with cellular technology.

ii. *ETSI Activities*: The European Telecommunication Standards Institute (ETSI) with its focus Industry Specification Group (ISG) has begun pre-standardization plans for RIS with the purpose of paving a way for the standardization of RIS. The ISG first phase report [163] highlights the RIS-related use cases and deployment scenarios.

iii. *Other Initiatives and Industry Alliances*: For other private initiatives on RIS experimentation, one has to look in the direction of those conducted by NTT DoCoMo and Metawave, who conducted an experiment that showed signal quality improvement with RIS. Other collaborations that have been formed to enhance the viability of RIS include the VISOSURF, funded by the European Union, and other private startup companies such as Greenerwave and Pivotal Commware have all been at the forefront of RIS research and standardization.

9.5 | Other Operational Challenges

The implementation and sustained operation of Reconfigurable Intelligent Surface (RIS) infrastructure necessitates comprehensive consideration of several critical domains. In the realm of maintenance and reliability, the fundamental requirement is ensuring operational continuity through environmental resilience. This encompasses the development of weatherized RIS architectures and the integration of autonomous diagnostic systems with remote monitoring capabilities.

Furthermore, the operational efficacy of RIS deployments is intrinsically dependent upon the availability of high-fidelity, real-time data streams. This necessitates the establishment of sophisticated data governance frameworks and robust pipeline architectures. Furthermore, the incorporation of edge computing methodologies facilitates proximate data processing, thereby minimizing latency and enhancing data integrity.

Security considerations within RIS implementations warrant particular attention, given the inherent vulnerabilities present in networked systems. The implementation of cryptographic protocols and authentication mechanisms for RIS control signaling represents a primary security measure. This is complemented by the development of artificial intelligence-driven threat detection systems specifically optimized for RIS-enabled network environments.

The regulatory framework (discussed in Section 9.4) surrounding RIS technology presents additional complexities that must be addressed through systematic approaches to compliance and interoperability. This encompasses active engagement with regulatory authorities in the development of RIS-specific standards and protocols. Moreover, the creation and dissemination of open-source reference implementations serve to facilitate broad interoperability across diverse network architectures.

Finally, the systematic address of these multifaceted challenges via innovative technological solutions and collaborative initiatives, RIS technology can achieve seamless integration with existing network infrastructure. This integration consequently enables the enhancement of wireless communication systems and facilitates novel applications across the diverse sectors of the economy.

10 | A Comparative Analysis of RIS-Aided Versus Relay-Aided Systems: A Case Study

This case study aims to provide a comprehensive performance analysis and optimization study of RIS compared to traditional relay systems in 5G new radio (5GNR) network. Several performance metrics captured in Section 5.2 are evaluated across urban, suburban, and rural environments using Monte Carlo simulations. Furthermore, to maximize the RIS signal strength, we will optimize the RIS phase shift using the Gradient Descent Algorithm.

The advent of 5G networks and beyond has come with unprecedented demands for higher data rates, low latency, enhanced coverage, and improved spectral and energy efficiency, conforming with the provisions laid down in the SDG. The long-standing reliability on the usage of relays to extend coverage and improve signal quality in challenging environments is severely threatened by the emergence of RIS technology, especially for real-time communication as it compensates for some of the drawbacks of the traditional relay systems.

As seen in Figure 9, we consider a single downlink scenario with a BS located at the center of the cell with M element uniform linear array (ULA) serving K single antenna users that are randomly distributed within the cell space. A RIS with N reflecting elements is strategically placed on the façade of a building to assist the communication. Furthermore, for fair comparison, an amplify-and-forward (AF) relay is positioned at the same location as the RIS. The cell is modeled as a circular area with radius, R with the BS at the center of origin, (0, 0, 0) while the RIS/relay is positioned at $\left(x_r, y_r, z_r\right)$.

10.1 | System Model

See Figure 9.

10.2 | Channel Model

To assume realistic conditions, we adopt the 3GPP TR 38.901 channel model with some extensions to accommodate the RIS-specific characteristics. We consider the following:

i. Direct BS-UE channel

The direct channel is given by

$$h_k = \varepsilon_k \sqrt{\beta_k} \tag{23}$$

where β_k denotes the large-scale fading (pathloss and shadowing), while ε_k is the small-scale fading vector.

ii. BS-Relay-UE channel

A. System Model

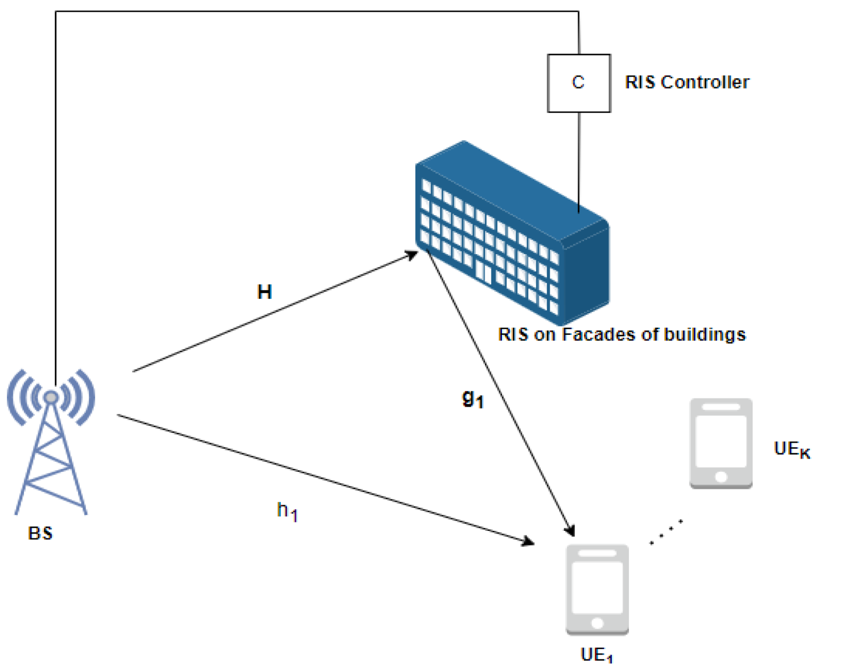

FIGURE 9 | Diagrammatic representation of a RIS-aided network.

When considering the AF relay, it is imperative to reflect on the two transmission phases, the direct BS-relay phase and the relay-UE phase, respectively, given by:

$$h_{br} = \varepsilon_{br}\sqrt{\beta_{br}} \tag{24a}$$

$$h_{ru} = \varepsilon_{ru}\sqrt{\beta_{ru}} \tag{24b}$$

iii. BS-RIS-UE channel

For the RIS, we consider the effective cascaded channel given by:

$$H_{RIS} = \sqrt{\beta_1} * H * \Phi * \sqrt{\beta_2} * G \tag{25}$$

where β_1 and β_2 are denote large scale fading between the BS and RIS and the RIS and UE respectively. H denotes the BS-RIS channel while G denotes the RIS-UE channel. Φ is the phase shift matrix of the RIS.

10.3 | Signal Model

The received signal (assuming a simple single user communication) for direct communication, relay-assisted communication, and the RIS-assisted communication can be respectively modeled as follows:

$$y_{direct} = \sqrt{P_t}hx + n \tag{26a}$$

$$y_{relay} = \sqrt{P_r}h_{ru}\left(\sqrt{P_t}h_{br}x + n\right) + n_r \tag{26b}$$

$$y_{RIS} = \sqrt{P_r}h_{ru}\left(\sqrt{P_t}h_{br}x + n\right) \tag{26c}$$

where P_t as the transmit power at the BS, P_r denotes the relay transmit power while x represents the transmitted signal. n_r and n denote the additive white Gaussian noise (AWGN) at the relay and user equipment respectively. The RIS is modeled as a Uniform Planar Array (UPA) with $N = N_x * N_y$ elements where N_x and N_y represent the number of elements in the horizontal and vertical directions respectively. Each element introduces a phase shift $\phi_n \in (0, 2\pi)$. The phase shift matrix is given by $\mathbf{\Phi} = \text{diag}\left(e^{j\phi_1}, e^{j\phi_2}, \ldots, e^{j\phi_N}\right)$.

10.4 | Power Consumption Model

Given that one of the metrics of concern is power efficiency, it is imperative to understand the power consumption model of each technology as well as the benchmark direct communication scenario. The power consumption model is as follows:

i. Direct BS-UE Communication:

$$\boldsymbol{P}_{\text{total}} = \boldsymbol{P_t} + \boldsymbol{P_c} \tag{27}$$

where $\boldsymbol{P_c}$ is the circuit power consumption at the BS.

ii. Relay-assisted power consumption:

$$\boldsymbol{P}_{\text{total}} = \boldsymbol{P_t} + \boldsymbol{P_c} + \boldsymbol{P_r} + \boldsymbol{P}_{\text{relay}} \tag{28}$$

where $\boldsymbol{P_t}$ is the power consumption at the relay

iii. RIS-assisted power consumption:

$$\boldsymbol{P}_{\text{total}} = \boldsymbol{P_t} + \boldsymbol{P_c} + \boldsymbol{P_{RIS}} \tag{29}$$

10.5 | Results and Analysis

To evaluate the performance of different communication methods—RIS-assisted communication, amplify-and-forward (AF) relay-assisted communication, and direct communication, which serves as a benchmark, we conducted extensive Monte Carlo simulations based on the system model outlined in Section 10.1. The goal is to analyze and compare how each of these techniques performs under various environmental and system conditions. The simulation setup was carried out using MATLAB R2021A, given its capability to provide an extensive 5GNR simulation library; however, we completed computations using Pytorch 2.3.

We performed 10 000 independent Monte Carlo simulation runs. This large number of runs ensures statistical robustness and allows us to capture a wide variety of user equipment (UE) positions and channel conditions. The results provide a reliable comparison of the different communication methods over varying random realizations of the system.

We consider a circular cell with a radius of 500 m. This represents a typical mid-range communication scenario, applicable to urban, suburban, and rural settings. By defining the cell radius, we can have a control of the area where the UEs are distributed. The BS is placed at the origin of the coordinate system at (0, 0, 30) m. The assumption of a BS height of 30 m is to follow real-life urban scenarios, commonly mounted on the facades of high-rise buildings or towers. Furthermore, the RIS/relay is placed at a coordinate (250, 0, 25) m, midway between the BS and the cell edge with the UEs uniformly distributed throughout the cell space. For optimized phase shifts, we employ gradient descent algorithm. We considered mmWave carrier frequency of 28 GHz and a bandwidth of a 100 GHz. The BS transmit power was set at 43 dBm and the relay power (for relay communication) was set at 30 dBm with a processing delay of 1 ms. The RIS consists of $N = 16 \times 16$ UPA. Simulation was conducted for the communication process in the urban, suburban and rural environment by the adjustment of the path loss exponents and shadowing standard deviations in accordance with the 3GPP TR 38.901 version 14 channel model [164]. Table 7 summarizes the simulation parameters utilized for the entire process.

TABLE 7 | Simulation parameters.

Simulation parameters	Values
Carrier frequency, f_c	28 GHz (mm Wave)
Bandwidth, B	100 GHz
RIS elements ($N_x \times N_y$)	16×16
Cell radius, R	500 m
Noise power spectral density	−174 dBm/Hz
BS transmit power	43 dBm
Relay transmit power	30 dBm
Pathloss exponents	$\alpha_U = 3.5$ **(Urban)**
	$\alpha_S = 3.0$ **(Sub-urban)**
	$\alpha_R = 2.4$ **(Rural)**
Delay	1 ms

10.6 | Spectral Efficiency Versus Distance

Figure 10a shows the spectral efficiency as a function of distance from the BS for RIS-assisted, AF relay-assisted, and direct communication in urban, suburban, and rural environments.

From the plot, it is observed that for all communication types, the spectral efficiency decreases with increasing distances for all environments. Furthermore, the RIS-assisted communication consistently outperforms both AF relay and direct communication across all distances and environments.

The performance gap between RIS and AF relay widens as distance increases, particularly in urban environments.

The AF relay shows improved spectral efficiency compared to direct communication at longer distances, but falls short of RIS performance. In rural environments, the spectral efficiency gap between the three methods narrows, but RIS still maintains an advantage.

The superior performance of RIS can be attributed to its ability to shape the propagation environment, effectively creating a virtual line-of-sight path. The AF relay, while improving upon direct communication at longer distances, is limited by its two-hop nature and processing delay. The performance difference is most pronounced in urban environments due to the RIS's effectiveness in mitigating multipath fading and interference.

10.7 | Energy Efficiency for Different Environments

Figure 10b shows a bar plot of the energy efficiency of the RIS, AF relay, and direct communication in urban, suburban, and rural environments. RIS demonstrates significantly higher energy efficiency across all environments compared to AF relay and direct communication. The energy efficiency advantage of RIS is most pronounced in urban environments.

AF relay shows lower energy efficiency than direct communication in most scenarios due to its higher power consumption.

The energy efficiency gap between the three methods is similar in all environments. The superior energy efficiency of RIS is primarily due to its passive nature, requiring minimal additional power beyond the BS transmission. In contrast, the AF relay's need for reception, amplification, and transmission processes results in higher power consumption. This difference becomes more significant in complex propagation environments like urban areas, where RIS can effectively optimize the channel with minimal energy cost.

10.8 | Coverage Probability Versus SINR Threshold

In Figure 10c, we plot the coverage probability as a function of SINR threshold for RIS, AF relay, and direct communication across different environments. It can be observed that the

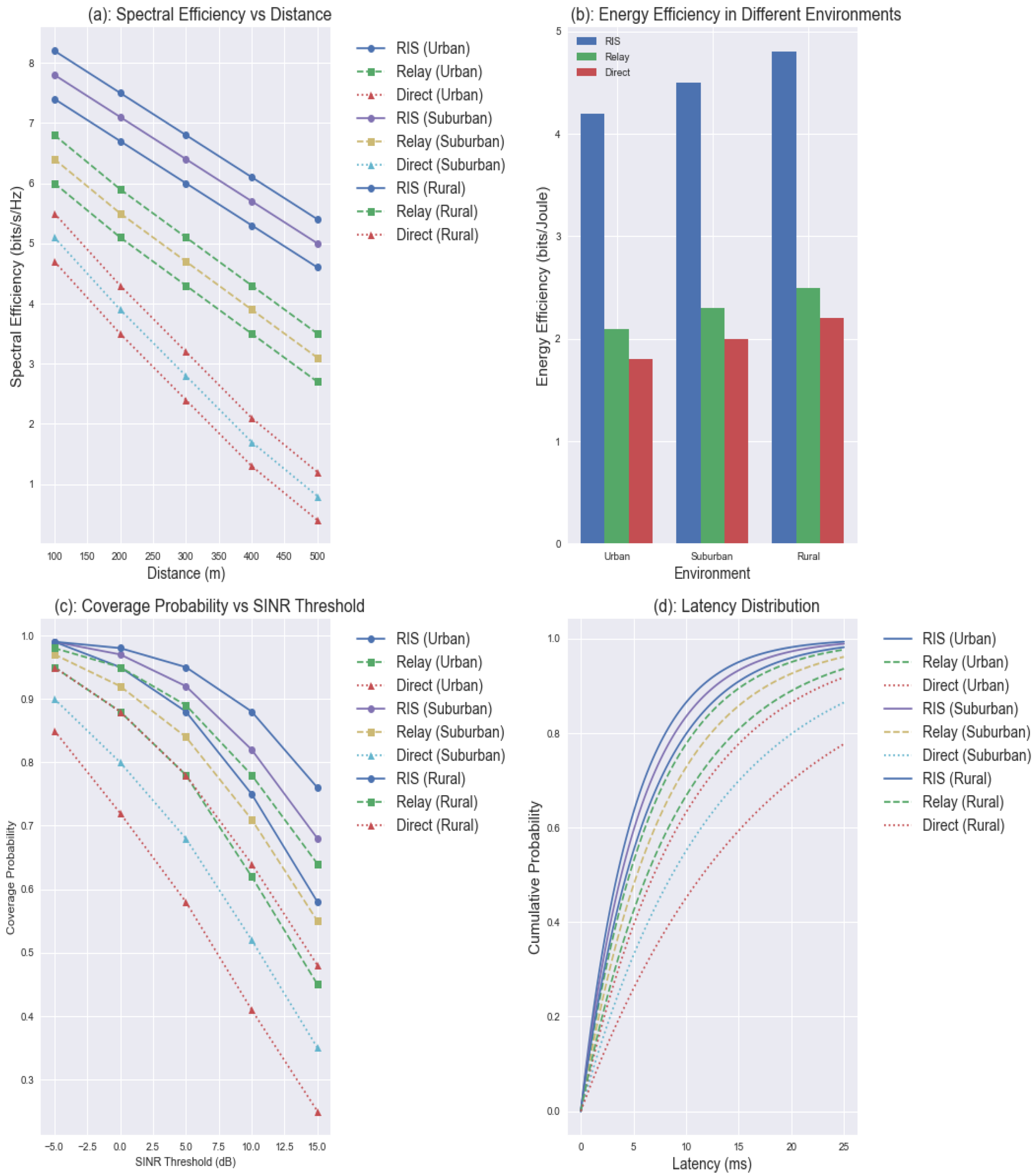

FIGURE 10 | Analysis of the different performance metrics for different environments.

RIS-assisted communication provides higher coverage probability across all SINR thresholds and environments. The coverage advantage of RIS is most significant at higher SINR thresholds, particularly in urban environments.

The relay-assisted communication improves coverage probability compared to direct communication, especially at lower SINR thresholds. In rural environments, the coverage probability gap between the three methods narrows, but RIS still maintains an advantage.

The analysis shows the superior coverage probability of the RIS-assisted communications, which can be attributed to its ability to optimize the propagation environment, effectively increasing the received signal power at the UE. Similarly, the AF relay improves coverage compared to direct communication by providing a two-hop path, but it is limited by its fixed position and the quality of both hops. RIS's advantage is particularly noticeable at higher SINR thresholds, indicating its potential to support high-quality links in challenging conditions.

10.9 | Latency Distribution

The cumulative distribution function (CDF) of latency for RIS, AF relay, and direct communication across different environments was highlighted in Figure 10d. It can be keenly observed that the RIS-assisted communication achieves lower latency compared to the AF relay across all environments.

Direct communication shows the lowest latency in short-distance scenarios. The latency advantage of RIS over AF relay is most significant in urban environments. AF relay consistently shows higher latency due to its processing delay for amplification and retransmission.

The analysis shows that the latency performance of RIS is superior to AF relay primarily due to the absence of amplification and retransmission delays. While direct communication shows the lowest latency at short distances, RIS outperforms it at longer distances by providing a stronger, more reliable signal path. The AF relay's higher latency is a trade-off for its ability to improve signal quality through amplification, which can be beneficial in low-SNR conditions but comes at the cost of increased delay.

10.10 | Key Takeaways From the Comparative Analysis

From the comparative analysis in the above subsections, it can be observed that RIS consistently outperforms AF relay systems in terms of spectral efficiency, particularly in urban environments and at longer distances. In terms of energy efficiency, the performance of RIS is substantial, showing up to 70% improvement over AF relays due to its passive nature. Furthermore, coverage probability is significantly enhanced with RIS, especially at higher SINR thresholds. Given our application of mm-Wave frequencies for the analysis, it can be observed that RIS demonstrates exceptional capability in mitigating high path loss, making it particularly valuable for future high-frequency deployments.

Based on our analysis, we observe that in urban environments, the RIS-aided communication shows the most pronounced gain over AF relay, with direct communication lagging further behind. In rural scenarios, the RIS-aided communications exhibit smaller performance gaps over the AF relay, though RIS maintains its advantages. However, the effectiveness of both technologies varies significantly with environmental conditions. Furthermore, in terms of system design implications, RIS offers superior flexibility through software-controlled reconfiguration, while AF relays remain valuable in scenarios requiring signal regeneration. For dense, more complicated networks, hybrid deployments might be optimal for the best results. Despite the successes of RIS in wireless communication for 5G and beyond networks, there are several important areas that warrant further investigation as listed in Section 9. In addition, there is a need to study more advanced hybrid schemes combining RIS and relay technologies.

The results of this study strongly suggest that RIS-aided communication systems represent a promising solution for enhancing 5G and beyond networks, particularly in challenging urban environments and high-frequency deployments. While AF relays remain relevant for specific use cases, RIS offers a more energy-efficient and flexible approach to improving network performance, making it an attractive option for future wireless communication systems.

11 | Conclusion

This paper explicitly reviews the state-of-the-art RIS-assisted wireless networks, especially open challenges relating to the B5G and 6G networks. This work presents an intensive study of recent research on RIS to provide an in-depth understanding of the underlying principles surrounding RIS operations, composition, and effect on EM waves. We also reviewed recent works comparing RIS with benchmark technologies, such as relays. This paper looks at the applicability of RIS-assisted wireless communication systems, emphasizing spectral efficiency, energy efficiency, and physical layer security. We also explored the advantages RIS enhancements can offer to future wireless communication networks. Despite the plethora of research on RIS-aided wireless communication networks, many assume perfect CSI at the BS, the RIS, and the user. However, in practice, systems' CSI can be imperfect. Furthermore, the passive nature of the RIS architecture that makes them energy efficient is also a limitation in its inability to perform the channel estimation task by transmitting and receiving pilot signals.

Furthermore, the paper discusses the integration of RIS with other emergent technologies, focusing on next-generation wireless networks. Emerging technologies like NOMA, UAV, and SWIPT have all enhanced the performance of a wireless communication system in terms of capacity, throughput, and power. Further integration with RIS will aim to improve the performance even further. Additionally, we looked at various contributions that employ machine learning solutions, especially as it is well suited to RIS-aided wireless communication with its extended state space and high computational costs. The paper also highlighted discussions on deep learning and reinforcement learning variants, especially for RIS-assisted wireless communication systems. The success of reinforcement learning stems from obtaining the sub-optimal solution to a control problem by interacting with the environment without needing enormous data. This feature makes RL computationally scalable and suited to most RIS-aided wireless communication designs. Furthermore, we present a performance analysis case study to draw comparisons between the RIS-aided communication, AF relay-aided communication, and the direct communications in terms of spectral efficiency, energy efficiency, coverage, and latency. Finally, the paper touches on the challenges and future directions in RIS research.

Data Availability Statement

Data sharing not applicable to this article as no datasets were generated or analyzed during the current study.

References

1. F. Tariq, M. R. A. Khandaker, K. K. Wong, M. Imran, M. Bennis, and M. Debbah, "A Speculative Study on 6G," ArXiv, 2019.

2. Ericsson, "Ericsson Mobility Report November 2020."

3. M. M. Rahman, C. Despins, and S. Affes, "Analysis of CAPEX and OPEX Benefits of Wireless Access Virtualization," in *2013 IEEE International Conference on Communications Workshops (ICC)* (IEEE, 2013), https://doi.org/10.1109/ICCW.2013.6649273.

4. J. Henroid, "Energy Efficient Wireless Communication Survey," http://www.cse.wustl.edu/~jain/cse574-16/ftp/energyef/index.html.

5. R. Chataut and R. Akl, "Massive MIMO Systems for 5G and Beyond Networks—Overview, Recent Trends, Challenges, and Future Research Direction," *Sensors* 20, no. 10 (2020): 2753, https://doi.org/10.3390/s20102753.

6. D. M. Renzo, M. D. Renzo, M. Debbah, et al., "Smart Radio Environments Empowered by Reconfigurable AI Meta-Surfaces: An Idea Whose Time Has Come," *EURASIP Journal on Wireless Communications and Networking* 2019, no. 1 (2019): 129, https://doi.org/10.1186/s13638-019-1438-9.

7. A. Welkie, L. Shangguan, J. Gummeson, W. Hu, and K. Jamieson, "Programmable Radio Environments for Smart Spaces," in *Proceedings of the 16th ACM Workshop on Hot Topics in Networks* (ACM, 2017), https://doi.org/10.1145/3152434.3152456.

8. A. A. A. Boulogeorgos and A. Alexiou, "Performance Analysis of Reconfigurable Intelligent Surface-Assisted Wireless Systems and Comparison With Relaying," *IEEE Access* 8 (2020): 94463–94483, https://doi.org/10.1109/ACCESS.2020.2995435.

9. W. Saad, M. Bennis, M. Chen, et al., "A Vision of 6G Wireless Systems: Applications, Trends, Technologies, and Open Research Problems," https://www.oulu.fi/6gflagship/.

10. K. David and H. Berndt, "6G Vision and Requirements: Is There Any Need for Beyond 5g?," *IEEE Vehicular Technology Magazine* 13, no. 3 (2018): 72–80, https://doi.org/10.1109/MVT.2018.2848498.

11. T. Hou, Y. Liu, Z. Song, et al., "Reconfigurable Intelligent Surface Aided NOMA Networks," 2019, http://arxiv.org/abs/1912.10044.

12. S. Gong, X. Lu, D. T. Hoang, et al., "Toward Smart Wireless Communications via Intelligent Reflecting Surfaces: A Contemporary Survey," *IEEE Communications Surveys and Tutorials* 22, no. 4 (2020): 2283–2314, https://doi.org/10.1109/COMST.2020.3004197.

13. S. Khan, K. S. Khan, N. Haider, and S. S. Young, "Deep-Learning-Aided Detection for Reconfigurable Intelligent Surfaces."

14. O. Tsilipakos, A. C. Tasolamprou, A. Pitilakis, et al., "Toward Intelligent Metasurfaces: The Progress From Globally Tunable Metasurfaces to Software-Defined Metasurfaces With an Embedded Network of Controllers," *Advanced Optical Materials* 8, no. 17 (2020): 2000783, https://doi.org/10.1002/adom.202000783.

15. M. di Renzo, A. Zappone, M. Debbah, et al., "Smart Radio Environments Empowered by Reconfigurable Intelligent Surfaces: How It Works, State of Research, and the Road Ahead," *IEEE Journal on Selected Areas in Communications* 38, no. 11 (2020): 2450–2525, https://doi.org/10.1109/JSAC.2020.3007211.

16. S. Khan, K. S. Khan, N. Haider, and S. Y. Shin, "Deep-Learning-Aided Detection for Reconfigurable Intelligent Surfaces," 2019, http://arxiv.org/abs/1910.09136.

17. A. Taha, Y. Zhang, F. B. Mismar, and A. Alkhateeb, "Deep Reinforcement Learning for Intelligent Reflecting Surfaces: Towards Standalone Operation," in *2020 IEEE 21st International Workshop on Signal Processing Advances in Wireless Communications (SPAWC)* (IEEE, 2020), https://doi.org/10.1109/SPAWC48557.2020.9154301.

18. C. Liaskos, S. Nie, A. Tsioliaridou, A. Pitsillides, S. Ioannidis, and I. Akyildiz, "A New Wireless Communication Paradigm Through Software-Controlled Metasurfaces."

19. C. Liaskos, S. Nie, A. Tsioliaridou, A. Pitsillides, S. Ioannidis, and I. Akyildiz, "A Novel Communication Paradigm for High Capacity and Security via Programmable Indoor Wireless Environments in Next Generation Wireless Systems," 2018.

20. "Vision on Software Networks and 5G," https://www.researchgate.net/publication/314141627.

21. S. Nie, J. M. Jornet, and I. F. Akyildiz, "Intelligent Environments Based on Ultra-Massive MIMO Platforms for Wireless Communication in Millimeter Wave and Terahertz Bands," 2019, http://arxiv.org/abs/1904.07958.

22. D. Muirhead, M. A. Imran, and K. Arshad, "A Survey of the Challenges, Opportunities and Use of Multiple Antennas in Current and Future 5G Small Cell Base Stations," *IEEE Access* 4 (2016): 2952–2964, https://doi.org/10.1109/ACCESS.2016.2569483.

23. R. Liu, Q. Wu, M. di Renzo, and Y. Yuan, "A Path to Smart Radio Environments: An Industrial Viewpoint on Reconfigurable Intelligent Surfaces," 2021, https://arxiv.org/abs/2104.14985.

24. N. Kaina, M. Dupré, G. Lerosey, and M. Fink, "Shaping Complex Microwave Fields in Reverberating Media With Binary Tunable Metasurfaces," *Scientific Reports* 4 (2014): 6693, https://doi.org/10.1038/srep06693.

25. S. N. Sur and R. Bera, "Intelligent Reflecting Surface Assisted MIMO Communication System: A Review," *Physical Communication* 47 (2021): 101386, https://doi.org/10.1016/j.phycom.2021.101386.

26. P. Hu, P. Zhang, M. Rostami, and D. Ganesan, "Braidio: An Integrated Active-Passive Radio for Mobile Devices With Asymmetric Energy Budgets," in *SIGCOMM 2016 – Proceedings of the 2016 ACM Conference on Special Interest Group on Data Communication* (Association for Computing Machinery, Inc, 2016), 384–397, https://doi.org/10.1145/2934872.2934902.

27. A. Zappone, M. di Renzo, and M. Debbah, "Wireless Networks Design in the Era of Deep Learning: Model-Based, AI-Based, or Both?," 2019, http://arxiv.org/abs/1902.02647.

28. Y. Vahabzadeh, N. Chamanara, K. Achouri, and C. Caloz, "Computational Analysis of Metasurfaces," arXiv, 2017, https://doi.org/10.1109/jmmct.2018.2829871.

29. C. Pan, H. Ren, K. Wang, et al., "Reconfigurable Intelligent Surfaces for 6G Systems: Principles, Applications, and Research Directions," 2020, http://arxiv.org/abs/2011.04300.

30. Y. Liu, X. Liu, X. Mu, et al., "Reconfigurable Intelligent Surfaces: Principles and Opportunities," 2020, http://arxiv.org/abs/2007.03435.

31. E. Basar, M. di Renzo, J. de Rosny, M. Debbah, M. S. Alouini, and R. Zhang, "Wireless Communications Through Reconfigurable Intelligent Surfaces," *IEEE Access* 7 (2019): 116753–116773, https://doi.org/10.1109/ACCESS.2019.2935192.

32. Y. Chen, Y. Wang, J. Zhang, and M. di Renzo, "QoS-Driven Spectrum Sharing for Reconfigurable Intelligent Surfaces (RISs) Aided Vehicular Networks," *IEEE Transactions on Wireless Communications* 20, no. 9 (2021): 5969–5985, https://doi.org/10.1109/TWC.2021.3071332.

33. S. Xu and F. Yang, "Reflectarray Antennas," in *Handbook of Antenna Technologies* (Springer Singapore, 2015), https://doi.org/10.1007/978-981-4560-75-7_45-1.

34. Ö. Özdogan, E. Björnson, and E. G. Larsson, "Intelligent Reflecting Surfaces: Physics, Propagation, and Pathloss Modeling," 2019, http://arxiv.org/abs/1911.03359.

35. K. Achouri, M. A. Salem, and C. Caloz, "General Metasurface Synthesis Based on Susceptibility Tensors," *IEEE Transactions on Antennas and Propagation* 63, no. 7 (2015): 2977–2991, https://doi.org/10.1109/TAP.2015.2423700.

36. D. R. Smith, O. Yurduseven, L. P. Mancera, P. Bowen, and N. B. Kundtz, "Analysis of a Waveguide-Fed Metasurface Antenna," *Physical Review Applied* 8, no. 5 (2017): 054048, https://doi.org/10.1103/PhysRevApplied.8.054048.

37. V. S. Asadchy, M. Albooyeh, S. N. Tcvetkova, A. Díaz-Rubio, Y. Ra'di, and S. A. Tretyakov, "Perfect Control of Reflection and Refraction Using Spatially Dispersive Metasurfaces," *Physical Review B* 94, no. 7 (2016): 075142, https://doi.org/10.1103/PhysRevB.94.075142.

38. 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* 7, no. 1 (2018): 90, https://doi.org/10.1038/s41377-018-0092-z.

39. S. Sun, Q. He, J. Hao, S. Xiao, and L. Zhou, "Electromagnetic Metasurfaces: Physics and Applications," *Advances in Optics and Photonics* 11, no. 2 (2019): 380, https://doi.org/10.1364/AOP.11.000380.

40. K. Wu, P. Coquet, Q. J. Wang, and P. Genevet, "Modelling of Free-Form Conformal Metasurfaces," *Nature Communications* 9, no. 1 (2018): 3494, https://doi.org/10.1038/s41467-018-05579-6.

41. G. Lavigne, K. Achouri, V. S. Asadchy, S. A. Tretyakov, and C. Caloz, "Susceptibility Derivation and Experimental Demonstration of Refracting Metasurfaces Without Spurious Diffraction," *IEEE Transactions on Antennas and Propagation* 66, no. 3 (2018): 1321–1330, https://doi.org/10.1109/TAP.2018.2793958.

42. F. Liu, A. Pitilakis, M. S. Mirmoosa, et al., "Programmable Metasurfaces: State of the Art and Prospects," in *IEEE International Symposium on Circuits and Systems (ISCAS)* (IEEE, 2018), https://doi.org/10.1109/ISCAS.2018.8351817.

43. O. Quevedo-Teruel, H. Chen, A. Díaz-Rubio, et al., "Roadmap on Metasurfaces," *Journal of Optics* 21, no. 7 (2019): 073002, https://doi.org/10.1088/2040-8986/ab161d.

44. C. L. Holloway, E. F. Kuester, J. A. Gordon, J. O'Hara, J. Booth, and D. R. Smith, "An Overview of the Theory and Applications of Metasurfaces: The Two-Dimensional Equivalents of Metamaterials," *IEEE Antennas and Propagation Magazine* 54, no. 2 (2012): 10–35, https://doi.org/10.1109/MAP.2012.6230714.

45. C. A. Balanis, *Advanced Engineering Electromagnetics*, 2nd ed. (Wiley, 2012).

46. L. Liang, M. Qi, J. Yang, et al., "Anomalous Terahertz Reflection and Scattering by Flexible and Conformal Coding Metamaterials," *Advanced Optical Materials* 3, no. 10 (2015): 1374–1380, https://doi.org/10.1002/adom.201500206.

47. M. di Renzo, M. Debbah, D.-T. Phan-Huy, et al., "Smart Radio Environments Empowered by AI Reconfigurable Meta-Surfaces: An Idea Whose Time Has Come," 2019, http://arxiv.org/abs/1903.08925.

48. W. Tang, M. Z. Chen, X. Chen, et al., "Wireless Communications With Reconfigurable Intelligent Surface: Path Loss Modeling and Experimental Measurement," *IEEE Transactions on Wireless Communications* 20, no. 1 (2021): 421–439, https://doi.org/10.1109/TWC.2020.3024887.

49. F. H. Danufane, M. di Renzo, J. de Rosny, and S. Tretyakov, "On the Path-Loss of Reconfigurable Intelligent Surfaces: An Approach Based on Green's Theorem Applied to Vector Fields," 2020, http://arxiv.org/abs/2007.13158.

50. E. Bjornson, O. Ozdogan, and E. G. Larsson, "Intelligent Reflecting Surface Versus Decode-and-Forward: How Large Surfaces Are Needed to Beat Relaying?," *IEEE Wireless Communications Letters* 9, no. 2 (2020): 244–248, https://doi.org/10.1109/LWC.2019.2950624.

51. T. Hou, Y. Liu, Z. Song, X. Sun, Y. Chen, and L. Hanzo, "MIMO Assisted Networks Relying on Intelligent Reflective Surfaces," 2019, http://arxiv.org/abs/1910.00959.

52. T. Hou, Y. Liu, Z. Song, X. Sun, Y. Chen, and L. Hanzo, "Reconfigurable Intelligent Surface Aided NOMA Networks," *IEEE Journal on Selected Areas in Communications* 38, no. 11 (2020): 2575–2588, https://doi.org/10.1109/JSAC.2020.3007039.

53. Z. Ding, R. Schober, and H. V. Poor, "On the Impact of Phase Shifting Designs on IRS-NOMA," 2020, http://arxiv.org/abs/2001.10909.

54. 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," 2020, http://arxiv.org/abs/2005.07472.

55. K. Ntontin, J. Song, and M. di Renzo, "Multi-Antenna Relaying and Reconfigurable Intelligent Surfaces: End-to-End SNR and Achievable Rate," 2019, http://arxiv.org/abs/1908.07967.

56. Z. Ding and H. Vincent Poor, "A Simple Design of IRS-NOMA Transmission," *IEEE Communications Letters* 24, no. 5 (2020): 1119–1123, https://doi.org/10.1109/LCOMM.2020.2974196.

57. 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," in *ICC 2020–2020 IEEE International Conference on Communications (ICC)* (IEEE, 2020), https://doi.org/10.1109/ICC40277.2020.9148610.

58. J. Lyu and R. Zhang, "Spatial Throughput Characterization for Intelligent Reflecting Surface Aided Multiuser System," *IEEE Wireless Communications Letters* 9, no. 6 (2020): 834–838, https://doi.org/10.1109/LWC.2020.2972527.

59. C. You, B. Zheng, and R. Zhang, "Intelligent Reflecting Surface With Discrete Phase Shifts: Channel Estimation and Passive Beamforming," 2019, http://arxiv.org/abs/1911.03916.

60. M. Di Renzo, K. Ntontin, J. Song, et al., "Reconfigurable Intelligent Surfaces vs. Relaying: Differences, Similarities, and Performance Comparison," *IEEE Open Journal of the Communications Society* 1 (2020): 798–807, https://doi.org/10.1109/OJCOMS.2020.3002955.

61. I. Yildirim, F. Kilinc, E. Basar, and G. C. Alexandropoulos, "Hybrid RIS-Empowered Reflection and Decode-and-Forward Relaying for Coverage Extension," *IEEE Communications Letters* 25 (2021): 1692–1696, https://doi.org/10.1109/LCOMM.2021.3054819.

62. U. Nations, "Transforming Our World: The 2030 Agenda for Sustainable Development."

63. Z. Yang, M. Chen, W. Saad, et al., "Energy-Efficient Wireless Communications With Distributed Reconfigurable Intelligent Surfaces," 2020.

64. V. Croisfelt, F. Saggese, I. Leyva-Mayorga, R. Kotaba, G. Gradoni, and P. Popovski, "A Random Access Protocol for RIS-Aided Wireless Communications," in *2022 IEEE 23rd International Workshop on Signal Processing Advances in Wireless Communication (SPAWC)* (IEEE, 2022), 1–5, https://doi.org/10.1109/SPAWC51304.2022.9833984.

65. Y. Chen, Y. Wang, J. Zhang, P. Zhang, and L. Hanzo, "Reconfigurable Intelligent Surface (RIS)-Aided Vehicular Networks: Their Protocols, Resource Allocation, and Performance," *IEEE Vehicular Technology Magazine* 17, no. 2 (2022): 26–36, https://doi.org/10.1109/MVT.2022.3158046.

66. S. Pala, M. Katwe, K. Singh, B. Clerckx, and C.-P. Li, "Spectral-Efficient RIS-Aided RSMA URLLC: Toward Mobile Broadband Reliable Low Latency Communication (mBRLLC) System," *IEEE Transactions on Wireless Communications* 23, no. 4 (2024): 3507–3524, https://doi.org/10.1109/TWC.2023.3309028.

67. F. Verde, D. Darsena, and V. Galdi, "Rapidly Time-Varying Reconfigurable Intelligent Surfaces for Downlink Multiuser Transmissions," *IEEE Transactions on Communications* 72, no. 6 (2024): 3227–3243, https://doi.org/10.1109/TCOMM.2024.3358954.

68. R. Matos and N. Pala, "VO2-Based Ultra-Reconfigurable Intelligent Reflective Surface for 5G Applications," *Scientific Reports* 12, no. 1 (2022): 4497, https://doi.org/10.1038/s41598-022-08458-9.

69. C. Wu, C. You, Y. Liu, X. Gu, and Y. Cai, "Channel Estimation for STAR-RIS-Aided Wireless Communication," *IEEE Communications Letters* 26, no. 3 (2022): 652–656, https://doi.org/10.1109/LCOMM.2021.3139198.

70. C. You, B. Zheng, and R. Zhang, "Wireless Communication via Double IRS: Channel Estimation and Passive Beamforming Designs," *IEEE Wireless Communications Letters* 10, no. 2 (2021): 431–435, https://doi.org/10.1109/LWC.2020.3034388.

71. K. Loa, C. C. Wu, S. T. Sheu, et al., "IMT-Advanced Relay Standards [WiMAX/LTE Update]," *IEEE Communications Magazine* 48, no. 8 (2010): 40–48, https://doi.org/10.1109/MCOM.2010.5534586.

72. H. Alves, M. Bennis, R. D. Souza, and M. Latva-aho, "Enhanced Performance of Heterogeneous Networks Through Full-Duplex Relaying," *EURASIP Journal on Wireless Communications and Networking* 2012, no. 1 (2012): 365, https://doi.org/10.1186/1687-1499-2012-365.

73. H. Li, X. Zhao, and Y. Xu, "Power Control for Cognitive Relay Networks With Sensing Uncertainties," *EURASIP Journal on Wireless Communications and Networking* 2016, no. 1 (2016): 74–80, https://doi.org/10.1186/s13638-016-0617-1.

74. S. Gautam, T. X. Vu, S. Chatzinotas, and B. Ottersten, "Cache-Aided Simultaneous Wireless Information and Power Transfer (SWIPT) With Relay Selection," *IEEE Journal on Selected Areas in Communications* 37, no. 1 (2019): 187–201, https://doi.org/10.1109/JSAC.2018.2872367.

75. A. Gupta and M. Sellathurai, "End-To-End Learning-Based Framework for Amplify-and-Forward Relay Networks," *IEEE Access* 9 (2021): 81660–81677, https://doi.org/10.1109/ACCESS.2021.3085901.

76. F. Shams, G. Bacci, and M. Luise, "A Q-Learning Game-Theory-Based Algorithm to Improve the Energy Efficiency of a Multiple Relay-Aided Network," in *2014 XXXIth URSI General Assembly and Scientific Symposium (URSI GASS)* (IEEE, 2014), 1–4, https://doi.org/10.1109/URSIGASS.2014.6929244.

77. Z. Wen, X. Liu, N. C. Beaulieu, R. Wang, and S. Wang, "Joint Source and Relay Beamforming Design for Full-Duplex MIMO AF Relay SWIPT Systems," *IEEE Communications Letters* 20, no. 2 (2016): 320–323, https://doi.org/10.1109/LCOMM.2015.2513768.

78. G. Kramer, M. Gastpar, and P. Gupta, "Cooperative Strategies and Capacity Theorems for Relay Networks," *IEEE Transactions on Information Theory* 51, no. 9 (2005): 3037–3063, https://doi.org/10.1109/TIT.2005.853304.

79. A. Huang, L. Qu, and M. J. Khabbaz, "Latency-Aware Computation Offloading in Multi-RIS-Assisted Edge Networks," *IEEE Open Journal of the Communications Society* 5 (2024): 1204–1221, https://doi.org/10.1109/OJCOMS.2024.3361383.

80. V. Hakami and M. Dehghan, "Distributed Power Control for Delay Optimization in Energy Harvesting Cooperative Relay Networks," *IEEE Transactions on Vehicular Technology* 66, no. 6 (2017): 4742–4755, https://doi.org/10.1109/TVT.2016.2610444.

81. Z. Li, L. Xiang, X. Ge, G. Mao, and H.-C. Chao, "Latency and Reliability of mmWave Multi-Hop V2V Communications Under Relay Selections," *IEEE Transactions on Vehicular Technology* 69, no. 9 (2020): 9807–9821, https://doi.org/10.1109/TVT.2020.3002903.

82. Q. Wu and R. Zhang, "Intelligent Reflecting Surface Enhanced Wireless Network: Joint Active and Passive Beamforming Design," 2018, http://arxiv.org/abs/1809.01423.

83. Y. Liu, Y. Ma, M. Li, Q. Wu, and Q. Shi, "Spectral Efficiency Maximization for Double-Faced Active Reconfigurable Intelligent Surface," *IEEE Transactions on Signal Processing* 70 (2022): 5397–5412, https://doi.org/10.1109/TSP.2022.3221345.

84. Q. Wu and R. Zhang, "Towards Smart and Reconfigurable Environment: Intelligent Reflecting Surface Aided Wireless Network," 2019, http://arxiv.org/abs/1905.00152.

85. E. Björnson and L. Sanguinetti, "Demystifying the Power Scaling Law of Intelligent Reflecting Surfaces and Metasurfaces," 2019, http://arxiv.org/abs/1908.03133.

86. Y. Gao, C. Yong, Z. Xiong, D. Niyato, Y. Xiao, and J. Zhao, "Reconfigurable Intelligent Surface for MISO Systems With Proportional Rate Constraints," 2020, http://arxiv.org/abs/2001.10845.

87. C. Huang, A. Zappone, M. Debbah, and C. Yuen, "Achievable Rate Maximization by Passive Intelligent Mirrors," in *2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)* (IEEE, 2018), https://doi.org/10.1109/ICASSP.2018.8461496.

88. M. Jung, W. Saad, M. Debbah, and C. S. Hong, "On the Optimality of Reconfigurable Intelligent Surfaces (RISs): Passive Beamforming, Modulation, and Resource Allocation," 2019, http://arxiv.org/abs/1910.00968.

89. Q. U. A. Nadeem, A. Kammoun, A. Chaaban, M. Debbah, and M. S. Alouini, "Asymptotic Max-Min SINR Analysis of Reconfigurable Intelligent Surface Assisted MISO Systems," *IEEE Transactions on Wireless Communications* 19, no. 12 (2020): 7748–7764, https://doi.org/10.1109/TWC.2020.2986438.

90. G. Yang, X. Xu, and Y.-C. Liang, "Intelligent Reflecting Surface Assisted Non-Orthogonal Multiple Access," 2019, http://arxiv.org/abs/1907.03133.

91. M. Fu, Y. Zhou, and Y. Shi, "Intelligent Reflecting Surface for Downlink Non-Orthogonal Multiple Access Networks," 2019, http://arxiv.org/abs/1906.09434.

92. C. Nwufo, Y. Sun, O. Simpson, and P. Cao, "Secrecy Energy Efficiency Maximization in Multi-RIS-Aided SWIPT Wireless Network," in *2023 IEEE 97th Vehicular Technology Conference (VTC2023-Spring)* (IEEE, 2023), 1–7, https://doi.org/10.1109/VTC2023-Spring57618.2023.10199952.

93. C. Nwufo, Y. Sun, and O. Simpson, "Secure Energy-Efficient Multi-RIS-Aided SWIPT Networks," in *2023 IEEE Virtual Conference on Communications (VCC)* (IEEE, 2023), 7–12, https://doi.org/10.1109/VCC60689.2023.10474823.

94. H. Xie and D. Li, "To Reflect or Not to Reflect: On–Off Control and Number Configuration for Reflecting Elements in RIS-Aided Wireless Systems," *IEEE Transactions on Communications* 71, no. 12 (2023): 7409–7424, https://doi.org/10.1109/TCOMM.2023.3315309.

95. T. Jiang and W. Yu, "Interference Nulling Using Reconfigurable Intelligent Surface," *IEEE Journal on Selected Areas in Communications* 40, no. 5 (2022): 1392–1406, https://doi.org/10.1109/JSAC.2022.3143220.

96. F. Xia, Z. Fei, X. Wang, P. Liu, J. Guo, and Q. Wu, "Joint Waveform and Reflection Design for Sensing-Assisted Secure RIS-Based Backscatter Communication," *IEEE Wireless Communications Letters* 13, no. 5 (2024): 1523–1527, https://doi.org/10.1109/LWC.2024.3381163.

97. M. Cui, G. Zhang, and R. Zhang, "Secure Wireless Communication via Intelligent Reflecting Surface," 2019, http://arxiv.org/abs/1905.10770.

98. L. Dong and H.-M. Wang, "Secure MIMO Transmission via Intelligent Reflecting Surface," 2020, http://arxiv.org/abs/2002.00990.

99. J. Liu, K. Xiong, Y. Lu, D. W. K. Ng, Z. Zhong, and Z. Han, "Energy Efficiency in Secure IRS-Aided SWIPT," *IEEE Wireless Communications Letters* 9, no. 11 (2020): 1884–1888, https://doi.org/10.1109/LWC.2020.3006837.

100. B. Feng, Y. Wu, and M. Zheng, "Secure Transmission Strategy for Intelligent Reflecting Surface Enhanced Wireless System," 2019, http://arxiv.org/abs/1909.00629.

101. S. Goel and R. Negi, "Guaranteeing Secrecy Using Artificial Noise," *IEEE Transactions on Wireless Communications* 7, no. 6 (2008): 2180–2189, https://doi.org/10.1109/TWC.2008.060848.

102. G. Li, L. Hu, P. Staat, et al., "Reconfigurable Intelligent Surface for Physical Layer Key Generation: Constructive or Destructive?," 2021, http://arxiv.org/abs/2112.10043.

103. J. Xu, W. Xu, and C. Yuen, "On Performance of Distributed RIS-Aided Communication in Random Networks," *IEEE Transactions on Wireless*

Communications 23, no. 12 (2024): 1, https://doi.org/10.1109/TWC.2024.3463796.

104. N. Ye, X. Zhuo, J. Li, B. Di, and J. An, "Secure Directional Modulation in RIS-Aided Networks: A Low-Sidelobe Hybrid Beamforming Approach," *IEEE Wireless Communications Letters* 11, no. 8 (2022): 1753–1757, https://doi.org/10.1109/LWC.2022.3180931.

105. C. Zou, K. An, Z. Lin, et al., "Multi-Layer RIS-Assisted Anti-Jamming Communications: A Hierarchical Game Learning Approach," *IEEE Communications Letters* 27, no. 11 (2023): 2998–3002, https://doi.org/10.1109/LCOMM.2023.3321897.

106. M. Fan, "Enhancing Physical Layer Security via Information Hiding and Chaotic Frequency-Hopping Signal," *Telecommunication Systems* 87, no. 2 (2024): 287–299, https://doi.org/10.1007/s11235-024-01146-1.

107. A.-T. Le, N.-D. X. Ha, D.-T. Do, A. Silva, and S. Yadav, "Enabling User Grouping and Fixed Power Allocation Scheme for Reconfigurable Intelligent Surfaces-Aided Wireless Systems," *IEEE Access* 9 (2021): 92263–92275, https://doi.org/10.1109/ACCESS.2021.3092335.

108. W. Feng, J. Tang, Q. Wu, et al., "Resource Allocation for Power Minimization in RIS-Assisted Multi-UAV Networks With NOMA," *IEEE Transactions on Communications* 71, no. 11 (2023): 6662–6676, https://doi.org/10.1109/TCOMM.2023.3298984.

109. G. C. Trichopoulos, P. Theofanopoulos, B. Kashyap, et al., "Design and Evaluation of Reconfigurable Intelligent Surfaces in Real-World Environment," *IEEE Open Journal of the Communications Society* 3 (2022): 462–474, https://doi.org/10.1109/OJCOMS.2022.3158310.

110. P. M. Raposo Pereira, R. A. A. de Souza, M. D. Yacoub, and Y. Li, "RIS Performance in a Comprehensive Fading Environment," in *2024 18th European Conference on Antennas and Propagation (EuCAP)* (IEEE, 2024), 1–5, https://doi.org/10.23919/EuCAP60739.2024.10501199.

111. Y. Gevez, Y. I. Tek, and E. Basar, "Dynamic RIS Partitioning in NOMA Systems Using Deep Reinforcement Learning," *Frontiers in Antennas and Propagation* 2 (2024): 4–16, https://doi.org/10.3389/fanpr.2024.1418412.

112. L. Guo, J. Jia, J. Chen, S. Yang, Y. Xue, and X. Wang, "RIS-Aided Secure A2G Communications With Coordinated Multi-UAVs: A Hybrid DRL Approach," *IEEE Transactions on Network Science and Engineering* 11, no. 5 (2024): 4536–4550, https://doi.org/10.1109/TNSE.2024.3396136.

113. A. Bhowal and S. Aissa, "RIS-Aided Communications in Indoor and Outdoor Environments: Performance Analysis With a Realistic Channel Model," *IEEE Transactions on Vehicular Technology* 71, no. 12 (2022): 13356–13360, https://doi.org/10.1109/TVT.2022.3143841.

114. M. Sadeghian, A. Pizzo, and A. Lozano, "RIS in Indoor Environments: Benchmarking Against Ambient Propagation," 2023.

115. L. Ibrahim, M. N. Mahmud, M. F. M. Salleh, and A. Al-Rimawi, "Joint Beamforming Optimization Design and Performance Evaluation of RIS-Aided Wireless Networks: A Comprehensive State-of-the-Art Review," *IEEE Access* 11 (2023): 141801–141859, https://doi.org/10.1109/ACCESS.2023.3342320.

116. N. Shlezinger and Y. C. Eldar, "Deep Task-Based Quantization," *Entropy (Basel, Switzerland)* 23, no. 1 (2021): 104, https://doi.org/10.3390/e23010104.

117. H. Guo, Y.-C. Liang, J. Chen, and E. G. Larsson, "Weighted Sum-Rate Maximization for Reconfigurable Intelligent Surface Aided Wireless Networks," 2019, http://arxiv.org/abs/1912.11999.

118. A. Rafieifar and S. M. Razavizadeh, "Secrecy Rate Maximization in Multi-IRS mmWave Networks," *Physical Communication* 48 (2021): 101436, https://doi.org/10.1016/J.PHYCOM.2021.101436.

119. C. Pan, H. Ren, K. Wang, et al., "Multicell MIMO Communications Relying on Intelligent Reflecting Surface," 2019, http://arxiv.org/abs/1907.10864.

120. W. Ni, Y. Liu, Z. Yang, H. Tian, and X. Shen, "Federated Learning in Multi-RIS-Aided Systems," *IEEE Internet of Things Journal* 9, no. 12 (2022): 9608–9624, https://doi.org/10.1109/JIOT.2021.3130444.

121. T. N. Do, G. Kaddoum, T. L. Nguyen, D. B. da Costa, and Z. J. Haas, "Multi-RIS-Aided Wireless Systems: Statistical Characterization and Performance Analysis," *IEEE Transactions on Communications* 69, no. 12 (2021): 8641–8658, https://doi.org/10.1109/TCOMM.2021.3117599.

122. Y. Li, M. Jiang, Q. Zhang, and J. Qin, "Joint Beamforming Design in Multi-Cluster MISO NOMA Intelligent Reflecting Surface-Aided Downlink Communication Networks," 2019, http://arxiv.org/abs/1909.06972.

123. W. Ni, X. Liu, Y. Liu, H. Tian, and Y. Chen, "Resource Allocation for Multi-Cell IRS-Aided NOMA Networks," *IEEE Transactions on Wireless Communications* 20 (2021): 4253–4268, https://doi.org/10.1109/TWC.2021.3057232.

124. A. S. de Sena, A. S. de Sena, D. Carrillo, et al., "What Role Do Intelligent Reflecting Surfaces Play in Multi-Antenna Non-Orthogonal Multiple Access?," *IEEE Wireless Communications* 27, no. 5 (2020): 24–31, https://doi.org/10.1109/MWC.001.2000061.

125. J. Xu, L. Liu, and R. Zhang, "Multiuser MISO Beamforming for Simultaneous Wireless Information and Power Transfer," *IEEE Transactions on Signal Processing* 62, no. 18 (2014): 4798–4810, https://doi.org/10.1109/TSP.2014.2340817.

126. Q. Wu and R. Zhang, "Intelligent Reflecting Surface Enhanced Wireless Network via Joint Active and Passive Beamforming," *IEEE Transactions on Wireless Communications* 18, no. 11 (2019): 5394–5409, https://doi.org/10.1109/TWC.2019.2936025.

127. C. Pan, H. Ren, K. Wang, et al., "Intelligent Reflecting Surface Aided MIMO Broadcasting for Simultaneous Wireless Information and Power Transfer," *IEEE Journal on Selected Areas in Communications* 38, no. 8 (2020): 1719–1734, https://doi.org/10.1109/JSAC.2020.3000802.

128. Q. Wu and R. Zhang, "Weighted Sum Power Maximization for Intelligent Reflecting Surface Aided SWIPT," *IEEE Wireless Communications Letters* 9, no. 5 (2020): 586–590, https://doi.org/10.1109/LWC.2019.2961656.

129. X. Liu, M. Chen, Y. Liu, Y. Chen, S. Cui, and L. Hanzo, "Artificial Intelligence Aided Next-Generation Networks Relying on UAVs," *IEEE Wireless Communications* 28, no. 1 (2021): 120–127, https://doi.org/10.1109/MWC.001.2000174.

130. 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 Communications* 27, no. 1 (2020): 16–23, https://doi.org/10.1109/MWC.001.1900292.

131. A. Vacca and H. Onishi, "Drones: Military Weapons, Surveillance or Mapping Tools for Environmental Monitoring? The Need for Legal Framework Is Required," *Transportation Research Procedia* 25 (2017): 51–62, https://doi.org/10.1016/j.trpro.2017.05.209.

132. S. Shakoor, Z. Kaleem, M. I. Baig, O. Chughtai, T. Q. Duong, and L. D. Nguyen, "Role of UAVs in Public Safety Communications: Energy Efficiency Perspective," *IEEE Access* 7 (2019): 140665–140679, https://doi.org/10.1109/ACCESS.2019.2942206.

133. T. Q. Duong, L. D. Nguyen, H. D. Tuan, and L. Hanzo, "Learning-Aided Realtime Performance Optimisation of Cognitive UAV-Assisted Disaster Communication," in *2019 IEEE Global Communications Conference (GLOBECOM)* (IEEE, 2019), https://doi.org/10.1109/GLOBECOM38437.2019.9014313.

134. T. Do-Duy, L. D. Nguyen, T. Q. Duong, S. R. Khosravirad, and H. Claussen, "Joint Optimisation of Real-Time Deployment and Resource Allocation for UAV-Aided Disaster Emergency Communications," *IEEE Journal on Selected Areas in Communications* 39, no. 11 (2021): 3411–3424, https://doi.org/10.1109/JSAC.2021.3088662.

135. K. K. Nguyen, N. A. Vien, L. D. Nguyen, M.-T. Le, L. Hanzo, and T. Q. Duong, "Real-Time Energy Harvesting Aided Scheduling in

UAV-Assisted D2D Networks Relying on Deep Reinforcement Learning," *IEEE Access* 9 (2021): 3638–3648, https://doi.org/10.1109/ACCESS.2020.3046499.

136. A. Huang, X. Mu, L. Guo, and G. Zhu, "Hybrid Active-Passive RIS Transmitter Enabled Energy-Efficient Multi-User Communications," *IEEE Transactions on Wireless Communications* 23, no. 9 (2024): 10653–10666, https://doi.org/10.1109/TWC.2024.3373900.

137. M.-H. T. Nguyen, E. Garcia-Palacios, T. Do-Duy, O. A. Dobre, and T. Q. Duong, "UAV-Aided Aerial Reconfigurable Intelligent Surface Communications With Massive MIMO System," *IEEE Transactions on Cognitive Communications and Networking* 8, no. 4 (2022): 1828–1838, https://doi.org/10.1109/TCCN.2022.3187098.

138. J. Tang, Z. Peng, D. K. C. So, X. Zhang, K.-K. Wong, and J. A. Chambers, "Energy Efficiency Optimization for a Multiuser IRS-Aided MISO System With SWIPT," *IEEE Transactions on Communications* 71, no. 10 (2023): 5950–5962, https://doi.org/10.1109/TCOMM.2023.3296631.

139. K. K. Nguyen, S. R. Khosravirad, L. D. Nguyen, T. Nguyen, and T. Q. Duong, "Intelligent Reconfigurable Surface-Assisted Multi-UAV Networks: Efficient Resource Allocation With Deep Reinforcement Learning," 2021.

140. M. Diamanti, M. Tsampazi, E. E. Tsiropoulou, and S. Papavassiliou, "Energy Efficient Multi-User Communications Aided by Reconfigurable Intelligent Surfaces and UAVs," in *2021 IEEE International Conference on Smart Computing (SMARTCOMP)* (IEEE, 2021), 371–376, https://doi.org/10.1109/SMARTCOMP52413.2021.00075.

141. J. Wang, W. Zhang, X. Bao, T. Song, and C. Pan, "Outage Analysis for Intelligent Reflecting Surface Assisted Vehicular Communication Networks," 2020.

142. U. Makarfi, K. M. Rabie, O. Kaiwartya, et al., "Reconfigurable Intelligent Surfaces-Enabled Vehicular Networks: A Physical Layer Security Perspective," 2020, http://arxiv.org/abs/2004.11288.

143. L. Kong, J. He, Y. Ai, S. Chatzinotas, and B. Ottersten, "Channel Modeling and Analysis of Reconfigurable Intelligent Surfaces Assisted Vehicular Networks," in *2021 IEEE International Conference on Communications Workshops (ICC Workshops)* (IEEE, 2021), https://doi.org/10.1109/ICCWorkshops50388.2021.9473681.

144. T. J. O'Shea and J. Hoydis, "An Introduction to Deep Learning for the Physical Layer," 2017, http://arxiv.org/abs/1702.00832.

145. Z. Qin, H. Ye, G. Y. Li, and B.-H. F. Juang, "Deep Learning in Physical Layer Communications," 2018, http://arxiv.org/abs/1807.11713.

146. A. Taha, M. Alrabeiah, and A. Alkhateeb, "Enabling Large Intelligent Surfaces With Compressive Sensing and Deep Learning," 2019, http://arxiv.org/abs/1904.10136.

147. 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," 2020, http://arxiv.org/abs/2006.02201.

148. C. Huang, G. C. Alexandropoulos, C. Yuen, and M. Debbah, "Indoor Signal Focusing With Deep Learning Designed Reconfigurable Intelligent Surfaces," 2019, http://arxiv.org/abs/1905.07726.

149. C. Huang, Z. Yang, K. Xiong, et al., "Hybrid Beamforming for RIS-Empowered Multi-Hop Terahertz Communications: A DRL-Based Method," https://doi.org/10.1109/GCWkshps50303.2020.9367503.

150. Z. Yang, Y. Liu, Y. Chen, and N. Al-Dhahir, "Machine Learning for User Partitioning and Phase Shifters Design in RIS-Aided NOMA Networks," *IEEE Transactions on Communications* 69, no. 11 (2021): 7414–7428, https://doi.org/10.1109/TCOMM.2021.3100866.

151. K. Feng, Q. Wang, X. Li, and C.-K. Wen, "Deep Reinforcement Learning Based Intelligent Reflecting Surface Optimization for MISO Communication Systems," *IEEE Wireless Communications Letters* 9, no. 5 (2020): 745, https://doi.org/10.1109/LWC.2020.2969167.

152. J. Lin, Y. Zou, X. Dong, S. Gong, D. T. Hoang, and D. Niyato, "Optimization-Driven Deep Reinforcement Learning for Robust Beamforming in IRS-Assisted Wireless Communications," 2020, http://arxiv.org/abs/2005.11885.

153. C. Huang, R. Mo, and C. Yuen, "Reconfigurable Intelligent Surface Assisted Multiuser MISO Systems Exploiting Deep Reinforcement Learning," *IEEE Journal on Selected Areas in Communications* 38, no. 8 (2020): 1839–1850, https://doi.org/10.1109/JSAC.2020.3000835.

154. A. Al-Hilo, M. Samir, M. Elhattab, C. Assi, and S. Sharafeddine, "Reconfigurable Intelligent Surface Enabled Vehicular Communication: Joint User Scheduling and Passive Beamforming."

155. J. Kim, S. Hosseinalipour, T. Kim, D. J. Love, and C. G. Brinton, "Multi-IRS-Assisted Multi-Cell Uplink MIMO Communications Under Imperfect CSI: A Deep Reinforcement Learning Approach."

156. M. Samir, M. Elhattab, C. Assi, S. Sharafeddine, and A. Ghrayeb, "Optimizing Age of Information Through Aerial Reconfigurable Intelligent Surfaces: A Deep Reinforcement Learning Approach," *IEEE Transactions on Vehicular Technology* 70, no. 4 (2021): 3978–3983, https://doi.org/10.1109/TVT.2021.3063953.

157. X. Liu, Y. Liu, Y. Chen, and H. V. Poor, "RIS Enhanced Massive Non-Orthogonal Multiple Access Networks: Deployment and Passive Beamforming Design," *IEEE Journal on Selected Areas in Communications* 39, no. 4 (2021): 1057–1071, https://doi.org/10.1109/JSAC.2020.3018823.

158. X. Liu, Y. Liu, and Y. Chen, "Machine Learning Empowered Trajectory and Passive Beamforming Design in UAV-RIS Wireless Networks," *IEEE Journal on Selected Areas in Communications* 39, no. 7 (2021): 2042–2055, https://doi.org/10.1109/JSAC.2020.3041401.

159. H. Yang, Z. Xiong, J. Zhao, D. Niyato, L. Xiao, and Q. Wu, "Deep Reinforcement Learning-Based Intelligent Reflecting Surface for Secure Wireless Communications," *IEEE Transactions on Wireless Communications* 20, no. 1 (2021): 375–388, https://doi.org/10.1109/TWC.2020.3024860.

160. Q. Zhang, W. Saad, and M. Bennis, "Millimeter Wave Communications With an Intelligent Reflector: Performance Optimization and Distributional Reinforcement Learning," 2020, http://arxiv.org/abs/2002.10572.

161. "A Study on NR Network-Controlled Repeaters (Rel-18), TR 38.867 (3Q22_21 p.)—On NR Network-Controlled Repeaters."

162. 3GPP, "RP-232884 WI Summary for NR Network-Controlled Repeaters."

163. ETSI, "Report on RIS, GR RIS 001—V1.1.1—Reconfigurable Intelligent Surfaces (RIS); Use Cases, Deployment Scenarios and Requirements," 2023, https://portal.etsi.org/TB/ETSIDeliverableStatus.aspx.

164. A. G. I. 3GPP, "TR 138 901—V14.0.0—5G; Study on Channel Model for Frequencies From 0.5 to 100 GHz (3GPP TR 38.901 Version 14.0.0 Release 14)," 2017, https://portal.etsi.org/TB/ETSIDeliverableStatus.aspx.