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RIS-Aided Cell-Free Massive MIMO Systems for 6G: Fundamentals, System Design, and Applications

This survey consolidates the state-of-the-art research contribution in RIS-aided cell-free massive MIIMO systems and highlights future directions.

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ABSTRACT | An introduction of intelligent interconnectivity for people and things has posed higher demands and more challenges for sixth-generation (6G) networks, such as high spectral efficiency and energy efficiency (EE), ultralow latency, and ultrahigh reliability. Cell-free (CF) massive multiple-input–multiple-output (mMIMO) and reconfigurable intelligent surface (RIS), also called intelligent reflecting surface (IRS), are two promising technologies for coping with these unprecedented demands. Given their distinct capabilities, integrating the two technologies to further enhance wireless network performances has received great research and development attention. In this article, we provide a comprehensive survey of research on RIS-aided CF mMIMO wireless communication systems. We first introduce system models focusing on system architecture and application scenarios, channel models, and communication protocols. Subsequently, we summarize the relevant studies on system operation and resource allocation, providing in-depth analyses and discussions. Following this, we present practical challenges faced by RIS-aided CF mMIMO systems, particularly those introduced by RIS, such as hardware impairments (HIs) and electromagnetic interference (EMI). We summarize the corresponding analyses and solutions to further facilitate the implementation of RIS-aided CF mMIMO systems. Furthermore, we explore an interplay between RIS-aided CF mMIMO and other emerging 6G technologies, such as millimeter wave (mmWave) and terahertz (THz), simultaneous wireless information and power transfer (SWIPT), next-generation multiple access (NGMA), and unmanned aerial vehicle (UAV). Finally, we outline several research directions for future RIS-aided CF mMIMO systems.

KEYWORDS | Cell-free (CF) massive multiple-input–multiple-output (mMIMO); hardware impairments (HIs); performance

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analysis; reconfigurable intelligent surface (RIS); signal processing; sixth generation (6G); system operation.

NOMENCLATURE

3GPP	Third Generation Partnership Project.
ADC	Analog-to-digital converter.
AP	Access point.
AoA	Angle-of-arrival.
AoD	Angle-of-departure.
BS	Base station.
CB	Conjugate beamforming.
CF	Cell-free.
CSI	Channel state information.
DAC	Digital-to-analog converter.
DL	Downlink.
FDD	Frequency-division duplex.
HI	Hardware impairment.
HST	High-speed train.
IoT	Internet of Things.
IRS	Intelligent reflecting surface.
ISAC	Integrated sensing and communication.
LoS	Line-of-sight.
LS	Least squares.
LSF	Large-scale fading.
mMIMO	Massive multiple-input–multiple-output.
MMSE	Minimum mean square error.
mMTC	Massive machine-type communication.
mmWave	Millimeter wave.
MR	Maximum ratio.
NLoS	Non-line-of-sight.
NGMA	Next-generation multiple access.
NOMA	Nonorthogonal multiple access.
OFDM	Orthogonal frequency-division multiplexing.
QoS	Quality of service.
RIS	Reconfigurable intelligent surface.
RF	Radio frequency.
RL	Reinforcement learning.
SAGIN	Space–air–ground integrated network.
SWIPT	Simultaneous wireless information and power transfer.
SC	Small cell.
THz	Terahertz.
TDD	Time-division duplex.
UL	Uplink.
UE	User equipment.
UAV	Unmanned aerial vehicle.
URLLC	Ultrareliable and low-latency communication.
XL-MIMO	Extremely large-scale multiple-input–multiple-output.

I. INTRODUCTION

A. Motivation

The 6G networks will be a vital component in all parts of society, industry, and life, given its primary mission to fulfill the communication needs of humans and intelligent machines. Innovative and eye-catching application scenarios will be realized with the advent of 6G networks, including holographic telepresence, e-health, ubiquitous connectivity in smart environments, massive robotics, 3-D massive unmanned mobility, augmented reality, virtual reality, and the Internet of Everything [1], [2]. In the last few decades, several new promising technologies for 6G networks have been introduced, including mmWave communications, mMIMO, and network densification. They provide more effective and efficient wireless communications than ever with an unprecedented increase in data rates, massive connectivity, high reliability, and low latency [3], [4]. Among them, mMIMO is particularly appealing due to its ability to provide excellent QoS, such as a ten times peak rate increase, to a large number of users in the network [5].

Conventional mMIMO systems consist of a centralized BS in one cell with a massive array of antennas to serve a smaller number of users simultaneously using the same time–frequency resources [6]. Furthermore, in various scenarios, the network throughput of mMIMO systems can approach the Shannon capacity via simple linear processing techniques such as MR or zero-forcing (ZF) processing [5]. In addition, as BS antennas are installed in a compact array, mMIMO systems have low-backhaul requirements [7]. However, traditional cellular networks have a significant problem due to intercell interference and path loss, resulting in a deteriorated system performance for users located at the cell edge [8], [9].

Different from co-located mMIMO systems, CF mMIMO has been introduced as a promising technology for realizing 6G networks [10], [11]. As depicted in Fig. 1, CF mMIMO is a network architecture that comprises numerous APs that are distributed geographically connected to a central processing unit (CPU). All APs collectively serve all UEs via spatial multiplexing on identical time–frequency resources [12]. Recently, several important aspects and fundamentals of CF mMIMO have been explored [13], [14], [15], [16]. The results reveal that the CF mMIMO system can achieve more satisfactory performance compared with the SC system in terms of cellular edge user throughput [17]. Besides, by adopting a distributed architecture and multilayer signal processing, the system can provide a more uniform QoS, especially for users at the edge of the coverage area [18]. Despite various advantages and potentials of CF mMIMO, ensuring an adequate QoS remains a challenge in harsh propagation environments with insufficient scattering or significant signal attenuation resulting from the existence of substantial obstacles [19]. Meanwhile, as the demand for wireless data throughput continues to soar, meeting increasingly stringent QoS requirements necessitates the implementation of additional advanced technologies.

The RIS or IRS, is an emerging technology that can alter radio waves at the electromagnetic level without the need for complex digital signal processing and active power amplifiers [20], [21]. Considering the 3GPP 5G initial

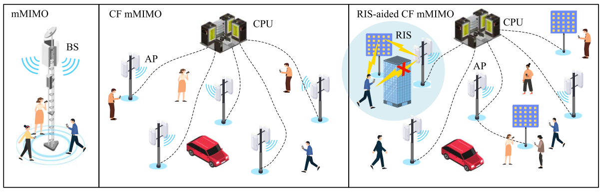

Fig. 1. ***Network model evolution. The wireless communication network has evolved from a traditional BS-centric cellular network to a user-centric CF mMIMO network and is further progressing into a more intelligent RIS-aided CF mMIMO network.***

access process [22], RIS can enhance signals and dynamically adjust the wireless propagation environment by connecting to the original communication system. Specifically, RIS can be flexibly deployed to assist users experiencing poor channel conditions in improving communication quality, as it is fabricated using low-power and low-cost material technology [23]. In fact, with the development of RIS technology, the types of RIS have become diverse. In addition to passive RIS, there are also active RIS [24], [25], hybrid active/passive RIS [26], and simultaneously transmitting and reflecting (STAR) RIS [27].[1] Recognized for their attractive characteristics, RIS is considered to be an effective solution for mitigating various challenges in commercial and civilian applications [29], [30]. However, RIS needs to be integrated with other technologies to play a better role. For example, Ren et al. [31] and Yang et al. [32] proposed an RIS-aided UAV system to enhance the communication quality and energy efficiency (EE) of the system. Lin et al. [33] and Zhao et al. [34] proposed an RIS-aided satellite communication to further improve communication quality and coverage. Besides, Khaleel and Basar [35] proposed a novel NOMA solution with RIS partitioning and revealed that RIS can be combined with NOMA technology to significantly improve the system performance. Also, the performance analysis and beamforming design of RIS-aided mMIMO systems have been extensively studied to improve the throughput of existing networks [35], [36], [37]. The results indicate that the performance of traditional communication systems with poor direct path conditions has a 30%–40% improvement with RIS.

Both RIS and CF mMIMO have the ability to achieve more uniform wireless coverage. Integrating RIS into the CF mMIMO system can further achieve 6G ubiquitous high-capacity communication coverage. Therefore, recently, the combination of CF mMIMO and RIS as an evolution of mMIMO system has also attracted widespread attention and research in the industry to achieve the vision of 6G [38], [39], [40], [41], [42], [43]. As shown in Fig. 1, the RIS-aided CF mMIMO system consists of a CPU, multiple distributed APs, and distributed RISs. All the APs and RISs are connected to the CPU without cell boundaries to serve all users by coherent transmission and reception over the same time–frequency resources through applying spatial multiplexing techniques [44]. However, the deployment of a large number of APs in the CF mMIMO system requires matching wiring for each AP, which inevitably leads to significant expenses and energy consumption. Also, when there are temporary hotspots that require communication enhancement, deploying additional APs is not practical. RIS, as an easy-to-deploy low-energy device, can solve these challenges of CF mMIMO systems and further improve the system performance. In fact, the RIS-aided CF mMIMO system is not simply a combination of the two technologies, but rather a revolutionary approach that introduces innovations in system architecture, protocols, signal processing, channel models, channel estimation, and other aspects. For example, Yang et al. [45] and Ge et al. [46] indicated that channel estimation becomes more difficult and estimation strategies are more diverse. For the system architecture, Shi et al. [39] pointed out that the RIS-aided CF mMIMO system is a 3.5-layer architecture, which brings more novel multilayer signal processing mechanisms. In this way, the system architecture can jointly exploit the advantages of CF mMIMO and RIS to further improve the communication performance. For instance, in [38], a joint AP and RIS precoding framework was proposed and proved to be able to greatly improve user QoS. In addition, previous research has highlighted a major potential of this technology in delivering significant system capacity and achieving superior EE while outperforming conventional cellular networks [39], [47]. Along with this, integrating emerging technologies, including NGMA, SWIPT, mmWave, THz, and UAVs into RIS-aided CF mMIMO systems, has significant potential. This integration can lead to major improvements in system performance, including better data rates, reliability, security, and connection density. These enhancements are crucial for fulfilling the demanding requirements of future 6G networks.

B. Comparisons and Key Contributions

To the best of the authors' knowledge, there are currently no full surveys on the RIS-aided CF mMIMO, but there are separate surveys on CF mMIMO [15], [48] and RIS [23], [28], [49]. More specifically, Elhoushy et al. [15] provided a comprehensive survey of different aspects of the CF mMIMO system from the general system model, the detailed system operation, and the limitations toward a practically implemented system to the potential of integrating the system with emerging techniques/technologies. Then, they presented several pertinent open problems and outlined future directions to fully realize the potential of CF mMIMO systems. Note that they believe that the RIS-aided CF mMIMO technology is an important direction in the future. Different from [15], Ammar et al. [48] investigated the emerging user-centric CF mMIMO network architecture that sets a foundation for future mobile networks. The key challenges in deploying a user-centric CF mMIMO network and solutions for

[1] Note that the characteristics of different RIS forms and the communication problems have been detailed in [23] and [28]. In this work, we focus on the architecture of RIS-aided CF mMIMO systems, thereby considering only a general type of RIS.

the main hurdles in CF mMIMO communications were proposed.

On the other hand, Liu et al. [23] reviewed the physics and communication basic principles of RIS from the perspectives of operating principles, performance evaluation, beamforming design, and resource management. Moreover, they focused on investigating the advantages and challenges of machine learning in RIS-enhanced wireless networks. Zhou et al. [28] provided a comprehensive survey on optimization techniques for RIS-aided wireless communications, including model-based, heuristic, and machine learning algorithms. Specifically, different objectives and constraints were summarized and introduced using various optimization algorithms such as alternating optimization (AO) and successive convex approximation (SCA). Moreover, they presented state-of-the-art machine learning algorithms and applications toward RISs, i.e., supervised and unsupervised learning, RL, federated learning, graph learning, transfer learning, and hierarchical learning-based approaches [50], [51]. Aboagye et al. [49] focused on RIS-assisted visible light communication (VLC) systems. They proposed a thorough exploration of optical RISs and drew comparisons between optical RISs, RF-RISs, and optical relays. The critical challenges were highlighted, including the design of RIS element orientations, assignment of RIS elements to APs or users, and positioning of RIS arrays. Also, there is a short overview paper [39] giving details of RIS-aided CF mMIMO systems from a wireless energy transfer (WET) perspective. They reviewed the opportunities and challenges of WET in RIS-aided CF mMIMO systems. Specifically, the paradigm of RIS-aided CF mMIMO systems for WET was proposed, including its potential application scenarios, system architecture, hardware design, and operating modes. However, they mainly focus on a single RIS/CF mMIMO technology and design or provide reviews from a particular perspective. They lack a holistic presentation and comparison of the technical aspects and technical tutorials of RIS-aided CF mMIMO systems.

To this end, we present a comprehensive survey on RIS-aided CF mMIMO systems. More specifically, the goal is to consolidate the state-of-the-art research contributions from the largely fragmented and sparse literature on RIS-aided CF mMIMO systems and highlight future directions. To the best of our knowledge, this survey is the first to comprehensively address the current research status of RIS-aided CF mMIMO across different aspects. The contributions are summarized as follows.

1) We overview RIS-aided CF mMIMO system architecture and major application scenarios in future IoT networks. We also survey channel models in different propagation environments and provide deep discussions on the main communication protocols.
2) We discuss the system operation and resource allocation, including comparing different channel estimations, and joint beamforming design methods. We also present the unique multilayer signal processing frameworks of RIS-aided CF mMIMO systems and summarize their advantages and limitations. We highlight and compare the differences between RIS-aided CF mMIMO and the separate, standalone RIS and CF mMIMO. Then, we analyze the importance of resource allocation in RIS-aided CF mMIMO systems, summarize the corresponding preliminary research, and provide some technical guidelines.
3) We investigate the performance of RIS-aided CF mMIMO systems under various practical system considerations, including HIs, electromagnetic interference (EMI), limited-fronthaul capacity, and RIS deployment. Notably, we emphasize the proposed solutions to address the challenges posed by these practical system characteristics, which further facilitates the implementation of RIS-aided CF mMIMO systems.
4) We provide a comprehensive up-to-date review on the combination of RIS-aided CF mMIMO and emerging technologies for 6G networks, including mmWave/THz, SWIPT, NOMA, and UAV. A thorough analysis of the current state-of-the-art and achieved results is provided for each technology. Subsequently, we delve into the limitations of existing works. Finally, we discuss various future directions and identify several open problems that need to be tackled to effectively exploit the potential of RIS-aided CF mMIMO systems.

C. Organization of the Survey

To enhance the coherence of this review, we present the definitions of acronyms used throughout the survey in the Nomenclature. Subsequently, as illustrated in Fig. 2, the survey is organized as follows. Section II presents the fundamental operating principles of the RIS-aided CF mMIMO system, namely, system architecture and application scenarios, channel model, and communication protocol. Then, Section III focuses on the system operation and resource allocation, including channel estimation, joint beamforming, multistage transmission procedure and signal processing, and resource allocation. Besides, the system performance analysis of practical system considerations is discussed in Section IV. Subsequently, the integration of RIS-aided CF mMIMO with other emerging technologies toward 6G networks is presented in Section V. In Section VI, future research directions and several open questions are given. Finally, the conclusions and the key lessons learned in this field are provided in Section VII.

II. RIS-AIDED CF mMIMO SYSTEM MODEL

In this section, we introduce the system architecture and major application scenarios of RIS-aided CF mMIMO systems. Meanwhile, different channel models among AP, UE,

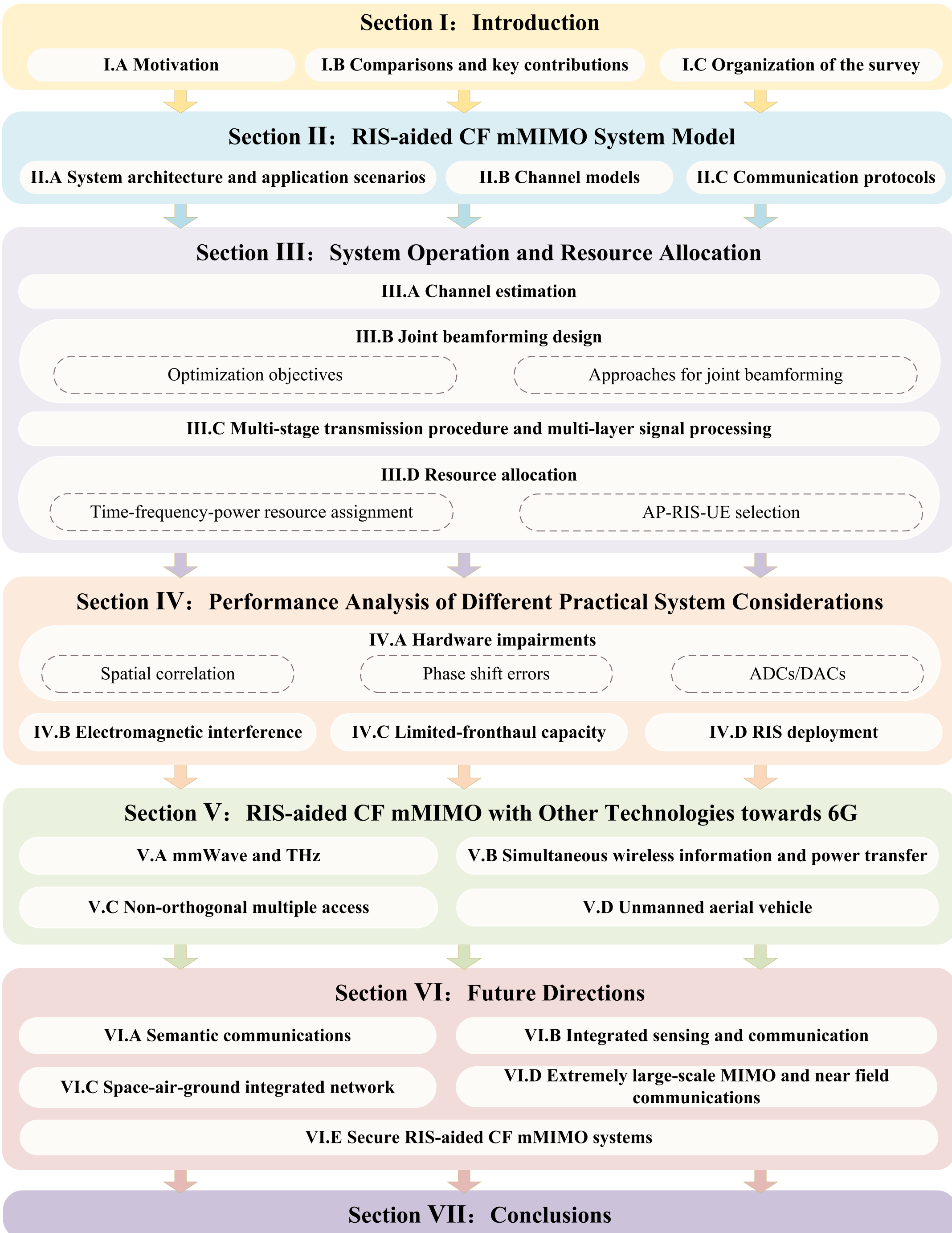

Fig. 2. *Organization structure of the survey.*

and RIS are compared and analyzed. Moreover, we discuss how the system operates with different communication protocols, such as FDD and TDD.

A. System Architecture and Application Scenarios

As shown in Fig. 3, the RIS-aided CF mMIMO system consists of L APs with M antennas, T RISs with N elements, and K UEs with single/multiple antennas that are randomly distributed [47]. All APs and RISs are connected to the CPU via fronthaul links, which facilitates the exchange of power control coefficients and payload data between the CPU and deployed APs/RISs. Based on that, by utilizing spatial multiplexing, facilitated by a much larger number of APs than UE, the CPU enables all APs and RISs to communicate with all users [52]. Indeed, RIS-aided CF mMIMO systems are based on CF mMIMO architecture with an "additional" RIS layer between the UEs and the APs. The CF mMIMO system is structured

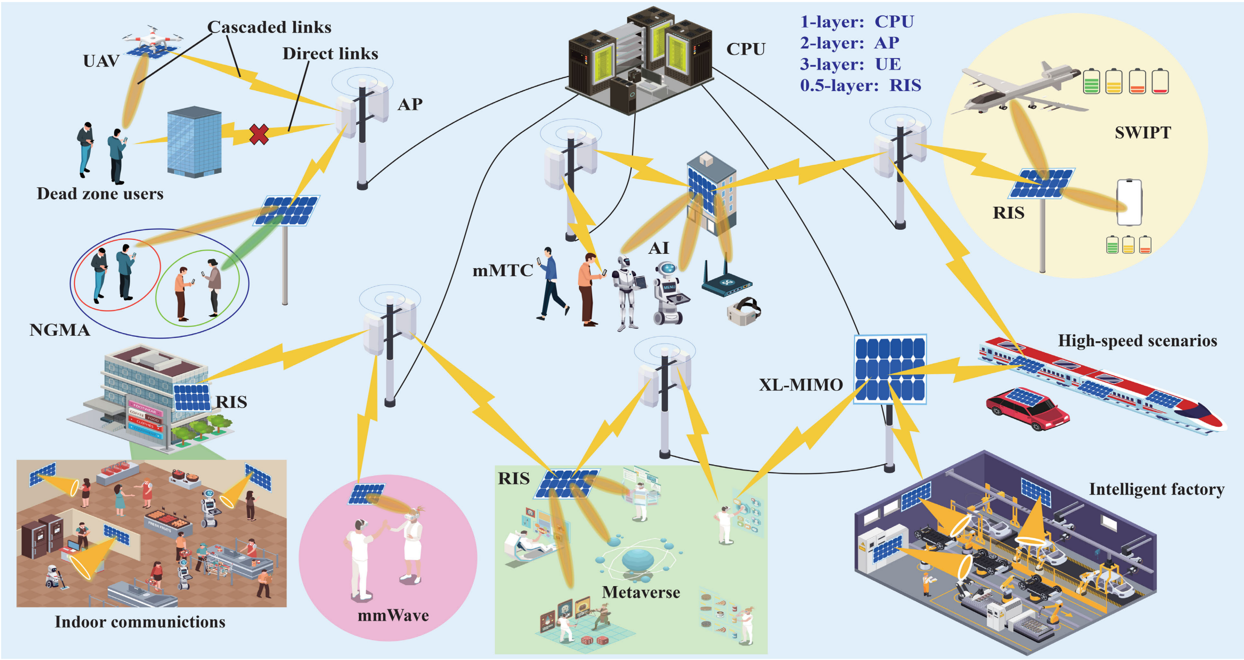

Fig. 3. ***Application scenarios of RIS-aided CF mMIMO systems. The scenarios mainly include data demand scenarios such as mMTC, high mobility, XL-MIMO, mmWave, and Metaverse, as well as energy demand scenarios such as WET in the physical layer.***

with three layers consisting of the CPU, APs, and UEs. The RIS-aided CF mMIMO system architecture introduces a 3.5-layer structure by including a cascading link via RISs. The first layer, the second layer, and the third layer are CPU, AP, and UE, respectively. In the presence of a direct path, the APs can receive the UE's signal through two UL paths: the direct link and the aggregated link through RISs. As such, the channels through RIS as an extra 0.5 layer [39]. The RIS layer is referred to as the 0.5 layer because, when the direct link is strong, communication can still function properly even without the RIS. In this scenario, the RIS plays a role in auxiliary enhancement. Based on this architecture, the system can ensure stable transmission of information and energy even when the direct path is obstructed.

The future wireless networks are expected to make full use of low, medium, and high spectrum resources to achieve seamless global coverage such that they can satisfy the stringent demand for establishing unlimited safe and reliable "human–machine–object" connections anytime and anywhere. Indeed, the success of this desired vision relies on the support of massive access required by the IoT, requiring higher transmission rates, lower delays, and higher reliability [53], [54]. Fortunately, RIS-aided CF mMIMO systems can be applied in various application scenarios due to their flexibility and reliability. Fig. 3 illustrates the applications of the system. First, RIS can be deployed for bypassing the obstacles between APs and UEs, such as adopting a UAV as a carrier to ensure communication connectivity [55]. In this way, not only can the flexibility of RIS be enhanced but also the use of RF links can be avoided, thereby reducing the energy consumption of UAVs and consequently extending their flight time. Also, RIS can serve as a ground communication enhancement device, strengthening the reliability and coverage of satellite communications [34], [56]. Besides, RIS, as a signal reflection device, can support mMTC and intelligent factory via interference mitigation [57]. In addition, RIS-aided CF mMIMO can enhance the electromagnetic signal and overcome the problem of mobile human body obstruction to serve indoor communications [58]. On the other hand, RIS-aided CF mMIMO can utilize the distributed architecture in which the RIS compensates for the power loss over long distances with mmWave/THz field and SWIPT networks [59], [60], [61]. Moreover, with the large-scale application of HST and intercity railways, the demand for high-speed mobile communications is surging. The RIS-aided CF mMIMO architecture can reduce the frequent handover of BSs through distributed architecture and introduce phase compensation to counteract the Doppler frequency shift [47]. Meanwhile, applying RIS-aided CF mMIMO systems to underwater acoustic communication (UWAC) represents a novel approach aiming at addressing the inherent challenges in underwater environments, such as severe path loss, multipath propagation, and limited bandwidth [62]. However, some problems and challenges need to be addressed, such as acoustic wave manipulation, deployment and maintenance, and integration with existing systems [63]. Besides, the combination of RIS-aided CF mMIMO and XL-MIMO technology can improve the intelligence of the network and utilize near-field characteristics to improve spatial resolution [64], [65]. Moreover, RIS-aided CF mMIMO-enabled URLLC technology can provide physical-layer support for the metaverse [66], [67]. To sum up, RIS-aided CF mMIMO systems can provide efficient and reliable physical-layer wireless communication foundational support for various application scenarios.

B. Channel Model

Different from traditional CF mMIMO channel models that have only one type of links, the RIS-aided CF mMIMO introduces aggregated links through RISs, which are formed by cascading channels between AP-RIS and RIS-UE. As shown in Fig. 1, the channels are divided into two types: the direct links from the APs to the UEs and the cascaded links through the RISs. Most of the recent works consider the direct link between UEs and APs as a Rayleigh/Rician fading channel, which assumes NLoS/LoS links between UEs and APs [8], [13], [14]. Meanwhile, RISs are deployed where there are LoS links between the APs and UEs to enhance the communication [68]. As such, the majority of works utilize the Rician fading to model the channel between AP-RIS and RIS-UE [19], [69], [70]. Besides, some works consider the sparsely scattered mmWave channel model to describe the channels among APs, UEs, and RISs [59]. Here, we present a typical case that the UE is equipped with a single antenna, and the channel between AP l and UE k is given by

$$\mathbf{o}_{lk} = \mathbf{g}_{lk} + \sum_{t=1}^{T} \mathbf{H}_{lt}^{\mathrm{H}} \mathbf{\Phi}_t \mathbf{z}_{tk}, \quad \forall l, k \tag{1}$$

where $\mathbf{g}_{lk} \in \mathbb{C}^{M\times 1}$, $\mathbf{H}_{lt} \in \mathbb{C}^{M\times N}$, and $\mathbf{z}_{tk} \in \mathbb{C}^{N\times 1}$ denote the direct link from AP l to UE k, one part of the cascaded channel from AP l to RIS t, and another part of the cascading channel from RIS t to UE k, respectively. $\mathbf{\Phi}_t = \mathrm{diag}(e^{j\varphi_{1t}}, e^{j\varphi_{2t}}, \dots, e^{j\varphi_{Nt}}) \in \mathbb{C}^{N\times N}$ represents the phase shift matrix of RIS t where $\varphi_{nt} \in [-\pi, \pi], n \in \{1, \dots, N\}, t \in \{1, \dots, T\}$. The direct channel is generally represented as $\mathbf{g}_{lk} \sim \mathcal{CN}(\overline{\mathbf{g}}_{lk}, \beta_{lk}\mathbf{R}_{lk})$, where $\overline{\mathbf{g}}_{lk}$ represents the deterministic LoS component, $\mathbf{R}_{lk} \in \mathbb{C}^{M\times M}$ is the channel correlation matrix of small-scale fading component, and β_{lk} is the LSF coefficient which can be obtained from [15].

As for the aggregated channel through RIS, some works consider it as a whole and then model the LSF coefficients $\beta_{l,\mathrm{RIS},k}$ [71], [72], while major works consider it as a cascade of two links [73], [74]. This is because the latter scenario, where there are two cascaded channels, ensures their independence from each other, making it closer to real-world channel conditions. In addition, during signal processing, it becomes possible to design each of the two-channel segments separately, providing greater flexibility [75]. In particular, $\mathbf{H}_{lt}$ and $\mathbf{z}_{tk}$ can be denoted as

$$\mathbf{H}_{lt} \sim \mathcal{CN}\left(\overline{\mathbf{H}}_{lk}, \tilde{\mathbf{R}}_{lt}\right), \mathbf{z}_{tk} \sim \mathcal{CN}\left(\overline{\mathbf{z}}_{tk}, \tilde{\mathbf{R}}_{tk}\right) \tag{2}$$

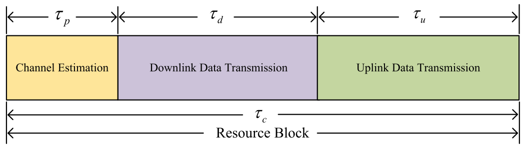

Fig. 4. *Illustration of the considered system frame structure under the TDD communication protocol.*

where $\overline{\mathbf{H}}_{lk}$ and $\overline{\mathbf{z}}_{tk}$ denote the LoS components of channel $\mathbf{H}_{lt}$ and $\mathbf{z}_{tk}$, respectively; and $\tilde{\mathbf{R}}_{lt} \in \mathbb{C}^{MN\times MN}$ and $\tilde{\mathbf{R}}_{tk} \in \mathbb{C}^{N\times N}$ are the spatial covariance matrices, which are generated by the joint action of the AP antennas and the RIS elements and will be discussed in Section IV-A.

C. Communication Protocol

The majority of the current works adopt the TDD mode as a candidate transmission protocol for RIS-aided CF mMIMO systems, primarily because it is simpler compared to FDD. To the best of our knowledge, there is currently little research on adopting the FDD mode for the systems, while Abdallah and Mansour [76], Kim and Shim [77], and Kim [78], and Guo et al. [79], Zhou et al. [80], and Chen et al. [81] have studied the application of FDD models in CF and RIS, respectively. As illustrated in Fig. 4, under the TDD mode, the UL and DL data transmissions take place over the same frequency band, and the frame is divided into three phases in each coherence block: channel estimation, DL data transmission, and UL data transmission. First, the UEs send τ_p pilot sequences to APs for channel estimation. Note that the introduction of RIS brings different operations to the channel estimation stage, such as whether RIS cascaded channels require independent estimation. Also, it is worth noting that during the channel estimation phase, the phase shift of RIS needs to be kept fixed. These are summarized in Section III-A on channel estimation. Then, utilizing the estimated channels, the vectors required for DL precoding in the DL data transmission phases can be computed by APs. Also, the CSI from UL channel estimation needs to be fed back to UEs before it is used for UL data transmission. We observe that under the TDD mode, the RIS aggregated channels and the direct channels have reciprocity for UL and DL communication [75]. As such, DL data precoding is performed by each AP using the UL estimate channels. The UEs decode the DL data depending on the channel statistics information obtained by channel estimation.

By contrast, in FDD systems, the UL and DL data transmissions occur simultaneously, but they are transmitted over two separate frequency bands. As such, the channel coefficients of UL and DL are not reciprocal, which requires the APs to acquire the DL estimated channel to perform the DL precoding procedure. Also, as for the RISs, using the same phase shifts will result in beam misalignment, thereby leading to performance degradation [79], [80]. Indeed, accurate channel estimation can be achieved by adding a DL training phase before DL data transmission. However, this method introduces additional time–frequency resource overhead, which reduces communication rates. In addition, when there are a number of APs, the exchanged CSI causes a high load to the network [76]. To tackle this issue, various CSI acquisition techniques have been proposed by utilizing the angle reciprocity in RIS-aided CF mMIMO systems under the FDD mode [81], [82]. However, implementing these methods in RIS-aided CF mMIMO systems requires further investigation.

III. SYSTEM OPERATION AND RESOURCE ALLOCATION

In this section, we investigate the system operation of RIS-aided CF mMIMO systems, including channel estimation, joint beamforming, and multilayer signal processing. Besides, we explore the resource allocation approach of the considered system. In particular, regarding the above system operation and resource allocation, we survey the specific issues of RIS-aided CF mMIMO systems and propose several feasible techniques to solve them.

A. Channel Estimation

The channel estimation is important for RIS-aided CF mMIMO systems to achieve high spectral and EEs [45], [90], [91], [92]. The channel estimation directly impacts the calculation of precoding and detection vectors adopted for DL and UL transmissions. The problem becomes more complicated with RIS as it is a passive device and cannot independently perform channel estimation itself. If the channel estimation is not accurate enough, it will seriously affect the design of RIS beamforming, leading to deviation in the focusing of the signal beam reflected by RIS. In particular, when multiple RISs need to serve multiple APs simultaneously, inaccurate channel estimation can lead to inaccurate beamforming of the APs and phase shift design of the RISs, causing mutual interference signals between multiple RIS and APs to increase, leading to communication performance degradation.

Taking this into account, various techniques are employed in the literature to perform channel estimation in RIS-aided CF mMIMO systems, and the techniques used vary based on the communication protocol adopted, such as TDD or FDD. Currently, most channel estimation studies consider TDD. As such, the pilot-based channel estimation techniques are widely adopted where UEs transmit τ_p-length pilot sequences to the APs, as shown in Fig. 4. The pilot sequences assigned to UEs can be either orthogonal or nonorthogonal, depending on the number of UEs and the channel coherence time. In general, the UEs can be assigned orthogonal pilot sequences in low mobility scenarios and a small number of UEs. By contrast, in high-mobility scenarios with a small τ_c as mentioned in [93] and [94], nonorthogonal pilot sequences are preferred to limit the amount of resources consumed in performing the channel estimation.

Different from traditional CF mMIMO systems, for the aggregated channel introduced by RIS, existing channel estimation studies consider dividing the aggregated channel into two parts, i.e., the direct channel and the cascaded channel, and estimating them separately, namely, separation channel estimation [85], [86]. In [85] and [86], the channel estimation was divided into $1 + NT$ subphases. In the first phase, all elements of RISs are turned off and each AP estimates the direct channels between itself and all UEs through the pilot transmitted by UEs. In the following NT phases, based on the previously estimated direct channels, the cascaded channels are estimated by sequentially turning on and off each RIS element. Besides, Tran and Ant [86] considered estimating the cascaded channel by sequentially turning on and off each RIS. However, the separation channel estimation method requires a large number of pilot sequence resources and training time slots and cannot capture the coupling relationship between different RIS element channels such as the spatial correlation of channels, especially when the number of RIS elements is large. Considering this, Van Chien et al. [73] and Nguyen et al. [83] have adopted an aggregated channel estimation approach in which the cascaded and direct channels are treated indifferently for channel estimation. For example, Van Chien et al. [73] assumed that UEs send orthogonal pilot signals simultaneously, and the APs detect the received pilot signals, directly estimating the aggregated channel. The results show that compared to separation channel estimation, this method realizes time savings that are proportional to the number of RIS elements. This suggests that as the number of RIS elements increases, the aggregated channel estimation method becomes more applicable. Also, considering the self-interference of RISs, the MMSE estimate is adopted to derive the effective channel that can reduce the error of channel estimation [83]. Besides, in [84], the pilot transmission strategy was considered where all UEs in the same cluster transmit the same pilot signal under the NOMA system. Then, the L-MMSE approach was adopted considering the spatial correlation of RIS elements. The aggregated channel estimation approach does not require high training time and pilot resources while capturing spatial correlation of RIS elements at the expense of the computational complexity. Furthermore, Yang et al. [45] proposed two-timescale channel estimation and adopted a compressive sensing technique to improve the accuracy of the estimated channel. In this regard, two distinct characteristics are identified: 1) a common channel between the AP and the RIS for all UEs and 2) a common channel between the RIS and the UE for all APs. Based on these two characteristics, two-timescale channel estimation issues are investigated, which refers to large-scale CSI that undergoes slow transformation and small-scale CSI that undergoes instantaneous changes. Subsequently, two solutions are presented to address these issues: a compressive sensing technique based on a 3-D multiple measurement vector (3D-MMV) for cascaded channel estimation and a multi-BS

Table 1 Different Techniques for Channel Estimation in RIS-Aided CF mMIMO Systems

Adopted Techniques	Implementation Method	Ref.	Description	Remark
Pilot-based technique	Aggregated channel estimation	[73]	User sends orthogonal pilot signals simultaneously, and AP detects the received pilot signals, directly estimating the aggregated channel.	The proposed approaches do not require high training time and pilot resources, while being able to capture spatial correlation of RIS.
		[83]	Considering self-interference of RISs, the MMSE estimate is adopted to derive the effective channel.	
		[84]	Considering all the users in the same cluster transmit the same pilot signal under NOMA system, and the LMMSE approach is adopted.	
	Separation channel estimation	[85]	Divide the training phase into $T \times N + 1$ sub-phases. First, all RISs are turned off to estimate the direct channels, and then switch on each element sequentially to estimate the cascading channel.	The proposed schemes require massive pilot sequence resources and training time slots, and cannot capture the spatial correlation between different RIS elements. They are applicable when the number of RIS elements is not large.
		[86]	Divide the training phase into $T + 1$ sub-phases. First, all RISs are turned off and then switched on each RIS sequentially to estimate aggregated channels.	
	Compressive sensing	[45]	A 3D-MMV framework is proposed to jointly estimate cascaded AoDs for all users and utilizes tensor contraction to present the 3D-MLAOMP.	The proposed scheme efficiently reduce the NMSE and the performance is close to Oracle LS.
Low vision estimation technique	No pilot requirement	[87] [88]	Low vision channel estimation method exploits the data symbols for channel estimation enhancement without pilot.	The proposed method achieves improvement in the accuracy of channel estimation while it noticeably reduces the training pilot overhead.
Generalized superimposed training	Simultaneous transmission of pilot and data	[89]	The pilots and data symbols are transmitted simultaneously in the coherence time. In OFDM multi-carrier case, a part of the sub-carriers is based on the GST, whereas the other part of subcarriers is used for data transmission only.	The GST scheme can achieve better channel estimation performance under centralized processing compared with local processing.
		[46]	The pilots and data symbols are transmitted simultaneously in the coherence time. The channel estimation and data detection processes are conducted based on the assumption of a certain correlation between pilot and data symbols.	The GST scheme can simultaneously reduce NMSE of channel estimation compared with the standard ST and the regular pilot scheme.

cooperative pilot-reduced methodology for two-timescale channel estimation. The results reveal that the proposed scheme efficiently reduces the normalized mean-squared error (NMSE) and the performance is close to Oracle LS.

Different from the pilot-based techniques, low vision channel estimation is widely used as an advanced channel estimation technique, which can reduce the number of pilots and increase resource utilization [95]. For example, in [87] and [88], the low vision channel estimation method was adopted to estimate the cascading channel through RIS for multiuser systems. The results show that the proposed method achieves improvement in the accuracy of channel estimation, while it reduces the training pilot overhead. However, to the best of our knowledge, there is no study on using low vision channel estimation methods to estimate channels in RIS-aided CF mMIMO systems, which is worth further exploration. Furthermore, Ge et al. [46] and [89] investigated the rate by adopting the generalized superimposed training (GST). In particular, GST involves transmitting pilot and data signals simultaneously within the channel coherence time τ_c, instead of sending them consecutively, as shown in Fig. 4. The channel estimation and data detection processes are then conducted based on the assumption of a certain correlation between the pilot and data symbols. For instance, Ge et al. [89] considered the OFDM multicarrier system where a part of the subcarriers is based on the GST, whereas the other part of subcarriers is used for data transmission only. The results show that applying the GST scheme can reduce the channel estimation NMSE compared with the standard superimposed training (ST) and the regular pilot scheme. We have summarized these in Table 1.

To the best of our knowledge, compared with the TDD mode, studies on channel estimation of RIS-aided CF mMIMO systems under FDD mode are relatively limited. Fortunately, there are some studies on FDD channel estimation of RIS in other systems [80], [96], [97]. It is worth noting that CSI acquisition and feedback overhead will pose a challenge for channel estimation in FDD-based RIS-aided CF mMIMO systems, as the amount of DL CSI feedback increases linearly with the number of antennas and APs. To tackle this issue, Dai and Wei [96] proposed a path selection-based feedback reduction and partial CSI-based beamforming scheme in RIS-assisted systems. Specifically, they assumed that the UL and DL multipath components are similar, including the UL AoA and DL AoD as well as the LSF coefficients. Then, a dominating path gain information (DPGI) estimation and feedback scheme was proposed, where both the length of DL pilot signals and the size of the feedback vector are reduced to the number of selected dominant paths. The results show that the SE of the DL is improved by updating the active and passive beamformers. Besides, to enable reliable DL channel estimation under FDD in the RIS-aided mMIMO system, Dai and Wei [96] proposed to leverage the distributed machine learning (DML) technique. In particular, the network architecture consists of a DL channel estimation neural network shared by all users, which can be collaboratively trained by the BS and users using the DML technique. The DML-based hierarchical neural network further improves the accuracy by extracting different channel features. Simulation results indicate that the proposed approach achieves better channel estimation performance and reduces pilot overhead for all users.

Remark 1: In the future 6G communication, channel estimation will confront unprecedented challenges, especially with the adoption of emerging technologies such as high-frequency bands (e.g., mmWave and THz), holographic MIMO, and RIS. Effective channel estimation techniques' guidelines should include but are not limited to: 1) developing efficient channel estimation methods suitable for ultrahigh-frequency bands and large-scale antenna arrays, and utilizing sparsity and angular domain information to reduce complexity and enhance accuracy; 2) leveraging the tunability of RIS by optimizing its phase configurations to assist in channel estimation, thereby improving estimation precision and range; 3) exploring machine learning-based channel estimation algorithms to adapt to complex and dynamic 6G communication environments, and enhancing channel estimation accuracy and efficiency through data-driven approaches; and 4) considering the heterogeneity and user density in 6G networks, and developing channel estimation strategies that are suitable for CF mMIMO and distributed network architectures.

B. Joint Beamforming Design

As described in Section II, RISs can adjust the phase of incoming electromagnetic waves to effectively improve the network performance. However, as a passive device, if proper beamforming design is not carried out, the beam reflected by the RIS will become interference signals in the electromagnetic propagation environment, leading to a decrease in the quality of the expected signal detection and causing degradation in user performance [40], [98]. In particular, in RIS-aided CF mMIMO systems where multiple APs exist, how to design the phase shift for RISs to provide collaborative services to multiple APs at the same time is an important challenge. Here, we review recent research contributions on the joint beamforming design in RIS-aided CF mMIMO systems in Table 2. Along the literature review, comparisons are provided among different objectives and methods for facilitating the joint beamforming design, accompanied by their benefits and limitations.

1) Optimization Objectives: In RIS-aided CF mMIMO systems, different application requirements will lead to different optimization objectives, which subsequently involve optimization problems and constraints. In the following, the related research works are reviewed according to the optimization objectives.

a) Sum-rate maximization: Focusing on network capacity, we usually consider the problem of maximizing the sum rate. The RIS-aided CF mMIMO system is composed of a large number of distributed independent APs with different positions, making it difficult to obtain real time and accurate channel information. Therefore, there are more optimization constraints, resulting in greater difficulty and complexity in optimization. For example, Zhang and Dai [38] considered differences in user importance and AP selection and attempted to maximize the weighted sum rate (WSR). By developing an AO framework, they decoupled the joint precoding problem and alternately solved the AP beamforming and RIS phase shift subproblems. Specifically, the RIS passive beamforming and AP precoding were designed by the primal–dual subgradient (PDS) approach. The results show that deploying RIS closer to users can achieve better performance than deploying RIS closer to a single AP. Also, by optimizing the phase shift of RIS, when RIS moves from a position 60 m away from the UEs cluster to a position 10 m away, the sum rate increases by more than twice. Moreover, the WSR maximization problem was investigated in [99], which adopted the algorithm unrolling-based distributed optimization. Specifically, they solved this problem by deep distributed alternating direction method of multipliers (D^2-ADMM), which is a monodirectional information exchange strategy with small signaling overhead. Unlike the AO algorithm in [38], which focuses on optimizing augmented Lagrangian functions, the ADMM algorithm involves alternating updates of raw variables and Lagrangian multipliers. This makes ADMM perform better on large-scale RIS-aided CF mMIMO systems. Moreover, Yang and Zhang [60] considered multiple energy receivers in the system and adopted the SCA algorithm at AP precoding and ADMM at the RIS beamforming to solve the SWIPT problem. The results show that as the number of

Table 2 Joint Transmit and RIS Passive Beamforming Design

Objectives	Ref.	UL/DL	CSI	Phase Shifts	AP/UE beamforming	RIS beamforming
max WSR	[38]	DL	perfect	continuous	PDS	PDS
	[99]	DL	perfect	continuous	DL	DL
	[59]	DL	perfect	continuous	MO	PDS
	[100]	DL	perfect	discrete	ADMM	MM
	[44]	DL	two-timescale	continuous	PDS	PDD
	[60]	DL	perfect	continuous	SCA	ADMM
max sum rate	[101]	DL	imperfect	continuous	Lagrangian dual sub-gradient	SDR and QCR
	[102]	DL	perfect	discrete	Water-filling	SRO
	[103]	DL	perfect	continuous	DCP	CGD
	[104]	DL	imperfect	continuous	SDP	ADMM
	[105]	UL	statistical CSI	continuous	MRC	GA
	[106]	DL	imperfect	continuous	DRL	DRL
maxmin rate	[107]	UL	imperfect	continuous	GP	Alternating maximization
	[108]	DL	two-timescale	continuous	ZF	SDR
max EE	[109]	UL	statistical CSI	continuous	DDPG	DDPG
	[41]	DL	perfect	continuous	IA	IA
	[110]	DL	perfect	continuous	SCA	SCA
	[111]	DL	perfect	continuous	ZF	SP
max EEF	[112]	UL	perfect	continuous	FP	FP
	[113]	UL	perfect	discrete	KKT	Lagrangian dual and quadratic transform
min information leakage	[52]	DL	statistical CSI	continuous	ZF	SDP
maxmin SEE	[114]	DL	imperfect	continuous	CCCP	SDP
max WSSR	[115]	DL	imperfect	discrete	SDR	SCA
min network-wide adaption gap	[116]	DL	perfect	continuous	SCA	SCA

AP antennas increases, the performance of only optimizing power gradually surpasses that of only optimizing the phase shift of RIS. It reveals that as the number of AP antennas increases, power optimization becomes relatively more important compared to phase shift optimization of RIS. Furthermore, as the AP maximum transmit power increases, the equal power transmission scheme exhibits deteriorated performance owing to the restricted design flexibility in allocating power among the RIS. In [103], the joint beamforming optimization problem was formulated with the objective of maximizing the aggregate throughput while ensuring the outage constraint of the users. A complex gradient descent (CGD)-based algorithm was proposed for the phase shift control, which addresses the unit-modulus constraint and ensures that the aggregate throughput increases monotonically in each iteration. Then, the authors in [103] designed a difference of convex programming (DCP)-based algorithm for AP beamforming optimization. The results show that the proposed algorithm achieves an aggregate throughput that is 53.8% and 25.1% higher than the cellular MIMO system with ZF beamformer and the RIS-aided CF mMIMO system with random phase shift control.

In contrast to the studies that considered ideal conditions mentioned above, some authors have considered more practical scenarios, such as imperfect CSI or discrete phase shift conditions [44], [100], [102], [104], [117]. For instance, Huang et al. [100] considered the discrete phase shift of RIS and, based on that, jointly designed beamforming for AP and RIS to maximize the weight sum rate. Specifically, they adopted the ADMM algorithm and proposed that it is not necessary to exchange all CSI among APs in each iteration. The results show that the quantization level of phase shifts is related to the size of RISs and the number of antennas. Zhang et al. [102] designed the digital beamforming and discrete RIS phase shift by a water-filling and iterative algorithm. The results show that when the discrete phase shift is based on 5-bit quantization, the system performance is almost consistent with the continuous phase shift. On the other hand, Yao et al. [104] considered the imperfect CSI with an error term and adopted the block coordinate descent (BCD) method to solve the joint beamforming design problem. Indeed, aiming to maximize the worst case system sum rate, the semi-definite programming (SDP)-based AP precoding and the ADMM-based RIS beamforming were designed. Xie et al. [117] considered both channel estimation error and discrete phase shift and adopted the alternate sequential optimization (ASO) method to solve the RIS beamforming problem. The results show that the RIS can achieve a robust performance against the CSI uncertainty in CF mMIMO systems. By contrast, Gan et al. [44] proposed the practical two-timescale CSI framework, i.e., statistical CSI of RIS beamforming and instantaneous

CSI for AP precoding. Then, they introduced the PDS and penalty dual decomposition (PDD) to solve the joint beamforming design. In the two-timescale framework, the phase shift design of RIS utilizes statistical CSI rather than instantaneous CSI, leading to reduced information exchange frequency, alleviated fronthaul link load, and more effective savings on time–frequency resources.

b) User fairness: Ensuring user fairness is an important measure to ensure the reliability of a communication system. It can prevent a large accumulation of resources among high-performance top-tier users, thereby avoiding resource wastage and enhancing overall user satisfaction [118]. Generally, user fairness is achieved by maximizing the minimum user rate. Ensuring that each user receives the minimum possible data rate may require introducing complex constraint conditions, which could involve interrelationships among multiple users, thereby increasing the number and complexity of constraints in the problem. Many studies have attempted to address this issue. For example, Dai et al. [105] focused on the Rician channel and proposed a design for the RISs passive beamforming using long-time statistical CSI while adopting the MR combining technique for the APs beamforming based on instantaneous CSI. They then derived closed-form expressions for the UL achievable rate and optimized the phase shifts of the RISs using a genetic algorithm (GA) to maximize the minimum user rate. The results demonstrate the effectiveness of the two proposed two-timescale schemes and demonstrate that RIS achieves a minimum user rate improvement of 1.5 times in the CF mMIMO system. Moreover, Zappone et al. [107] maximized the minimum SINR of the RIS-aided CF mMIMO system, where the imperfect CSI and discrete phase shift of RIS were considered. In particular, the receiver filter design was formulated as a generalized eigenvalue problem leading to a closed-form solution, and the RIS phase shifts were designed using an alternating maximization algorithm. It reveals that utilizing statistical CSI has the potential to outperform the scheme based on instantaneous CSI for a moderate to large number of RIS elements, as it reduces the channel estimation overhead. Noh and Choi [108] proposed a novel two-step algorithm, the long-term passive beamformers using semidefinite relaxation (SDR) at RISs and short-term active ZF precoders and long-term power allocation at APs. Notably, the approach can reduce computational complexity and signaling overhead. Jin et al. [119] considered single-user and multiuser scenarios with practical discrete phase shifts and aimed to maximize the minimum achievable rate. Specifically, the integer linear program (ILP)-based algorithm and the ZF-based successive refinement algorithm were adopted for the single-user and multiuser scenarios, respectively. With the proposed algorithm, the minimum achievable rate of the RIS-aided CF mMIMO system is significantly increased, and using 2-bit discrete phase shifts can practically achieve the same performance as continuous phase shifts.

c) EE and EE fairness maximization: With an increase in the number of antennas, energy consumption has become an important issue that constrains the development of RIS-aided CF mMIMO systems [1]. Therefore, many works have tried to find technologies and methods to improve EE [109], [112]. Zhang et al. [40] investigated a hybrid beamforming (HBF) scheme consisting of the RIS-based analog beamforming and the digital beamforming at APs to maximize the EE for the DL. The iterative algorithm is designed to solve this problem and the results show that the considered system has a better EE performance than those of traditional ones, including conventional distributed antenna system (DAS). The same problem was further investigated by Le et al. [41] by taking into account the limited-fronthaul capacity constraints. To solve this problem, they introduced the inner approximation (IA) approach. Besides, Lyu et al. [110] explored an RIS-aided CF mMIMO system utilizing hybrid RISs comprising a combination of active and passive elements that can amplify and reflect the incoming signal, respectively. To maximize the EE of the system, a BCD-based algorithm was proposed to decouple variables, and then, the SCA method was used to iteratively address the nonconvexity of the subproblems. The results show that the proposed hybrid RIS schemes can attain 92% of the sum rate while achieving 188% of the EE of purely active RIS schemes. Different from the above solutions, Li et al. [109] proposed machine learning to solve the problem of maximizing long-term EE. In practice, considering the statistical CSI, the distributed novel hybrid deep deterministic policy gradient (DDPG) framework was adopted to reduce outage probability and enhance robustness. It reveals that the proposed hybrid DDPG-based algorithm has a faster convergence speed and requires less computational resources and communication overhead during the model training compared with the centralized algorithm.

As an extension of maximizing EE, some researchers consider the issue of EE fairness (EEF) [112], [113]. Specifically, Liu and Zhang [113] formulated the precoding design problem to maximize the EE of the worst user in a wideband RIS-aided CF network. To solve the above problem, an iterative precoding algorithm was proposed to design the subcarrier assignment, power allocation, combining, and precoding by adopting Lagrangian transform and fractional programming (FP). Moreover, Wang and Peng [112] investigated the EEF maximization problem with active RISs in the CF mMIMO system and introduced a joint beamforming and resource allocation (JBRA) algorithm. These two studies indicate that both active and passive RISs, with well-designed beamforming, can improve the worst user EE by 13.8% and 50%, respectively. However, even with random phase shift, active RIS can still achieve a 40% improvement in worst user EE.

d) Information security: Wu and Zhang [20] highlighted that the utilization of RIS, through the beamforming techniques, can effectively safeguard physical-layer security by thwarting the unauthorized interception of

Table 3 Approaches for Joint Beamforming Design

Techniques	Approaches	Pros	Cons	Ref.
Traditional optimization	SDP	• Relax to convex problem • Fast convergence • Support complex constraints	• Require rank-one solution construction • High computational complexity • Not suitable for large-scale problems	[52], [104], [108], [115]
	Iterative algorithm	• Good complexity-performance tradeoff • Handle large-scale problems • Support non-convex problems	• May converge to local optimal solution • Slow convergence speed • Sensitive to initialization	[40], [60], [100], [110]
	Subgradient	• Nonsmooth optimization problems • Low computational complexity	• Need to adjust step size • Slow convergence speed	[38], [44], [59]
	Manifold optimization	• Suitable for high-dimensional, nonlinear, non Euclidean space problems • Fast convergence • High accuracy and efficiency	• High mathematical understanding threshold • High computational complexity • Highly problem-specific	[59], [121], [122]
Machine learning	Deep/ Reinforcement learning	• Can learn from multidimensional data • High accuracy and stability • Automatically extract features and patterns	• Lack of interpretability and transparency • Require large amounts of labeled data • May not guarantee global optimality	[106], [109], [123]

desired information by potential eavesdroppers. However, in CF mMIMO systems, the presence of multiple APs causes vulnerability for eavesdroppers to intercept information from various sources. Designing RIS to ensure information security poses greater challenges in such scenarios [120]. To solve this problem, Elhoushy et al. [52] investigated the potential of RIS in boosting the secrecy capacities of CF mMIMO systems under spoofing attacks. Indeed, they jointly designed the RIS phase shifts and AP power coefficients in the DL to minimize the information leakage to eavesdroppers while maintaining a certain SE for legitimate users. Specifically, they considered that the APs only have the statistical CSI and apply the ZF precoding for data transmission along with SDP for RIS phase shift design. The results reveal that only two RIS panels activated can significantly improve the secrecy capacity and boost the robustness against the higher power of spoofing pilot attacks. In addition, Hao et al. [114] formulated a max-min secure EE (SEE) problem and then proposed the constrained convex–convex procedure (CCCP) and SDP techniques for AP precoding and RIS beamforming. The results show that continuously increasing the number of AP antennas and transmission power is not the optimal choice, and the SEE performance is the best when the transmission power is 15 dBm with three antennas. Hao et al. [115] aimed to max weighted sum secrecy rate (WSSR) by jointly optimizing the active precoding at the APs and passive beamforming at the RISs with imperfect CSI and discrete phase shift. In particular, due to the CSI of RIS being difficult to obtain, a scheme for optimizing RIS matching UE based on CSI was proposed, and linear conic relaxation (LCR) relaxation constraints were used to transform this problem into an SDP problem for solution. The results indicate that compared to traditional RIS-aided CF mMIMO systems, matching three UEs per RIS can achieve nearly fully connected performance.

2) Approaches for Joint Beamforming: Based on the above survey, it can be observed that the current approaches for joint beamforming design in RIS-aided CF mMIMO systems mainly fall into two categories: traditional optimization and machine learning. For traditional optimization, due to the involvement of nonconvex optimization problems with multiple variables, the approach often relies on the AO methods. The advantage of this approach is that the active beamforming design becomes a conventional problem once the passive beamforming vector is determined, which has been extensively studied [16]. However, designing the passive beamforming under given transmit beamforming vectors remains a challenging problem. As for machine learning, there is relatively limited research in this direction, with only few works. However, considering the complexity of multivariable optimization, machine learning holds promise as a potential direction for future exploration and discussion [124], [125], [126]. In the following, we review the approaches employed in current research contributions for joint beamforming design. Table 3 summarizes the characteristics of the approaches.

1) *Semi-definite programming (SDP):* A commonly employed approach for addressing the nonconvex unit-modulus constraint involves converting the passive beamforming vector into a rank-one positive semi-definite matrix. Then, the original nonconvex problem becomes a convex SDP problem that has fast convergence and supports complex constraints that can be solved by using many efficient convex

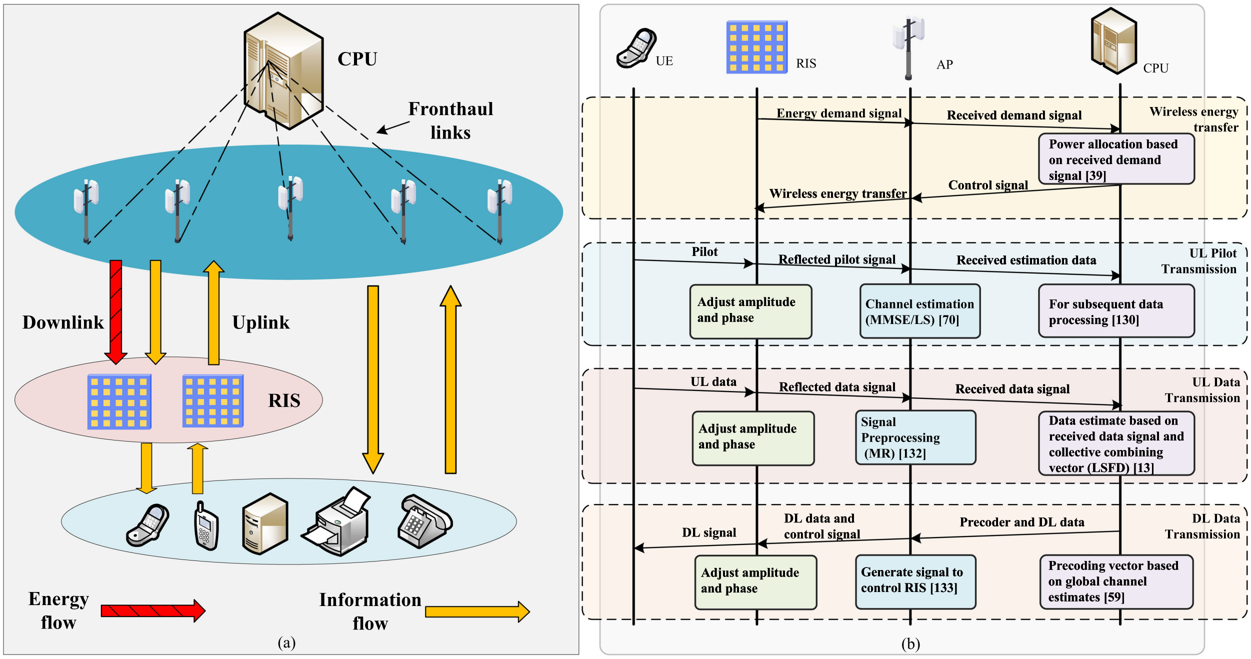

Fig. 5. ***Multistage transmission procedure and multilayer signal processing of RIS-aided CF mMIMO systems. (a) Illustration of the system architecture. (b) Illustration of the four-stage transmission procedure, including the WET, UL pilot transmission, UL data transmission, and DL data transmission.***

optimization tools [104]. Nevertheless, the rank-one solution constructed in this manner is typically suboptimal and may potentially be infeasible for the original passive beamforming design problem [119]. This not only leads to performance degradation but also hinders the convergence of the AO-based iterative algorithm.

2) *Iterative algorithm:* Iterative algorithm is a commonly used method that strikes a tradeoff between complexity and performance, making it suitable for large-scale problems [100]. In particular, it can also obtain a solution of nonconvex optimization problems. However, it may converge to a local optimal solution and have a slow convergence speed [40], [110]. Most importantly, the results are highly sensitive to initialization.
3) *Subgradient:* The subgradient method is a common approach for solving nonsmooth optimization problems. It does not require global derivatives or computations of higher order derivatives, reducing the computational complexity [38], [44], [59]. However, its convergence speed is slow, and the results are highly sensitive to the choice of initialization.
4) *Manifold optimization:* Manifold optimization (MO) is a common approach for addressing high-dimensional, nonlinear, or problems with specific geometric structures. MO has the characteristics of fast convergence and high accuracy [121]. However, this method has high computational complexity and is only applicable to some specific problems, with low universality.
5) *Machine learning:* It can be broadly categorized into several major types, including deep learning, RL, and (un)supervised learning [127]. For multivariable optimization problems, machine learning has distinct advantages [124], [128]. Machine learning can learn features and patterns from complex data, allowing for higher accuracy and stability in the optimization process [109], [129]. However, currently, there is a lack of interpretability and transparency in machine learning methods. It often requires a large amount of labeled data to ensure the reliability of results and cannot guarantee global optimality.

C. Multistage Transmission Procedure and Multilayer Signal Processing

As shown in Fig. 5(a), the RIS-aided CF mMIMO system is based on the CF architecture with an additional RIS layer between the APs and the UEs. Different from the existing CF mMIMO system, which is a three-tier structure, the RIS-aided CF mMIMO system realizes a 3.5-layer architecture, which adds a cascading link through RIS [39]. Based on the multilayer nature of the system, performing multistage transmission procedures and multilayer signal processing can reduce interuser interference and enhance the system performance, which is unmatched by traditional cellular networks. In the following, we introduce the multilayer characteristics of the system in detail, as shown in Fig. 5(b).

Stage 1 (WET): Due to the low power consumption of RIS, some works have proposed WET technology to further

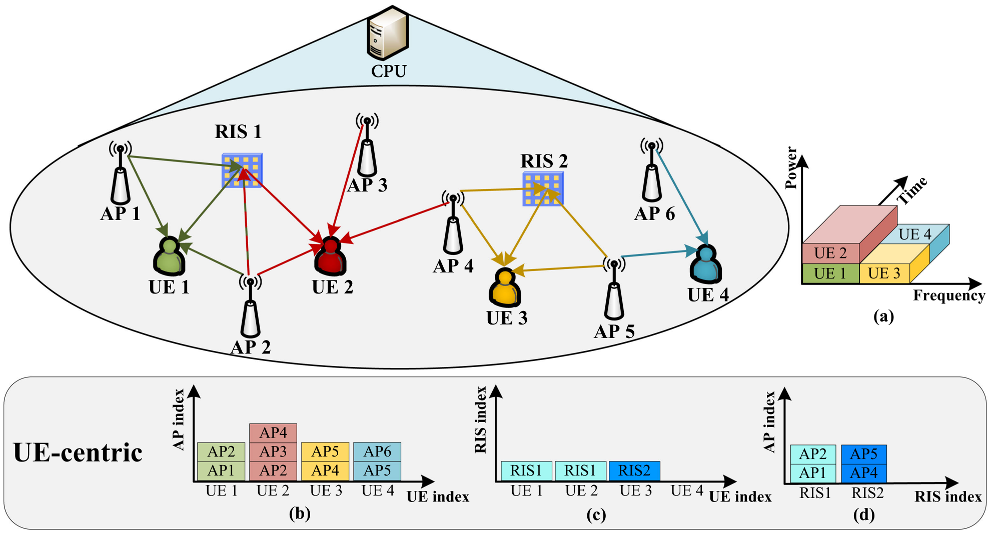

Fig. 6. ***Illustration of resource management in UE-centric RIS-aided CF mMIMO systems, including the AP-RIS-UE selection and time–frequency–power resource allocation. (a) Time–frequency–power resource assignment. (b) UE-AP selection. (c) UE-RIS selection. (d) RIS-AP selection.***

improve the EE of the system [39]. First, the CPU receives information transmitted by the AP via the fronthaul and provides energy control commands to the AP after signal detection. Then, the AP determines whether to transmit wireless energy signals to the RIS for energy harvesting based on the received signals. Specifically, when the energy level stored in the RIS surpasses a predefined threshold, the RIS controller sends feedback signals to the AP to cease the energy transmission.

Stage 2 (UL Pilot Transmission): In the system, each UE is assigned a pilot sequence, which can be allocated randomly or based on a certain metric algorithm [130], [131]. The UE then transmits this pilot signal directly or via the RIS to reach the AP. After receiving the pilot signal, the APs perform local channel estimation, e.g., MMSE and LS channel estimation, to obtain estimated channel information [70]. Subsequently, the APs send the required channel estimation data, such as large-scale information, to the CPU for subsequent data transmission processing. Note that during this stage, it is important to keep the phase shift of RISs fixed to ensure the accuracy of channel estimation.

Stage 3 (UL Data Transmission): The UEs send their UL data to the AP via a direct link as well as the cascaded link through RIS beamforming. Then, the AP executes local signal combining based on the previously estimated channel information. Techniques, such as MR/GMR or MMSE combining, can be adopted, as proposed in [83] and [132]. Subsequently, the local estimates are passed to the CPU for final decoding, where the simple central decoding or LSFD can be employed based on the global channel estimation [13].

Stage 4 (DL Data Transmission): The DL data signal is produced by the DL precoder at the CPU and subsequently transmitted to the AP, allowing it to be conveyed to the UEs through the RIS [59]. In parallel, the AP generates control signals to regulate the phase adaptation of the RIS. It is important to emphasize that if the AP intends to achieve dynamic control over the RIS, adaptations to the frame structure and the inclusion of dedicated control time slots become imperative [133]. Consequently, the deployment of signal processing modules at the RIS may be required to effectively respond to the control signals.

The multistage transmission procedure and multilayer signal processing mechanism are brought about by the inherent distributed structure of the RIS-aided CF mMIMO system. By utilizing the hierarchical signal processing of CPU, AP, and RIS, the performance limits of the system can be further explored while reducing resource costs caused by multiread information interaction. However, this requires strict protocols and standard guidance to ensure the orderly operation of the system.

D. Resource Allocation

As shown in Fig. 6, in large-scale RIS-aided CF mMIMO networks, proper resource allocation is essential to ensure network stability and efficiency. Specifically, the key difference between RIS-aided CF mMIMO networks and traditional cellular networks is their user-centric nature, where multiple APs and RISs coexist to cater to multiple UEs. In this scenario, addressing time–frequency–power resource assignment and AP-RIS-UE selection is crucial to ensuring their effective coordination and optimizing network performance.

1) Time–Frequency–Power Resource Assignment: The mainstream research on RIS-aided CF mMIMO systems focuses on system design considering the same time–frequency resources. However, properly assigning users to different subchannels enhances the bandwidth efficiency.

In practice, the reflection coefficients of RIS are frequency-dependent. Indeed, when RIS elements lack frequency selectivity, a common RIS reflection matrix must be applied across all subchannels, leading to challenging optimization problems [134], [135], [136]. To solve this difficulty, Li et al. [109] proposed a DDPG-based algorithm to solve joint beamforming and RIS deployment design for the RIS-aided CF mMIMO NOMA networks to maximize the EE. The introduction of successive interference cancellation (SIC) as an additional optimization constraint in NOMA network optimization has made the optimization problem even more complex. Also, Vasa et al. [84] derived a closed-form DL SE expression by considering imperfect CSI and employing imperfect SIC. For clustering, they followed the mechanism where the UEs that have the smallest distance from each other are paired. The results indicate that when AP transmission power is 40 dBm, the incorporation of NOMA results in a 30% improvement in SE performance compared to OMA. Besides, Rafieifar et al. [137] designed CB for active and passive beamforming at the APs and RISs, respectively. For the RIS assignment, RIS was assigned to the UE with the least distance. Subsequently, they proposed a low computational complexity distance-aware UE clustering algorithm where two UEs with the least distance were selected as a pair or cluster. However, this simple grouping approach can also bring many limitations. For example, the spatial distribution of users is often uneven, and users in close proximity may not necessarily have similar channel conditions or requirements. This can lead to a decrease in the performance of some users as they may experience interference or competition. In addition, the distances and channel conditions between users may change over time with mobility. Therefore, a better approach is to group users based on their channel quality. Grouping users with similar channel quality together can maximize the overall system throughput. These works emphasize different aspects of RIS-aided CF mMIMO systems with NOMA, including joint beamforming and RIS deployment optimization, and UE clustering. However, there are still many research directions that require further investigation, such as dynamic user clustering algorithms, joint time–frequency resource allocation designs, and power allocation problems.

2) AP-RIS-UE Selection: In multi-APs serving UE communication, where there are no longer constraints of cell boundaries, achieving UE-centric communication becomes crucial. To address this, Chen et al. [17] and Björnson and Sanguinetti [138] proposed a scalable AP-UE selection mechanism to increase the efficiency of CF mMIMO networks. However, an introduction of RIS in CF networks brings forth new challenges in access design, such as UE-RIS and RIS-AP selections. Therefore, the previous AP-UE selection problem has evolved into a joint AP-RIS-UE selection problem. In this context, the optimization problem becomes much more sophisticated.

1) *UE-AP selection:* Many research studies, such as [47], [117], and [139], considered scenarios where all APs serve all UEs. However, this approach significantly increases the computational complexity of the network, especially when a large-scale RIS with a large number of elements is considered. For the UE-AP selection, RIS will change the channel propagation environment and affect the user performance, which inevitably leads to differences in the selection results compared to a CF network. Whether the previous UE-centric CF network selection strategies can be extended in the RIS-aided CF mMIMO network is a question to be answered. For example, Ma et al. [59] proposed a partially connected CF mMIMO (P-CF-mMIMO) framework to alleviate heavy communication costs. Then, the problem of BS selection was formulated as a binary integer quadratic programming (BIQP) problem, and a relaxed linear approximation algorithm was proposed to address this BIQP problem. The results demonstrate that this optimized UE-AP selection scheme can achieve performance improvement compared with the UE-AP full access scheme while reducing resource consumption. However, there are still many directions that can be explored, including how to quantify the impact of RIS during the selection process, designing selection strategies, and optimizing the frame structure.
2) *UE-RIS selection:* In multi-RIS assisted multi-UE systems, generally, the UE-RIS selection schemes determine the overall network performance such that how to associate UEs to different RISs is an important problem. Considering a multi-RIS aided CF mMIMO system, Bie et al. [140] assumed that the RISs were deployed near the UE with poor performance and provided one-to-one service for the nearest UE. The results show that when RIS is 100 m away from the user, this selection method can achieve a performance improvement of five times for the worst performing user compared to without RIS. In addition, Zhang and Dai [38] assumed that the number of RISs accessed to each UE was limited, and based on this consideration, they formulated the maximum sum-rate optimization problem. For such a zero-one programming problem, they employed LCR to solve it.
3) *RIS-AP selection:* The energy of the signals reflected by passive RIS is limited and needs to be focused on specific APs in order to achieve significant performance improvements. For simplicity but without loss of generality, Shi et al. [19] adopted a heuristic distance selection scheme to determine the access of RIS and AP, i.e., each RIS only served the closest AP. However, getting the distance information, especially for RIS, can be challenging in practice. Indeed, in network security scenarios, the selection of RIS and AP is particularly important as it can effectively prevent eavesdroppers [47], [141].

Table 4 RIS-Aided CF mMIMO System With Spatial Correlations

Hardware impairments	UL/DL	Ref.	RIS element spatial correlation	AP antenna spatial correlation	Major observation
Spatial correlation	UL/DL	[73]	✓	✗	• The spatial correlation of RIS leads to system performance degradation. • The system performance degradation caused by correlation is minimal at a half wavelength spacing of RIS elements.
	UL	[146]	✓	✗	
	UL	[19]	✓	✗	
	UL	[69]	✓	✓	• The RIS element correlation in the aggregated channel affects the AP antenna correlation, resulting in both negative impacts of SE.

3) Discussion and Outlooks: In large-scale RIS-aided CF mMIMO networks, resource management is an important direction that has not been fully explored. Based on the above survey, selecting suitable optimization algorithms based on various strategies for AP-RIS-UE selection design is another aspect that needs further research. Possible strategies include channel quality-based grouping strategies [142], service quality-based grouping strategies [59], and deep learning-based dynamic grouping strategies [143]. In addition, using machine learning methods to optimize dynamic resource allocation schemes and achieve efficient utilization of time–frequency resources is a promising direction [144], [145]. This will contribute to the efficient and stable operation of the system.

IV. PERFORMANCE ANALYSIS OF DIFFERENT PRACTICAL SYSTEM CONSIDERATIONS

Although RIS-aided CF mMIMO systems have the potential to enhance UEs' performance, several practical limitations may cause severe degradation in system performance. In particular, the integration of RIS and CF will introduce coupling impacts between the inherent practical factors of both, such as spatial correlation and phase shift errors. In this section, we emphasize the impacts of different practical system considerations on system performance and provide insights for the implementation of RIS-aided CF mMIMO systems.

A. Hardware Impairments

RIS is fabricated with low power and low cost, which can be flexibly deployed to assist users to improve communication quality. However, this inevitably leads to simple hardware design and limited phase shift accuracy. On the other hand, as the wireless network expands, deploying massive APs will lead to a sharp increase in hardware costs. Therefore, realistic systems tend to deploy low-cost hardware to address cost issues, which can cause degraded system performance. Meanwhile, the HIs of RIS and CF mMIMO systems will couple with each other and cause new impacts. In the following, we enumerate several crucial HIs that significantly affect practical deployments and subsequently comprehensive investigations to unveil their influence on the system's performance.

1) Spatial Correlation: The presence of spatial correlation in a channel disrupts its inherent characteristics, affecting the accuracy of beamforming and resulting in degraded system performance. Shi et al. [19] indicated the existence of two types of spatial correlation in RIS-aided CF mMIMO systems: RIS element spatial correlation and AP antenna spatial correlation. These two types of correlation are mutually coupled, exacerbating the impact on system performance. Table 4 summarizes some studies in the literature that analyzed system performance with spatial correlations of AP antennas and RIS elements.

For example, Shi et al. [19] and Van Chien et al. [73], [146] considered the impact of RIS element spatial correlation and derived the closed-form expressions of UL and DL SE. In practice, the spatial correlation of RIS elements is modeled by the sinc function introduced in [74]. The results reveal that the spatial correlation of RIS elements leads to a decrease in system performance gain from the square of the number of RIS elements to a linear increase in the number of RIS elements. Note that at the half-wavelength spacing of RIS elements, the system performance degradation is minimal. Furthermore, Shi et al. [69] simultaneously considered the spatial correlation of both the RIS elements and AP antennas and derived a closed-form expression for the system average SE utilizing multidimensional matrices. Fig. 7 illustrates the cumulative distribution function (cdf) of average SE per UE under different spatial correlations of AP antennas and RIS elements of RIS-aided CF mMIMO systems. It is clear that the existence of spatial correlations has a negative impact on the system performance, especially the correlation in RIS elements, which leads to poor passive beamforming at the RIS. Note that different from the conclusion that AP antenna spatial correlation is beneficial for CF mMIMO systems in [147], the RIS elements correlation in the aggregated channel affects the AP antenna's spatial correlation, resulting in both types of correlations having a negative impact on system performance. In summary, spatial correlation among RIS elements causes system performance degradation, but in practice, designing them for half-wavelength minimizes the impact.

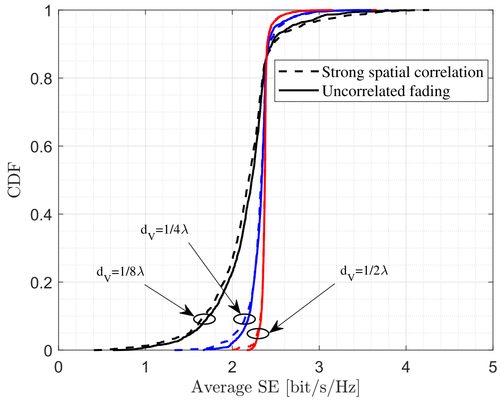

Fig. 7. ***CDF of the UL average SE per UE under different spatial correlations of AP antennas and RIS elements of RIS-aided CF mMIMO systems. The numbers of AP, UE, and RIS element are 40, 10, and 36, respectively. Please refer to [69] for more details.***

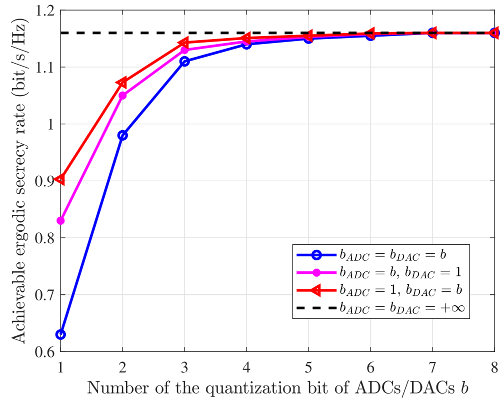

Fig. 9. ***Achievable ergodic secrecy rate versus the number of quantization bits of the low-resolution ADCs/DACs. The numbers of RIS, RIS element, and AP are 10, 400, and 100, respectively. Please refer to [152] for more details.***

2) Phase Shift Errors: The primary role of passive RIS in communication systems is to manipulate the phase of the incident electromagnetic waves. Therefore, if the phase of the RIS is inaccurate, it can lead to deviations in beamforming and ultimately affect the signal reception at the AP, thereby impacting the performance of CF mMIMO systems. For this consideration, Zhang et al. [102] considered discrete phase shifts of RIS in CF mMIMO systems and quantized the precision using the number of bits. As shown in Fig. 8, when using 3-bit quantization, the performance is already close to that of continuous phase shift. Furthermore, the performance obtained using 5-bit quantization is nearly indistinguishable from continuous phase shift. In practice, considering a tradeoff between cost and performance, it is common to consider 2- and 3-bit quantization precision of RIS elements, which has been provided in [38] and [100]. It is worth mentioning that the existence of phase shift error introduces additional challenges to the design of joint beamforming optimization algorithms for RIS-aided CF mMIMO systems, especially the discontinuity of RIS phase shift optimization variables. To address this issue, potential solution approaches include approximation algorithms and machine learning techniques [148], [149].

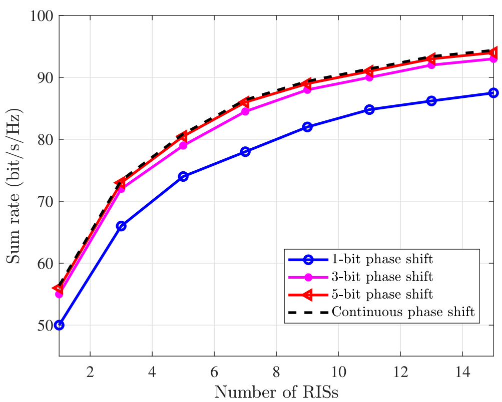

Fig. 8. ***Sum rate of the DL RIS-aided CF mMIMO systems under different phase shift quantization accuracies. The numbers of AP antenna, UE, and RIS element are 8, 8, and 64, respectively. Please refer to [102] for more details.***

3) Analog-to-Digital Converters/Digital-to-Analog Converters: The presence of numerous distributed APs in networks makes the implementation of ideal high-resolution ADCs/DACs costly and power-intensive [150], [151]. An efficient solution is the utilization of low-resolution ADCs/DACs in cost-effective and energy-efficient CF mMIMO systems. Based on that, Zhang et al. [152] investigated the impact of low-resolution ADCs/DACs under physical-layer security of RIS-aided CF mMIMO systems and derived a closed-form expression of the achievable ergodic secrecy rate. Fig. 9 illustrates the achievable ergodic secrecy rate versus the number of quantization bits of the low-resolution ADCs/DACs [152]. We can see that 5-bit ADCs/DACs provide sufficiently close results to that of the ideal ADCs/DACs in actual system design.

To sum up, it has been demonstrated that all of the HIs can cause varying degrees of performance degradation in the system. Among them, ADCs/DACs are the most severely damaged as they can simultaneously affect the signals from both the direct link and the RIS cascaded link, resulting in severe distortion of the received signal. However, current research has only focused on the impact of individual factors, lacking a comprehensive consideration of their joint effects. In reality, these HIs coexist and may affect each other. Hence, it is imperative for future research to incorporate a comprehensive consideration of various HIs simultaneously.

B. Electromagnetic Interference

In future wireless propagation environments, spatial EMI is ubiquitous [153]. RISs as passive components not

Table 5 RIS-Aided CF mMIMO System With EMI

Target	Scenario	Ref.	Major observation	Future direction
EMI	RIS-aided SISO/uplink	[153]	Due to the presence of EMI, the SNR gain of the RIS degrades from N^2 to N.	• Joint beamforming design
	RIS-aided SISO/downlink	[154]	Although RIS aperture can capture much EMI, many reflecting elements allow RIS to mitigate EMI effect by means of spatial filtering partially.	
	RIS-aided CF mMIMO/uplink	[155]	EMI can degrade system performance, and increasing the number of elements can mitigate the impact of EMI.	• Channel estimation

only reflect useful signals but also reflect EMI signals [154]. This phenomenon introduces inaccuracies in beamforming, subsequently impacting system performance. As shown in Fig. 10, in RIS-aided CF mMIMO systems, where the number of APs is substantial, the presence of spatial EMI signals is reflected by RIS. Therefore, when combining RIS with CF mMIMO systems, it is essential to incorporate EMI modeling into the system framework to achieve more accurate performance characterization. Fortunately, Shi et al. [155] considered the EMI to further evaluate the RIS-aided CF mMIMO system performance of the actual environment. Then, they derived a closed-form expression for the system SE with the MR combining at the APs and the LSFD at the CPU. Also, the EMI-aware power control methods were proposed to further improve the system performance. As shown in Fig. 11, EMI significantly degrades the system performance. Also, the performance gap becomes smaller and is less sensitive to the increases of RIS elements N. It reveals that increasing the element number of RIS in RIS-aided CF massive MIMO systems is beneficial to naturalizing the impairment caused by EMI. However, the current research on EMI mainly focuses on performance analysis, and the design of joint beamforming and channel estimation considering EMI scenarios can be a future direction, for instance, how to utilize existing hardware devices for detection and employ traditional optimization algorithms or emerging tools such as artificial intelligence to mitigate EMI from RIS, thereby achieving the ideal system performance enhancement with RIS. Table 5 summarizes the related studies and future directions regarding the consideration of EMI in RIS-aided CF mMIMO systems.

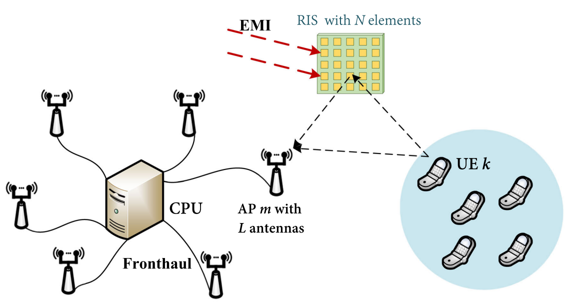

Fig. 10. *RIS-aided CF mMIMO system with EMI.*

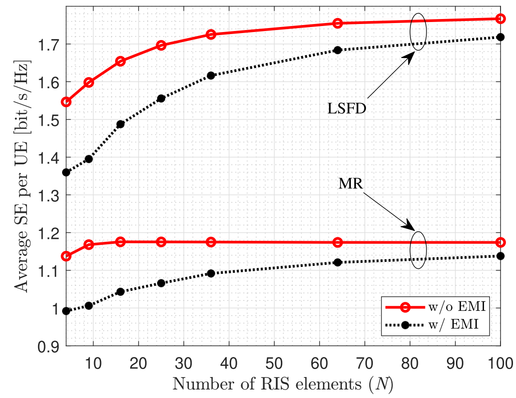

Fig. 11. *UL average SE against the number of RIS elements N with/without EMI by LSFD/MR. The numbers of AP, AP antenna, and UE are 10, 1, and 5, respectively. Please refer to [155] for more details.*

C. Limited-Fronthaul Capacity

Unlike centralized architectures, RIS-aided CF mMIMO system performance is greatly limited by the fronthaul link capacity. On the one hand, the APs require fronthaul links to connect to the CPU for UL and DL data transmission, and the CPU needs to manage power control and beamforming coefficients for different APs [158], [159]. On the other hand, although the RIS is a passive element, it still requires control units for dynamic beamforming design, and obtaining channel information and beamforming instructions from the system requires the fronthaul links [160]. As such, Le et al. [41] focused on maximizing the EE of the RIS-aided CF mMIMO system while considering the constraints of limited-fronthaul link capacity. It is assumed that perfect CSI is available for the APs and RISs. Then, the alternating descent-based iterative algorithm is proposed to solve the maximum EE problem. However, obtaining perfect CSI in large-scale networks is challenging. Therefore, Yao et al. [156] considered robust beamforming design against the impact of imperfect CSI, under the constraint of limited-fronthaul capacity. Regarding the optimization subproblem for RIS phase shift, they utilized the

Table 6 RIS-Aided CF mMIMO System With Limited-Fronthaul Capacity

Target	Ref.	CSI	Setting
Limited fronthual	[41]	perfect	Fronthual link capacity as a constraint for optimization problems.
	[156]	imperfect	
	[100]	perfect	Do not have to exchange all CSI among BSs in each iteration.
	[157]	perfect	Active beamforming vectors are obtained by local APs.

penalty convex–concave procedure (P-CCP) to attain a stationary solution and establish a robust initialization. As for the AP precoding optimization subproblem, they adopted the SCA method, ensuring convergence toward a Karush–Kuhn–Tucker (KKT) solution with guaranteed reliability. The results show that when the fronthaul capacity is less than 80 Mb/s, the centralized BS demonstrates a superior performance. Unlike the above works, which consider the fronthaul link capacity as a constraint for global optimization, the works [100], [157] took a different approach by considering the exchange of partial channel information to alleviate the capacity requirement of the fronthaul link. For example, Ni et al. [157] considered that the active beamforming vectors are obtained by local APs and the passive beamforming vector for RIS is optimized by the CPU so that the fronthaul links do not need to transmit all channel information to the CPU. Table 6 summarizes the related studies regarding the consideration of limited-fronthual capacity in RIS-aided CF mMIMO systems.

However, the above studies assume that the RIS can be controlled instantaneously, without considering the fronthaul link of the RIS. In practice, RIS can be directly connected to the CPU or connected to the local AP for independent phase shift control. For the RIS connected to the CPU, real-time control can be achieved by the CPU conveying processed instructions to the RIS. Conversely, if the RIS is connected to the local AP, the CPU needs to transmit the control signals to the target AP, which decodes the signals and forwards control instructions to the RIS. In this case, the design of the fronthaul link needs to consider an additional fronthaul capacity requirement for the signals generated to the RIS. Currently, the fronthaul link limitation issue of RIS is still open and worth investigating.

D. RIS Deployment

The path loss of the cascading link via RIS is more severe compared to the direct link. Therefore, the deployment location design of RIS is necessary to achieve the desired performance enhancements. Numerous studies have indicated that deploying RIS near the BS or UE can achieve satisfactory performance in BS-centric MIMO systems [161], [162], [163], [164], [165]. However, in CF mMIMO systems with a large number of distributed APs and RISs, determining the optimal deployment of RISs to achieve the best global performance becomes a challenging problem. The reason is that the optimization problem has to be transformed from a point-to-point scenario to a multipoint-to-multipoint scenario, introducing additional complexities in resource allocation and interference management. We summarize related studies on RIS deployment in RIS-aided CF mMIMO systems in Table 7. Zhang et al. [166] considered maximizing the DL UE sum rate by alternately optimizing the RIS position and phase shift with perfect CSI. The results show that when UEs are densely distributed, the optimal location for RIS should be closer to the UEs. Furthermore, in [139], the joint power allocation, the placement, and the reflection phase shift parameters of the RIS were optimized to maximize the UE achievable rate. However, the above works considered scenarios with only a single RIS and assumed that both the APs and UEs were equipped with a single antenna. This simplification significantly reduces the complexity of optimization, but its usefulness is also limited. In practice, RIS-aided CF mMIMO systems involve multiple RISs, UEs, and APs with multiple antennas, which introduces additional challenges in optimizing the deployment of RIS and interference management. Based on that, Zhang and Dai [38] considered the system with multi-RIS and multiantenna APs/UEs, and then, a joint precoding design scheme at APs and RISs was proposed to maximize the network capacity by adopting a PDS algorithm. The results indicate that deploying RISs in close proximity to UE clusters leads to significant performance improvement. Specifically, in the scenario of two UEs and two APs, RIS improves the sum rate 2.3 times when RIS is 10 m away from the UE cluster compared to 60 m away from the UE cluster. However, in scenarios where APs and UEs are uniformly and randomly distributed throughout the entire system without any UE clustering, the deployment of RIS poses new challenges. Considering this fact, Shi et al. [155] considered one RIS serving the CF network where APs and UEs uniformly and randomly distributed within a 1×1 km area. They concluded that deploying a single RIS in the center of the region yields the best system performance, achieving an average SE improvement of 7% compared to deploying RIS at the edge. Based on the above discussion, we illustrate the optimal deployment positions of RISs for

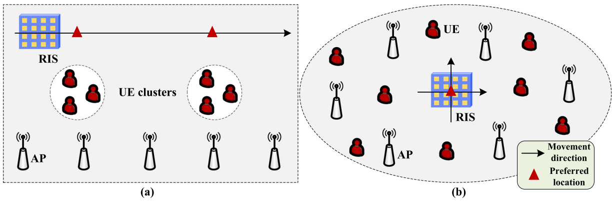

Fig. 12. *RIS deployment for different scenarios of APs' and UEs' distribution. Two different distribution scenarios are given. (a) Illustration of the preferred location of RIS in linear deployment APs and clustered UEs scenarios. (b) Illustration of the preferred location of RIS in uniformly random distributed APs and UEs scenarios.*

different distributions of APs and UEs in Fig. 12. To sum up, RIS should be carefully deployed based on the different characteristics of user distribution in RIS-aided CF mMIMO systems.

This section conducts a corresponding survey on the RIS-aided CF mMIMO system from the perspective of practical system considerations and provides some performance analysis results and guiding suggestions. It is worth noting that when the system is launched, it will face many practical problems, such as HIs and limited capacity, and most of these problems will lead to a degradation of system performance. Therefore, we must find the main and secondary factors through reasonable modeling analysis to achieve a tradeoff between performance and cost.

V. RIS-AIDED CF mMIMO WITH OTHER ENABLING TECHNOLOGIES TOWARD 6G

In this section, we provide an overview of the integration of different 6G technologies with RIS-aided CF mMIMO systems. Specifically, we discuss the potential benefits of mmWave/THz, SWIPT, NOMA, and UAV technologies with the RIS-aided CF mMIMO systems. Subsequently, we summarize the current research progress and highlight the existing challenges that require further investigation.

A. mmWave and THz

Utilizing mmWave and THz technology in CF mMIMO systems brings significant benefits, including the large bandwidths for high data rates and increased system capacity, as well as the ability to leverage highly directional beamforming and overcome traditional cellular interference, resulting in improved network performance [167], [168], [169], [170]. Meanwhile, RIS enables effective beamforming and interference management for mmWave and THz, thereby further enhancing the performance and coverage of mmWave/THz communications [58], [171], [172], [173], [174]. Therefore, several studies consider the application of mmWave and THz in RIS-aided CF mMIMO systems, which are summarized as follows.

Ma et al. [59] considered an mmWave communication system with perfect CSI and designed joint beamforming of AP and RIS to maximize the WSR. Also, the channels, including one LoS path and three NLoS paths, are described by the Saleh–Valenzuela model [175]. Furthermore, they design an AP-UE partially connected framework to further alleviate the heavy communication overhead in conventional RIS-aided CF mMIMO systems. In addition, Xu et al. [99] considered an mmWave channel with perfect CSI, but they employed a distributed cooperation ADMM, which adopted a monodirectional information exchange strategy with a small signaling overhead to tackle the joint beamforming problem. The monodirectional information exchange strategy means that all APs have a monodirectional topology, that is, one-way chain propagation of information. The results demonstrate that significant sum-rate improvements can be achieved by employing beamforming designs for mmWave communication in the considered system. However, Ma et al. [59] and Xu et al. [99] all overlooked the issue of obtaining the CSI of the mmWave channel. Fortunately, Lan et al. [176] considered deploying an extra AP near the RIS to approximate the mmWave channel from the RIS to the UE and effectively tackled the channel estimation. The results indicate that this approach can achieve system performance close to that with perfect CSI, but deploying a separate AP for RIS channel estimation will introduce additional AP cost overhead. At present, research on THz-based RIS-aided CF mMIMO systems is limited, although there are already some investigations into THz-based RIS communication. For example, Su et al. [170] investigated the beam split effect of a single RIS-aided MIMO system. Then, a wideband precoding design was proposed to compensate for the severe array gain loss, and the performance analysis on the array gain was also provided. The results demonstrate that the proposed subconnected RIS significantly alleviates the beam split effect with a small number of time-delay modules. Furthermore, Huo et al. [58] considered a distributed RIS for energy-efficient indoor THz communications. Specifically, they applied the 3-D ray-tracing technique to study a realistic indoor THz propagation scenario, considering the presence of human obstacles. The results show that distributed RIS can significantly overcome the problem of mobile human body obstruction and improve the coverage of THz signals.

The aforementioned analysis emphasizes the importance of beamforming in RIS-aided CF mMIMO systems with mmWave/THz. However, in practical implementation, there are several challenges. First, mmWave/THz channels exhibit highly directional and sparse characteristics, making accurate channel estimation challenging. Proper estimation and tracking techniques are required to effectively utilize passive RISs in mmWave/THz-based RIS-aided CF systems [177]. Second, deploying RISs in mmWave/THz-based CF mMIMO systems requires careful planning and optimization of the RIS locations. A large number of RIS elements and their precise alignment

Table 7 Deployment of RIS in RIS-Aided CF mMIMO Systems

Target	Ref.	UL/DL	AP/UE antenna	RIS number	UE distribution	Major observations
RIS deployment	[166]	DL	Single/single	One	Cluster	RISs in close proximity to UE clusters leads to significant performance.
	[139]	DL	Single/single	One	Cluster	
	[38]	DL	Multiple/multiple	Multiple	Cluster	
	[155]	UL	Multiple/single	One	Uniform random distribution	RIS in the center of the region yields the best system performance.

impose deployment challenges in terms of cost and practical implementation.

B. Simultaneous Wireless Information and Power Transfer

A fast-growing application of the IoT resulted in the proliferation of wireless sensors that communicate over the Internet infrastructure [178]. Ensuring the long-term operation and self-sustainability of the sensor and IoT devices is a critical consideration in network design. To address this challenge, SWIPT technology has emerged as a promising solution to extend the lifetime of IoT sensors [179], [180]. CF mMIMO networks have widely adopted SWIPT techniques. Extensive works have demonstrated that the CF network architecture is well suited for providing energy to UEs that harvest energy, thereby enhancing system-level EE [181], [182], [183]. In addition, RIS, as a passive component, exhibits low power consumption. Thus, when WET techniques can be utilized to power the RIS, it can further improve network EE and eliminate the need for a dedicated power supply for RIS deployment [31], [184]. Motivated by the aforementioned insights, numerous studies investigated the application of SWIPT techniques in RIS-aided CF mMIMO systems. In the following, we summarize the relevant research findings in this direction, as shown in Fig. 13.

Yang and Zhang [60] investigated the performance of RIS-aided CF mMIMO systems with SWIPT. Specifically, they considered that there were multiple information receivers and multiple energy receivers. Based on the assumption that the harvested energy by the UEs should not fall below a threshold, they designed a joint beamforming scheme to maximize the achievable sum rate. Then, an SCA-based algorithm was proposed to tackle the energy harvesting constraints, and the ADMM-based algorithm was proposed to iteratively satisfy the norm constraints of RIS reflection elements by applying auxiliary variables and penalty terms. The results show that RIS can effectively enhance the sum rate even without a phase shift design. However, increasing the number of APs or transmitting power is not an ideal choice if the APs adopt equal power transmission due to the simultaneous increase in interference signal strength. Khalil et al. [61] utilized UAVs as mobile APs to provide data communication and energy supply for IoT devices [185]. To achieve fairness, the max–min rate algorithm was applied to the CPU because the CPU knows the global CSI. The results demonstrate that a uniform deployment of RISs can achieve better performance in terms of energy harvesting. In contrast to the previous works that focus on the joint provision of information and energy services by APs and RISs to UEs, Shi et al. [39] considered the scenario where the APs provide energy to the RISs. As such, the RIS can be deployed without any wired connections. Based on that, they proposed a four-stage transmission mechanism for SWIPT and introduced three RIS operating modes: centralized RIS, noncooperative distributed RIS, and cooperative distributed RIS. Also, they proposed three different RIS hardware design schemes, namely, centralized, semi-distributed, and fully distributed, to gradually improve the energy reception efficiency.

However, for a large number of APs and RISs, a control protocol must be designed to ensure efficient communication and manage energy interference among devices.

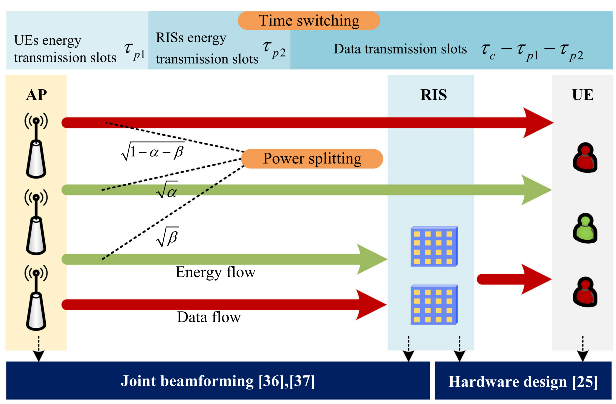

Fig. 13. ***SWIPT of RIS-aided CF mMIMO systems includes joint beamforming, hardware design, power splitting technique, and frame structure design.***

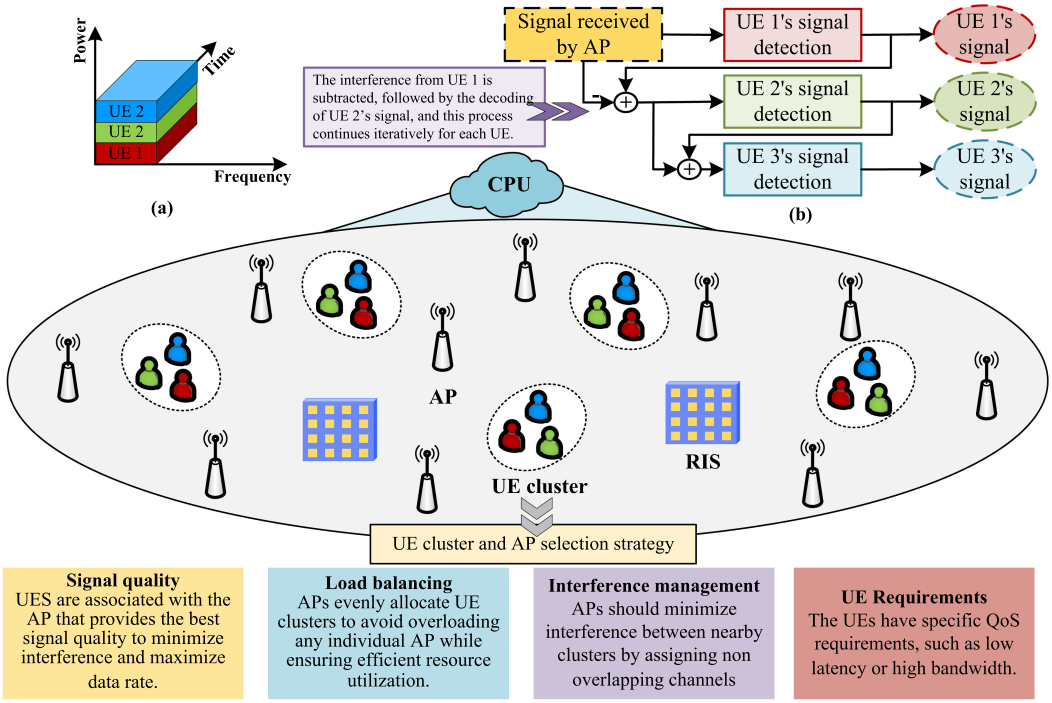

Fig. 14. *RIS-aided CF mMIMO system with power-domain NOMA where UEs are grouped into clusters. Each cluster includes I UEs, I = 3. (a) Resource assignment in one cluster. (b) 3-UE SIC with NOMA.*

For example, as shown in Fig. 13, a frame comprises τ_p number of energy transmission time slots and $\tau_c{-}\tau_p$ number of data transmission time slots, with τ_{p1} for UEs energy transmission and τ_{p2} for RISs energy transmission. Furthermore, in complex networks, factors, such as joint beamforming and power splitting, are coupled, making the problems nonconvex and challenging to solve. Computationally efficient DML algorithms serve as attractive solutions, as they have been successfully applied to address large-scale optimization problems [28], [186]. In addition, the hardware design for energy harvesting introduces additional complexity when manufacturing RISs. In fact, designing wireless energy harvesting components at the wavelength level poses significant challenges in controlling cost overhead while ensuring energy harvesting efficiency. Moreover, it is crucial to consider how to avoid coupling interference between power components and information elements at the circuit level.

C. Nonorthogonal Multiple Access

The key idea of NOMA is to differentiate signals from different users through different power and coding allocations [187], [188], [189]. Unlike traditional OMA, NOMA achieves parallel transmission among multiple users by decoding their signals in a nonorthogonal manner. At the receiver, SIC techniques can be employed to separate and recover the original data signals. As shown in Fig. 14, for the RIS-aided CF mMIMO system with power-domain NOMA, UEs are grouped into spatial clusters, where the UEs within each cluster share the same time–frequency resources and transmit data symbols with different power levels. Specifically, the AP employs the SIC technique on the received UL signals that the signals from UEs 2 and 3 are treated as interference during the decoding process of the signal of UE 1. Then, the interference from UE 1 is subtracted, followed by the decoding of the signal of UE 2, and this process continues iteratively for each UE. Accordingly, NOMA can improve the spectral efficiency, EE, massive connectivity, and high reliability of RIS-aided CF mMIMO systems [84], [109], [137], [190]. In the following, we review the works that considered the UL and DL performance of NOMA-based RIS-aided CF mMIMO systems.

Vasa et al. [84] and Rafieifar et al. [137] examined the DL performance of RIS-aided CF mMIMO systems employing power-domain NOMA. In particular, Vasa et al. [84] investigated the system SE with the imperfect CSI and imperfect SIC at the UEs under spatial correlation RIS. Then, the closed-form DL SE expression was derived by using the linear MMSE channel estimation and statistical CSI. In addition, Rafieifar et al. [137] proposed the simple, practical, and independent UE clustering and RIS assignment to UE algorithms in NOMA. For simplicity, but without loss of generality, the CB scheme was adopted for passive and active beamforming at the RISs and APs, respectively. Differently, Li et al. [109] considered the UL transmission and aimed to maximize the EE of the NOMA-based RIS-aided CF mMIMO system. Then, they proposed the DDPG-based algorithm to design the joint beamforming for EE enhancement. The key findings in these studies are summarized as follows: 1) the NOMA-based RIS-aided CF mMIMO system operation outperforms

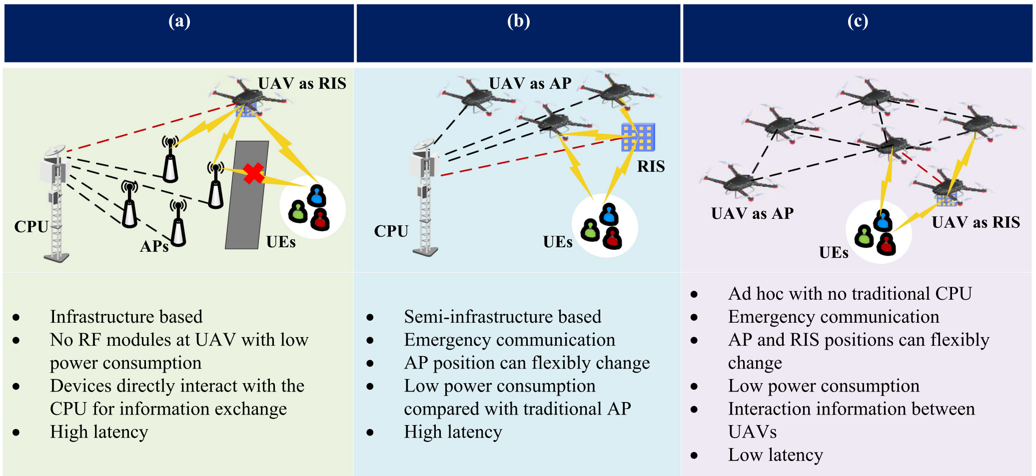

Fig. 15. *UAV with different functions assisted RIS-aided CF mMIMO systems. Two different UAV network modes are provided and their characteristics are analyzed [191]. (a) UAV-assisted RIS-CF networt—star network. (b) UAVs replace APs—star network. (c) UAVs replace CPU, APs, and RISs—mesh network.*

the OMA-based RIS-aided CF mMIMO system operation in terms of the number of simultaneously served UEs; 2) applying NOMA results that the RIS-aided link is more beneficial at lower transmit power regions where the direct link between AP and UE is weak; 3) a small number of RISs increases the ergodic rate, and however, a large number of RISs can impact intertier and intratier interference resulting in a slight decrease in the ergodic rate; and 4) adopting the multiagent DDPG-based algorithm for the joint beamforming design of RIS and AP can significantly enhance the performance of the considered system.

However, the enhancement of RIS-aided CF mMIMO systems with NOMA relies on optimal clustering of a large number of UEs and making appropriate matching of RIS-assisted UEs and APs. Furthermore, efficient beamforming and power control designs are important to mitigate interuser interference.

D. Unmanned Aerial Vehicle

Recently, UAVs have emerged to support diverse applications such as military operations, surveillance, and telecommunications [191], [192], [193], [194], [195]. As illustrated in Fig. 15, UAVs function as flying BSs, capable of dynamically adjusting their positions to enhance network coverage and capacity [196], [197]. In addition, deploying UAVs in CF mMIMO networks benefits users compared to increasing the number of ground-based APs. This advantage arises from UAVs' ability to navigate obstacles effectively, thereby establishing LoS communication links with served users [198], [199]. In RIS-aided CF mMIMO systems, in addition to serving as mobile APs, UAVs can carry RISs for flexible and mobile deployment of RISs, as shown in Fig. 15(a). This significantly reduces the hardware requirements of UAVs as they no longer need to be equipped with high-energy-consuming RF units, thereby extending their flight endurance [200]. Khalil et al. [201] pointed out that by jointly optimizing the trajectory of UAV and joint beamforming of RIS-aided CF mMIMO systems, the system SE significantly improved. Due to the benefits and potential, several works have investigated the integration of UAVs with the systems, and our summarized findings are given as follows.

To investigate the gain of UAVs in the RIS-aided CF mMIMO system, Al-Nahhas et al. [202] studied the DL rate based on the assumption that the total power allocated by the CPU to the communication with the UAV and ground UEs was fixed. Specifically, they designed CB precoding of RIS and optimized power allocation factors to further improve the DL rate. The results demonstrate that the combination of UAV and RIS can achieve a 50% increase in the average system rate, but their effectiveness depends largely on the UAV's height and the number of RIS elements. For example, with 60 elements of RIS, the UAV has a performance improvement of 75% at a height of 16 m compared to a height of 100 m. Khalil et al. [61] investigated the enhancement of RIS-aided CF mMIMO networks using UAVs and SWIPT technology to improve device energy harvesting efficiency. In particular, they utilized UAVs to replace APs for SWIPT, with each UAV directly controlled by the CPU via fronthaul. The results demonstrate that the deployment of UAV and RIS achieve a 1.5-fold and onefold increase in system SE and EE, respectively. Furthermore, compared to centralized and edge RIS deployments, a uniform RIS deployment achieves more desirable performance. In [201], an extended study was presented, which introduced a deep learning-based channel estimation framework to eliminate the dependency on traditional closed-form equation-based channel estimation methods, such as LS and MMSE estimation. In addition, a UAV deployment trajectory planning scheme was proposed to further improve SE. The results indicate that the UAV-empowered RIS-aided CF mMIMO system based on deep learning networks achieves an average SE improvement of 57% compared to the conventional RIS-aided CF mMIMO system.

In fact, there are different integration schemes for UAVs in RIS-aided CF mMIMO systems, as illustrated in Fig. 15. According to the different functionalities of UAVs, the schemes can be classified as UAVs replacing RISs, UAVs replacing APs, and UAVs replacing CPUs. Furthermore, based on different network configurations, they can be further categorized into conventional star networks and mesh networks [203]. In a star topology, all UAVs are directly connected to the CPU, and all communication between UAVs is routed through the CPU. The star network can achieve global optimal results through centralized optimization and UAV operation at the CPU. However, this configuration can lead to link blockages, increased latency, and a need for high-bandwidth DLs. In contrast, mesh networks offer greater flexibility, reliability, and improved performance. In a wireless mesh network, UAV nodes are interconnected and can communicate directly through multiple links. Packets can traverse intermediate nodes, finding their way from any source to any destination through multiple hops. Fully connected wireless networks provide advantages in terms of security and reliability. A promising technique for mesh network configurations is multiagent deep RL (MADRL) that has been widely applied to multinode problems and has shown excellent performance [129], [204]. As shown in Fig. 15(a), with a traditional infrastructure of CF mMIMO systems, the deployment of UAVs equipped with RIS can effectively address coverage gaps when users are located in low vision spots. For example, Yu et al. [205] proposed a max–min throughput problem in RIS-UAV-enabled mobile vehicle communication. The original problem was broken down into three subproblems: optimizing joint passive beamforming and mobile vehicle scheduling, power allocation, and trajectory. These subproblems were effectively solved using the SCA method and the results show that after adding trajectory optimization, the worst case user throughput increases by 21%. This strategy works with the existing network and offers the advantage of RIS mobility. Furthermore, UAVs equipped with RIS have lower power consumption and longer endurance compared to active relay UAVs, as they do not require RF modules. As illustrated in Fig. 15(b), in situations where deploying a wired network is impractical, e.g., for emergency communication, the UAVs can act as alternatives to APs for delivering communication services. For example, Samir et al. [206] utilized the UAVs to provide coverage to vehicles entering a highway that was not covered by other infrastructure. Then, they framed the decision-making process for trajectory planning as a Markov decision process (MDP). Subsequently, deep RL (DRL) was employed to introduce a method for learning the optimal trajectories of the deployed UAVs. The results show that deploying two UAVs can achieve a 25% increase in coverage compared to deploying one UAV. However, UAVs necessitate periodic energy recharging to sustain their operation. To tackle this issue, several studies have proposed leveraging WET technology to provide power supply for UAVs [39]. While the star network relies on a ground-based CPU, as shown in Fig. 15(c), the mesh network can have UAVs perform the roles of CPU, APs, and RISs. The mesh network enables a decentralized architecture, facilitating seamless communication among UAVs without the need for centralized CPU involvement. By establishing a self-organizing network, the RIS-aided CF mMIMO systems can benefit from UAV-to-UAV information exchange. Moreover, the UAV closest to the RIS can provide control of the RIS phase shift. This novel UAV mesh network enables full-fledged mobility with the utmost flexibility in positioning while maintaining low power consumption and latency. However, due to the lack of a fixed central processing unit, the interaction of global information and the orderly control of UAVs have become the main challenges [207]. Specifically, considering the joint optimization of UVA trajectory, RIS and UAV beamforming, and power control in mobile scenarios is the main technical challenge.

To sum up, there are still many challenges for the UAV-enhanced RIS-aided CF mMIMO systems, such as optimizing UAV trajectory and communication interaction based on partial information [208]. Furthermore, joint beamforming and collaboration between multiple UAVs and multiple RISs are necessary for network intelligence and orderliness.

VI. FUTURE DIRECTIONS

In this section, we discuss several future research directions for the RIS-aided CF mMIMO system, including semantic communications, ISACs, SAGIN, XL-MIMO, near-field communications, and secure RIS-aided CF mMIMO systems.

A. Semantic Communications

Embracing the era of 6G wireless communications, it is imperative to explore more advanced technologies that can enhance the intelligence and effectiveness of communication networks. Semantic communications, as an emerging paradigm, is such a technology that considers the semantic information of the transmitted data and optimizes the communication process accordingly [209].

RIS-aided CF mMIMO systems can benefit from integrating semantic communications by exploiting semantic information for effective resource allocation [210]. More specifically, for the RIS-aided CF mMIMO systems, semantic communications can be implemented in the following ways.

1) In channel estimation and signal processing, a synergistic approach that contemplates semantic information, such as content type and priority, can be effectively employed. Through RIS phase shift optimization and beamforming, this semantic information can be integrated, facilitating communication more tailored to the unique requirements of the data.
2) In the transmission phase, semantic information about the context, e.g., the location, movement patterns, and data usage behavior of the UEs, can be

leveraged for dynamic RIS configuration, enabling an agile response to changing network conditions and user requirements [211], [212].

3) In the resource allocation and networking phase, semantic information transmission scheduling can be implemented. For instance, in a scenario where edge users transmit high-priority or delay-sensitive data, the CF mMIMO network, powered by semantic information, could dynamically allocate more resources to these users [118], ensuring their QoS.

The integration of semantic communications with RIS-aided CF mMIMO systems is an area of ongoing exploration. This integration could resolve critical issues and provide symbiotic benefits. For instance, interuser interference, a notable problem in RIS-aided CF mMIMO systems, could be alleviated by leveraging semantic information and its priority to allocate network resources in an intelligent and dynamic way [213].

B. Integrated Sensing and Communication

ISAC is a novel paradigm aimed at unifying the capabilities of sensing and communication into a single network infrastructure with the same time/frequency resources. The concept of ISAC revolves around the idea of using wireless signals for both data transmission and environment sensing [214]. ISAC plays a crucial role in various application scenarios, such as autonomous driving, smart cities, and the IoT [215]. However, the joint design and optimization of sensing and communication functions in a unified system pose significant challenges, primarily due to their different requirements for radio resources [211].

The integration of ISAC into RIS-aided CF mMIMO systems opens up opportunities for enhancing the performance and functionality of these networks [109], [123].

1) The distributed nature of CF mMIMO systems makes them an ideal candidate for implementing ISAC. The spatially distributed APs can collaboratively perform sensing tasks and communication services simultaneously, leading to more accurate and extensive environmental perception [216].
2) RIS, with its ability to control the radio propagation environment, can provide hardware-level support for implementing ISAC [86], [211]. By intelligently adjusting the phase shifts of the RIS elements, the system can control the direction and power of the reflected signals, thereby enhancing the sensing capabilities of the network [99], [106]. Moreover, the RIS can help in mitigating the potential interference between sensing and communication signals, thereby improving the overall network performance [217].

However, an integration of ISAC and RIS-aided CF mMIMO systems also introduces new challenges, such as the joint optimization of sensing and CF-aided communication functions and the design of RIS phase shifts for enhancing the sensing capability. Thus, this integration necessitates further research and investigation.

C. Space–Air–Ground Integrated Network

SAGIN is a promising architecture designed to provide seamless coverage, high data rates, and reliable communication services by integrating space, aerial, and terrestrial networks [218]. It aims to overcome terrestrial networks' coverage limitations and satellite networks' communication latency issues by leveraging their complementary characteristics. This integrated architecture brings significant benefits, such as expanded coverage area, enhanced network robustness, and improved QoS [218].

Incorporating the RIS-aided CF mMIMO framework into SAGIN introduces new dimensions for improving network performance and system functionality.

1) CF mMIMO can extend the terrestrial coverage by spatially distributing multiple APs over a large area, thus overcoming the limitations of traditional cellular networks [198]. This spatial distribution guarantees consistent service quality throughout the coverage zone and introduces technical challenges and opportunities. Specifically, it necessitates solutions for joint trajectory planning, effective mobility management, and adaptive beamforming [219].
2) RIS can enhance both terrestrial and nonterrestrial networks by intelligently controlling the propagation of radio waves, thereby improving the coverage and reducing the energy consumption [33], [220]. Moreover, it can aid in the seamless integration of heterogeneous networks by improving internetwork communication and mitigating internetwork interference.

However, the efficient and seamless integration of heterogeneous networks poses significant challenges, including network synchronization, efficient resource allocation, and seamless handover management [221].

D. Extremely Large-Scale MIMO and Near-Field Communications

XL-MIMO technology is another remarkable area where RIS-aided CF MIMO systems can bring significant enhancements. XL-MIMO systems, characterized by the deployment of a massive number of antennas, have the potential to boost spectral efficiency, significantly increase data rates, and improve the EE of wireless communications [222], [223], [224]. Integrating XL-MIMO into RIS-aided CF mMIMO systems to replace existing APs presents exciting opportunities for enhancing network performance and functionality [225].

1) *Dimensionality and near-field channel characteristics:* The increase of antenna numbers in XL-MIMO augments the system's dimensionality, intensifying the inherent complexities of near-field channel characteristics [226]. These complexities are further exacerbated by the addition of IRSs in the RIS-aided CF

mMIMO system, which, while enhancing signal coverage, also necessitates an advanced understanding and management of the emerging channel characteristics [227].

2) *Signal focusing and multipath fading:* The substantial antenna array in XL-MIMO provides robust signal-focusing capabilities [228]. Yet, the amalgamation of RIS-aided CF mMIMO introduces challenges related to interference management. The utilization of IRSs for beamforming certainly aids in reducing interference, but it also amplifies the concerns associated with multipath fading [229], [230].

3) *Network adaptability and configuration:* Although the distributed architecture of CF facilitates a seemingly fluid integration of XL-MIMO, adapting to communication demands across different scenarios with the ever-evolving RIS technology adds layers of complexity in terms of network configuration, deployment, and real-time adaptability [78].

Although the combination of XL-MIMO and RIS-aided CF mMIMO technologies holds tremendous potential, it also brings forth various challenges, such as the unique characteristics of near-field channels arising from the substantial increase in XL-MIMO antenna quantity and high signal processing complexities introduced by the ultra-large-dimensional channel matrix between RIS and XL-MIMO [231]. Therefore, RIS-aided CF XL-MIMO systems require further research and exploration.

E. Secure RIS-Aided CF mMIMO Systems

In the rapidly evolving field of wireless communication, ensuring security against sophisticated eavesdropping techniques is paramount [232], [233], [234]. The incorporation of RIS in CF mMIMO systems has emerged as a potential solution to address these challenges [235].

1) *Countering active eavesdropping with RIS:* Active eavesdroppers, often referred to as Eves, present unique challenges in CF mMIMO systems. Specifically, they can exploit pilot contamination attacks, causing increased rates of information leakage. One of the effective ways to mitigate this risk is through the joint optimization of DL power coefficients at APs and the RIS's phase shifts. This strategy was shown to significantly minimize the risk of information leakage to active Eves, harnessing the unique capabilities of RISs to boost security in CF mMIMO systems [52].

2) *Balancing EE and security in RIS-aided CF networks:* With an increasing number of legitimate users and eavesdroppers in CF networks, achieving EE and security becomes a complex optimization problem. Addressing this, researchers have explored the joint design of distributed active beamforming, artificial noise (AN) at BSs, and passive beamforming at RIS. Leveraging techniques such as fractional programming, this iterative approach has shown promising results in enhancing EE while ensuring robust security against potential eavesdroppers [114].

3) *Harnessing AN against passive eavesdropping:* The distributed nature of CF mMIMO offers spatial diversity benefits, not just to legitimate users but, unfortunately, also to passive eavesdroppers. This dual-edged sword necessitates innovative countermeasures. One such solution is the deployment of an AN-aided secure power control scheme. This technique exploits spatial diversity for legitimate users and strategically deploys AN to neutralize the gains made by passive eavesdroppers. The outcome is an improved secrecy performance, vital in ensuring secure communications in CF mMIMO networks [236].

In essence, integrating RIS in CF mMIMO systems promises enhanced communication capabilities and a robust shield against eavesdropping. As these technologies converge, there is a compelling case for further research to design more secure and efficient wireless communication paradigms.

VII. CONCLUSION

The 6G wireless systems are expected to surpass existing limits and realize a vision of ubiquitous connectivity, ultralarge capacity, ultralow latency, enhanced coverage, and green communications, thereby enabling the Internet of Everything. Integrating user-centric CF mMIMO and RIS has brought new vitality and potential to support the ambitious goals of 6G wireless networks. In this context, we comprehensively review RIS-aided CF mMIMO systems. First, we presented the distinctive features of the RIS-aided CF mMIMO system model, particularly highlighting the difference in introducing RIS on CF mMIMO systems. Subsequently, various approaches for channel estimation and joint beamforming design were proposed, and a comprehensive investigation on resource allocation was conducted, providing essential fundamentals and insights for the research on RIS-aided CF mMIMO systems. Also, the unique multilayer transmission procedure and signal processing mechanisms were emphasized. Then, we underscored the novel practical challenges brought by the integration of RIS in CF mMIMO systems. Insightful simulation results were provided to guide system deployment and practical implementation. Moreover, we summarized the integration of other key technologies with the RIS-aided CF mMIMO system and offered valuable insights into their feasibility. Finally, we presented many RIS-aided CF mMIMO-empowered application scenarios and potential future directions. Our survey serves as a guideline for primary RIS-aided CF mMIMO research works in future 6G communications from the perspective of system modeling, resource allocation and operation, practical performance analysis, the integration of other key technologies, RIS-aided CF mMIMO-empowered application scenarios, and promising future directions. ■

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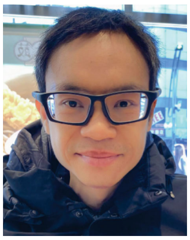

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