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Survey on Resource Allocation for Future 6G Network Architectures: Cell-Free and Radio Stripe Technologies

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Abstract: Future beyond fifth-generation (B5G) and sixth-generation (6G) communication systems require a higher quality of service (QoS) along with meeting multiple objectives and traffic demands. Consequently, new multi-antenna technologies and massive multiple-input-multiple-output (mMIMO) architectures have been proposed in recent years. This paper delves into the foundational concepts that form the basis for the design of two potential future mMIMO network topologies: cell-free (CF) network and its successor, the radio stripe (RS) system. Key aspects of the mMIMO and CF network concepts are addressed, along with a practical sequential implementation based on RSs. This exploration encompasses intricate details of the channel estimation (CE) phase, as well as the uplink (UL) and downlink (DL) transmission and reception phases. We then focus on analyzing optimization concepts that underpin resource allocation (RA) algorithms, specifically those applied in UL power allocation and access point selection (APS) schemes in both CF and RS networks. This comprehensive understanding serves as a robust foundation for addressing the challenges inherent in achieving the conflicting B5G and 6G major key performance indicators (KPIs), such as enhancements on spectral efficiency (SE), power efficiency (PE), and computational complexity or load balance (LB).



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1. Introduction

The communication systems of beyond fifth-generation (B5G) and sixth-generation (6G) are envisioned for diverse applications scenarios, spanning further enhanced mobile broadband (FeMBB), ultra-massive machine-type communications (umMTC), enhanced ultra-reliable and low-latency communications (eURLLC), long-distance and high mobility communications (LDHMC), and extremely low-power communications (ELPC) [1]. In [2], the authors describe emerging technologies, such as artificial intelligence (AI), terahertz (THz), CF communications, and wireless optical technology, among others that can guarantee 6G quality of service (QoS) requirements. Ref. [3] provides an overview of the latest research on the promising techniques evolving to 6G networks, including, among others, physical-layer transmission techniques and security approaches. The authors in [4] devise a taxonomy based on enabling technologies and use cases. Ref. [5] provides a similar overview while identifying future research challenges and directions. In [6], the authors identify four paradigm shifts for 6G including the requirement for global coverage, increased spectral usage, handling big datasets, and improving network security. In [7], the authors provide a forward-looking vision of 6G including a roadmap towards it, identifying the primary drivers of 6G systems, the target 6G performance requirements, and the enabling technologies. Ref. [8] presents a discussion on autonomous network architectures

to provide ubiquitous and unlimited wireless connectivity, AI, machine learning (MaL), and promising technologies for the 6G ecosystem. Ref. [9] offers a comprehensive overview of the key benefits and designs of the ultra mMIMO technology and the associated challenges. In [10], a survey about the key enabling technologies for 6G networks is presented, including the envisioned potential applications and current state-of-the-art research.

The future network designs mandate robust support for high per-user equipment (UE) data rates (up to 1 Gbps), coupled with unprecedented enhancements in area capacity (up to 1 Gbps/m²), spectral efficiency (SE) (peaking at 1 Tbps), and power efficiency (PE) (experiencing a 100–1000 fold increase over 5G). These advancements are further complemented by increased reliability (targeting a 99.99% success rate), extensive connectivity (up to 10⁷ devices/km²), persistent availability with high mobility (up to 1000 km/h), low latency (ranging from 25 µs to 1 ms), and enhanced hardware (HW) efficiency within wireless mobile networks, meeting the traffic demands and delivering a ubiquitous experience to the UEs [1,11,12].

Meeting these stringent requirements necessitates the exploration of novel multi-antenna technologies, massive multiple-input-multiple-output (mMIMO) topologies with coordinated communications, alternative waveforms, and efficient channel estimation (CE) to meet the requirements of the services. Additionally, resource allocation (RA) in 6G networks becomes crucial as it directly impacts the applications' reliability and performance. Efficient RA involves the dynamic distribution of network resources to optimize network performance, ensure QoS, and maximize UE experience. RA techniques include enhanced SE, PE, latency optimization through the spectrum, interference, and UE mobility management. Innovative RA strategies can depend on AI, MaL, blockchain, and collaborative and cooperative communication [1,7].

Various concepts are emerging to fulfill these demands, including small cells (pico and femtocells), cell-free (CF), large intelligent surfaces (LISs), and radio stripes (RSs) [13–16]. Notably, the prevailing trend in B5G research involves the utilization of expansive surfaces or infrastructures functioning as antenna arrays, where the number of antenna elements is scaled up to unprecedented levels [17]. Several surveys in the literature describe the opportunities, challenges, and fundamentals of CF technology. In [18], key challenges and their corresponding solutions for deploying CF networks are presented, including issues related to fronthaul capacity, CF, RA, latency, and scalability. Ref. [19] provides a comprehensive survey of the CF mMIMO system, covering everything from the system model to the potential integration with emerging technologies, along with opportunities and challenges. The authors of [20] offer an overview of the integration between CF mMIMO and ultradense networks, discussing topics such as low-complexity architecture and processing, scalable RA and CE, and synchronization. Additionally, there are several other surveys focusing on specific sub-topics within CF mMIMO, such as [21] for pilot assignment, and the integration of CF technology with other enabling technologies, like reconfigurable intelligent surfaces in [22] or unmanned aerial vehicles in [23].

In this paper, the fundamental concepts forming the solid foundation of the CF and RS networks are studied, shedding light on some RA algorithmic techniques pivotal for the development of several optimization schemes. In laying the groundwork for systems included in these concepts, some essentials of mMIMO are explored, encompassing crucial elements such as MIMO systems and correlated Rayleigh and Rician fading. Furthermore, an in-depth analysis of both CF and RS system models is conducted, going into detail about the CE phase, as well as the uplink (UL) and downlink (DL) transmission and reception phases. It also navigates some works employing optimization concepts supporting RA, exploring some algorithms instrumental in UL power allocation and access point (AP) to UE association. Therefore, the main contributions of our paper are that, to the best of the authors' knowledge, it is the first survey to include an open discussion about the current work developed within the RS network architecture. Additionally, it provides a comprehensive and detailed discussion of RA techniques for both CF and RS networks,

including a comparative analysis of the computational complexity between them. Therefore, the contributions are the following:

- It serves as a comprehensive survey, analyzing current research trends, opportunities, and challenges in CF and RS networks, thereby consolidating knowledge in this rapidly evolving field.
- It delves into emerging RA algorithmic techniques essential for optimizing CF and RS networks. This includes a detailed analysis of algorithms supporting UL and DL power allocation along with AP selection (APS) or AP-UE association.
- It includes a detailed overview specifically focused on RS network architecture, outlining its potential and current research developments.
- It provides a comparative analysis of the computational complexity between CF and RS networks, offering insights into the feasibility and efficiency of RA techniques in these contexts.

This paper uses the following notation: lower-case bold lettering (e.g., $\mathbf{s}$) denotes a vector of samples in the time domain. In contrast, non-bold lower-case lettering (e.g., s) denotes the samples of each of those vectors. Furthermore, $\mathbf{A}^T$ and $\mathbf{A}^H$ denote the transpose and hermitian of matrix $\mathbf{A}$, respectively. Additionally, $\text{tr}(\mathbf{A})$ denotes the trace of $\mathbf{A}$. $\mathbf{I}_n$ is an $n \times n$ identity matrix, $\mathbb{E}\{\cdot\}$ is the expected value operation, $\mathcal{N}(a, b)$ is a Gaussian distribution with mean a and standard deviation b and $\mathcal{N}_{\mathbb{C}}(\mathbf{0}, \mathbf{R})$ is a circularly symmetric complex Gaussian distribution with correlation matrix $\mathbf{R}$.

2. Massive MIMO

The enhancement of mobile network efficiencies can be achieved through network densification, involving the addition of more base stations (BSs) and APs to optimize spatial reuse of the spectrum [24]. While this approach proves effective, a more streamlined and impactful method involves boosting the network's SE, denoting the amount of data transmitted per second per unit of bandwidth [25,26]. A particularly promising strategy for significantly elevating the network's SE involves the implementation of multiple antennas at both the transmitter and receiver, commonly referred to as MIMO technology.

mMIMO [25–29] has revolutionized wireless communication by deploying an extensive array of transmitter antennas on the BSs. This innovative approach embraces a cell-centric design, efficiently serving a multitude of UEs' terminals within a cell simultaneously in the same time-frequency resources. Spatial separation is achieved through the use of highly directive signals, minimizing capacity requirements in the fronthaul while facilitating expansive coverage. Operating within the frequency range 1 (FR1) and frequency range 2 (FR2) frequency bands (sub-6 GHz and above 24 GHz), mMIMO exploits multipath propagation to enhance data rates. The strategy involves increasing the number of concurrently transmitted data streams or fortifying communication link reliability through redundant data transmission [25]. Primarily adopting the time-division duplex (TDD) mode, mMIMO strategically manages channel state information (CSI) acquisition overhead, which is crucial in scenarios with multiple antennas. As a foundational technology for the 5G New Radio standard released by the Third Generation Partnership Project (3GPP), mMIMO significantly contributes to wireless communication systems. It delivers high spatial diversity, beamforming gains, and spatial multiplexing capabilities for UEs, thereby elevating throughput, reliability, PE, and SE through streamlined signal processing. The technology achieves these advancements while concurrently reducing inter-cell interference (ICI) by leveraging characteristics of the channel hardening (CH) phenomena and exploiting the resulting favourable propagation (FP) conditions [29–31].

A mMIMO network is characterized by the following key features: It is a cellular network comprising L cells, all operating under a synchronous TDD protocol, ensuring synchronized UL and DL transmissions. Each BS in the network is equipped with a single antenna or, more commonly, an extensive array of antennas, denoted as $N_t \gg 1$, which are strategically deployed to exploit CH. Signal processing at each BS involves the use of linear receiver combining and linear transmitter precoding techniques. Notably, each BS

simultaneously serves a significant number of UEs, denoted as K , totalizing N_r antennas where the condition $\frac{N_t}{N_r} > 1$, or $\frac{LN_t}{N_r} \gg 1$ holds [25–27].

2.1. MIMO System

The coherence block, denoted as τ_c , signifies the duration during which a channel is treated as approximately constant and flat-fading. It is intricately connected to the channel's coherence bandwidth, B_c , and time coherence, T_c , through the relationship $\tau_c = B_c \cdot T_c$. This implies that the random responses of the channel can be statistically characterized within each coherence block, irrespective of temporal and/or frequency separations [25–27,32]. This analysis is based on the assumption of a block fading model, where channel realizations are considered independent between consecutive time-frequency blocks of τ_c samples.

The size of a coherence block is determined by factors such as the propagation environment, mobility of UEs, and carrier frequency. Concurrently, the number of pilots, UL, and DL signals per coherence block is influenced by network traffic and the requirements of specific application services. A general TDD coherence block frame has $\tau_c = \tau_p + \tau_u + \tau_d$ complex-valued samples, which are located in time and frequency and segregated into three distinct phases: τ_p for UL orthogonal training pilot sequences, allowing CE [14,16], τ_u for UL transmission of payload signals, and τ_d for DL transmission of payload signals.

Under the assumption of a flat-fading channel between the transmitter and receiver, the $N_r \times N_t$ channel response matrix for a MIMO system, denoted as $\mathbf{h}$, is formulated as per [33].

$$\mathbf{h} = \begin{bmatrix} h_{11} & \cdots & h_{1N_t} \\ \vdots & \ddots & \vdots \\ h_{N_r 1} & \cdots & h_{N_r N_t} \end{bmatrix} \quad (1)$$

where $h_{ij} \in \mathbb{C}$, where $i = 1, \dots, N_t$ and $j = 1, \dots, N_r$ represents the channel fading coefficients between transmitter antenna i and receiver antenna j . The connection between input and output signals can be succinctly expressed using the discrete Fourier transform (DFT), as follows:

$$\mathbf{y} = \mathbf{h}\mathbf{x} + \mathbf{w}. \quad (2)$$

Here, $\mathbf{y} = [y_1, \dots, y_{N_r}]^T$ and $\mathbf{x} = [x_1, \dots, x_{N_t}]^T$ represent column vectors containing the signals at the receivers and transmitters in the frequency domain, respectively. Simultaneously, the term $\mathbf{w} = [w_1, \dots, w_{N_r}]^T$ denotes the receiver additive white Gaussian noise (AWGN) vector.

2.2. Correlated Rayleigh and Rician Fading

The conventional definition of mMIMO assumes that each BS is equipped with $N_t = N$ antennas, while the UEs are single-antenna devices, signified by $N_r = K$ [25–27]. This configuration establishes the channel response vector between the k th UE (where $k = 1, \dots, K$) and the BS in cell $l = 1, \dots, L$ as $\mathbf{h}_{kl} \in \mathbb{C}^{N \times 1}$, encompassing coefficients from the UE to all N antenna elements of the BS. Represented as $\mathbf{h} \in \mathbb{C}^{N \times 1}$, this vector is characterized by its norm and direction in the vector space, which are treated as random variables in fading channels. The distribution and statistical interdependence of these variables determine whether a channel is spatially correlated or uncorrelated. In the context of uncorrelated Rayleigh fading, the channel's gain, $\|\mathbf{h}\|^2$, and direction, $\frac{\mathbf{h}}{\|\mathbf{h}\|}$, emerge as independent random variables. Here, the channel direction uniformly distributes over the unit sphere in $\mathbb{C}^{N \times 1}$ [27]. Alternatively, if these variables are correlated, the channel is considered spatially correlated.

Real-world channels exhibit correlation, stemming from the spatial characteristics of the physical propagation environment. This correlation is influenced not only by the likelihood of specific directions carrying more signals but also by antenna gains and non-uniform radiation patterns of transmitters and receivers [34]. Consequently, during each coherent block interval, an independent realization of a spatially correlated channel is

generated. In the context of the Rayleigh propagation channel model, the channel is defined by a non-line-of-sight (nLoS)-dominated correlated Rayleigh fading distribution, expressed as

$$\mathbf{h}_{kl} = \mathbf{h}_{kl}^{\text{NLoS}} \sim \mathcal{N}_{\mathbb{C}}(\mathbf{0}_N, \mathbf{R}_{kl}), \quad (3)$$

where $\mathbf{R}_{kl} \in \mathbb{C}^{N \times N}$ is a known positive semi-definite spatial correlation matrix at the BS. This matrix captures the macroscopic spatial correlation characteristics of the propagation scenario between the antennas, encompassing their gains and radiation patterns at the transmitter and receiver [34]. The Gaussian distribution accommodates the small-scale fading (SSF) variations in the model. The large-scale fading (LSF) coefficient, which remains constant over a high number of coherent intervals, includes the PL and SF effects. It is related to $\mathbf{R}_{kl}$ by the following expression [32]:

$$\beta_{kl} = \beta_{kl}^{\text{NLoS}} = \frac{\text{tr}(\mathbf{R}_{kl})}{N}. \quad (4)$$

Hence, the term β_{kl} in Equation (4) denotes the average channel gain from each antenna of the BS to UE k in cell l .

For the Rician scenario, where a LoS probability exists, a correlated Rician fading channel model is defined by [35]

$$\mathbf{h}_{kl} = \mathbf{h}_{kl}^{\text{LoS}} + \mathbf{h}_{kl}^{\text{NLoS}}, \quad (5)$$

where $\mathbf{h}_{kl}^{\text{NLoS}}$ is given by Equation (3), and

$$\mathbf{h}_{kl}^{\text{LoS}} = \beta_{kl}^{\text{LoS}} e^{j2\pi\Theta d_H}, \quad (6)$$

represents the LoS component for UE k and BS in cell l . Here, d_H is the antenna spacing, and

$$\Theta_{kl}(n) = \sin(\theta_{kl}) + n \times \sin(-\theta_{kl}), n = 1, \dots, N, \quad (7)$$

is an N -sized vector accounting for the phase difference between the antennas from the BS, where θ_{kl} is the angle between UE k and BS in cell l . In this Rician scenario,

$$\beta_{kl}^{\text{LoS}} = \frac{\kappa_{kl}}{\kappa_{kl} + 1} \beta_{kl}, \quad (8)$$

and

$$\beta_{kl}^{\text{NLoS}} = \frac{1}{\kappa_{kl} + 1} \beta_{kl}, \quad (9)$$

where

$$\kappa_{kl} \sim \mathcal{N}(\kappa_m, \kappa_{std}), \quad (10)$$

represents the Rician factor for UE k and BS in cell l .

In contrast, under uncorrelated Rayleigh fading,

$$\mathbf{R}_{kl} = \beta_{kl} \mathbf{I}_N. \quad (11)$$

The path-loss (PL) or signal attenuation in a obstruction-free (LoS) propagation scenario for a radio frequency (RF) signal is directly proportional to

$$P_r(d) \propto \left(\frac{\lambda}{4\pi d} \right)^2, \quad (12)$$

where $P_r(d)$ represents the receiver signal power at a distance d from the transmitter, and λ is the wavelength of the carrier signal. The PL is a large-scale channel attenuation effect indicating the extent of signal power reduction as radio signals traverse free space. It

increases inversely proportional to the square distance between the transmitter and the receiver [36]. A log-distance PL is expressed as

$$PL = PL_{ref} - 10\iota \log_{10} \left(\frac{d}{d_{ref}} \right), \quad (13)$$

where ι is the PL exponent, dependent on obstruction levels, and PL_{ref} is the PL value in free space for the reference distance d_{ref} . These parameters are influenced by carrier frequency, antenna gains, and vertical heights of the antennas, derived from fitting Equation (13) to empirical measurements [26,27]. To incorporate attenuation from obstacles and the surrounding environment, measurements indicate that the actual signal loss at distance d follows a log-normal distribution [36]. Therefore, the shadow fading (SF) effect accounts for the random and faster distance-based attenuation effects of the signal and is integrated into the PL model. The total loss in dBs is described by the LSF coefficient

$$\beta_{kl} = PL_{ref} - 10\iota \log_{10} \left(\frac{d_{kl}}{d_{ref}} \right) + F_{kl}, \quad (14)$$

where

$$F_{kl} \sim \mathcal{N}(0, \sigma_{sf}^2), \quad (15)$$

is a normally distributed random variable representing the SF effect, introducing random variations around the nominal value. The variance σ_{sf}^2 quantifies the scale of these random variations.

3. Cell-Free Concepts

The cell-centric networks are designed in a way that forces new UEs to adapt to the network configuration, making quality-of-service (QoS) largely dependent on their location within the network. Consequently, the deployment of cell-centric approaches leads to ICI, resulting in diminished signal quality at the edges of the cell.

One of the most promising advancements in standard cellular network topology, capable of meeting the stringent requirements of B5G and 6G systems, is the delivery of a ubiquitous service experience to UEs, irrespective of their location, achieved through distributed mMIMO (D-mMIMO). Additionally, cloud radio access network (C-RAN) technology has been explored for future wireless communication systems [37]. In this scenario, a baseband unit replaces traditional BSs in cells and oversees the centralized signal processing of the network by connecting multiple remote radio heads, distributed and linked via high-speed connections. The synergy between mMIMO and C-RAN technologies forms the foundation for several other advancements, such as D-mMIMO [38,39], coordination multipoint with joint transmission (CoMP-JT) [33,40,41], multi-cell MIMO cooperative networks [42], and distributed antenna system (DAS) [43,44]. In CoMP-JT, various BSs can communicate via a backhaul network, facilitating joint data transmission, suppressing ICI, and enhancing coverage and SE. In multi-cell MIMO cooperative networks [42], the ICI is mitigated as multiple BSs cooperatively process UEs' data, simulating a large virtual mMIMO array. DAS [43,44] involves placing multiple antennas in different geographical locations, connected through high-bandwidth, low-latency links, acting collectively as a single BS, thereby improving coverage and capacity in cellular systems. In essence, the principle of D-mMIMO is that the cellular system enables BS to collaborate in serving UEs jointly, reducing ICI. However, the co-processing of signals by BSs demands sophisticated computational techniques with high fronthaul overhead.

This gave rise to the concept of CF mMIMO, a practical and scalable iteration of network mMIMO and CoMP-JT. In CF mMIMO, the traditional delineations of cell boundaries dissolve, and UEs are simultaneously served by all APs through joint transmission and reception via a central processing unit (CPU), facilitating robust macro diversity [14,18,32,34,45–58]. Unlike conventional cell-centric mMIMO systems, where a multitude of antennas is concentrated

in a single BS within a cell, in CF mMIMO a substantial number of antennas are grouped in APs, as illustrated in Figure 1. This arrangement allows antenna arrays to form several APs dispersed geographically across a cellular network. These APs collaborate in transmission and reception, each equipped with an independent fronthaul link and power supply, concurrently serving a relatively smaller number of UEs within a specified area, all within the same time and frequency resources. As a consequence of the APs being placed near the UEs, the lower propagation distances result in lower free-space PL, allowing for the use of millimeter wave (mmWave) communications [59]. This in turn allows for higher data throughput and less inter-user interference (IUI).

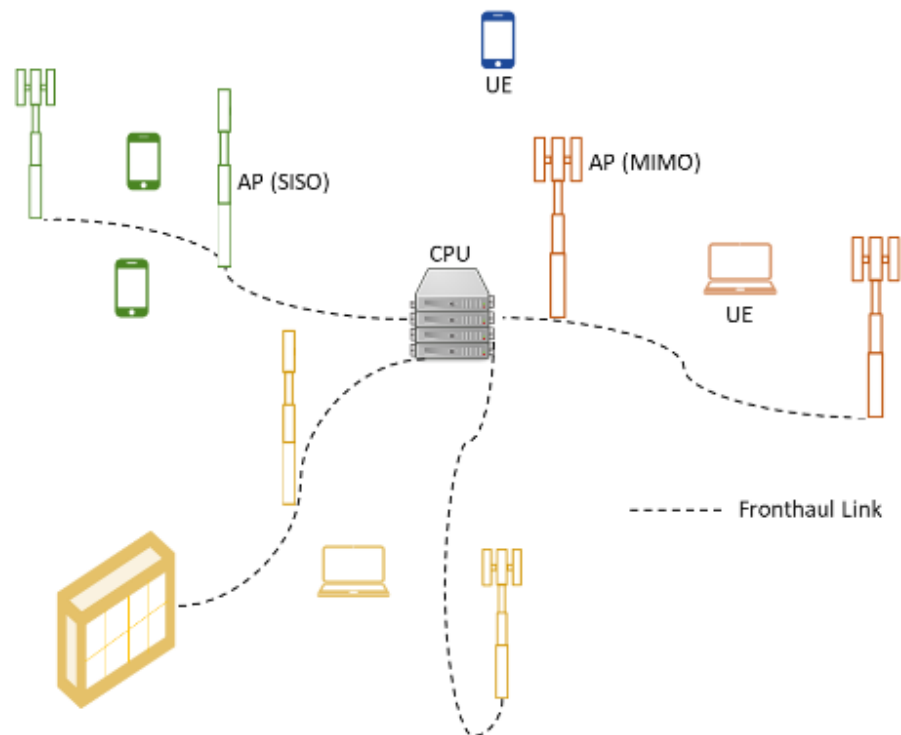


Figure 1. General CF mMIMO network.

In the UL, pilot training sequences are typically employed to acquire CSI locally at each AP, utilizing a TDD mode [14,32,45,48,51,54]. The CE vectors for each UE can be utilized in the UL for data detection, which can be locally performed at each AP by applying an arbitrary receiver combining vector [16]. These vectors can also be used for precoding in the DL. In this process, the CPU selectively transmits the payload data and power control coefficients to the APs, while exclusively retrieving post-processed feedback UL data from them. Subsequently, it engages in linear joint detection [32,55]. To facilitate coordination among APs, fronthaul connections to CPUs are necessary. The data signal processing carried out by the signal processing units of each AP may be coordinated by one or more CPUs through backhaul links. However, in CF mMIMO systems, the pronounced CH property is less pronounced. Consequently, by leveraging channel reciprocity, DL channel estimation at the UE can yield effective gains and can also be performed [31,60,61].

In [32,50,55], the authors conducted a comprehensive analysis of various implementations of the UL CF mMIMO. The derived SE expressions in this study account for spatially correlated fading channels among antennas of APs, imperfect CSI, multi-antenna APs, and arbitrary receiver combining schemes for the UL. Their comparison involved a fully centralized network, where all decoding is centralized at the CPU, and a mixed centralized and distributed network, where partial decoding is performed at the APs. Despite the flexibility in coherent cooperation levels among APs for data detection, a fully centralized UL CPU processing emerged as exhibiting higher SE. The study also demonstrated that with

centralized or local minimum mean square error (LMMSE) combining, the SEs achieved in CF systems surpass those in conventional cellular mMIMO and small cell networks. In [62,63], the authors proposed a precoding design for CF networks called team MMSE, based on centralized MMSE precoding and adapted to a distributed scenario using specific CSI vectors. This work explores a scalable CF architecture founded on UE-centric network clustering techniques, making the precoding technique scalable [50]. In [54], a UE-centric approach is introduced, where each UE is served by a small subset of APs to enhance SE and reduce fronthaul overhead. Additionally, in [64], novel distributed and scalable algorithms for CF mMIMO operation are presented under a UE-centric approach. This involves forming a dynamic cooperation cluster where each UE is served by the subset of APs providing the best channel conditions.

In this study, a CF mMIMO network is assumed to be comprising randomly distributed K single-antenna UEs and L APs, each equipped with N antennas. All APs are connected to dedicated CPUs via fronthaul links, while multiple CPUs can be interconnected through backhaul links. In the conventional operation of CF mMIMO, all UEs are served by all APs. Consequently, the channel between AP $l = 1, \dots, L$ and UE $k = 1, \dots, K$ is denoted by $\mathbf{h}_{kl} \in \mathbb{C}^{N \times 1}$.

3.1. Uplink Pilot Transmission and Channel Estimation

In the initial phase of the UL transmission frame, τ_p mutually orthogonal pilot signals, each consisting of τ_p symbols, are transmitted. Each UE k is allocated a pilot signal from the orthogonal base $\{\Phi_t : \Phi_t \in \mathbb{C}^{\tau_p \times 1} \wedge t=1, \dots, \tau_p\}$, with a power of $\|\Phi_t\|^2 = \tau_p$. These pilot signals are transmitted to each AP [32,55]. Typically, the number of UEs in the system exceeds the number of mutually orthogonal pilot sequences, i.e., $K > \tau_p$, leading to pilot contamination interference in the CE vectors. Following the notation used in [32], the index of the pilot assigned to UE k is denoted as $t_k \in \{1, \dots, \tau_p\}$, and $\mathcal{P}_k \subset \{1, \dots, K\}$ represents the subset of UEs sharing the same pilot as UE k . The received pilot signal at AP l is given by $\mathbf{Z}_l \in \mathbb{C}^{N \times \tau_p}$.

$$\mathbf{Z}_l = \sum_{k=1}^K \sqrt{\check{p}_k} \mathbf{h}_{kl} \Phi_{t_k}^T + \mathbf{N}_l, \quad (16)$$

where $\check{p}_k \geq 0$ represents the power utilized in pilot transmission for UE k , and $\mathbf{N}_l \in \mathbb{C}^{N \times \tau_p}$, following a complex Gaussian distribution $\mathcal{N}_{\mathbb{C}}(\mathbf{0}, \sigma^2)$, denotes the receiver AWGN with power σ^2 .

Utilizing the received pilot sequence, AP l can estimate the channel to each UE k by projecting $\mathbf{Z}_l$ onto the normalized pilot signal assigned to UE k , denoted as $\Phi_{t_k} / \sqrt{\tau_p}$, leading to the following:

$$\mathbf{z}_{t_k l} = \mathbf{Z}_l \Phi_{t_k}^* / \sqrt{\tau_p} = \sqrt{\check{p}_k} \tau_p \mathbf{h}_{kl} + \sum_{k' \in \mathcal{P}_k, k' \neq k} \sqrt{\check{p}_{k'}} \tau_p \mathbf{h}_{k' l} + \mathbf{n}_{t_k l}. \quad (17)$$

In Equation (17), the pilot contamination interference is attributed to the second term, where $\mathbf{n}_{t_k l}$ represents the resulting noise. Assuming that the correlation matrices, $\mathbf{R}_{k' l}, k' \in \mathcal{P}_k$, are locally available at AP l , the CE from AP l to UE k can be performed using the MMSE technique [27]. Upon receiving the signal in Equation (16) and considering the operation in Equation (17), the resulting CE vector can be denoted as $\hat{\mathbf{h}}_{kl}$ and is given by:

$$\hat{\mathbf{h}}_{kl} = \sqrt{\check{p}_k \tau_p} \mathbf{R}_{kl} \Gamma_{t_k l}^{-1} \mathbf{z}_{t_k l}, \quad (18)$$

where

$$\begin{aligned} \Gamma_{t_k l} &= \mathbb{E} \left\{ (\mathbf{z}_{t_k l} - \mathbb{E} \{ \mathbf{z}_{t_k l} \}) (\mathbf{z}_{t_k l} - \mathbb{E} \{ \mathbf{z}_{t_k l} \})^H \right\} \\ &= \sum_{k \in \mathcal{P}_k} \check{p}_k \tau_p \mathbf{R}_{kl} + \mathbf{I}_N, \end{aligned} \quad (19)$$

is the correlation matrix of the signal in Equation (17), and the CE vector $\hat{\mathbf{h}}_{kl}$ follows a complex Gaussian distribution $\mathcal{N}_{\mathbb{C}}(\mathbf{0}, \hat{\mathbf{R}}_{kl})$, with

$$\hat{\mathbf{R}}_{kl} = \check{\rho}_k \tau_p \mathbf{R}_{kl} \mathbf{\Gamma}_{t_{kl}}^{-1} \mathbf{R}_{kl}. \quad (20)$$

3.2. Uplink Data Transmission and Reception

After the pilot transmission and CE phase, the UL data transmission phase ensues. The received baseband complex signal at AP l , denoted as $\mathbf{y}_l \in \mathbb{C}^{N \times 1}$, encompasses the data transmitted by all K UEs and is expressed as [32]

$$\mathbf{y}_l = \sum_{k=1}^K \mathbf{h}_{kl} s_k + \mathbf{n}_l, \quad l = 1, \dots, L. \quad (21)$$

Here, $s_k \sim \mathcal{N}_{\mathbb{C}}(0, p_k)$ represents the symbol transmitted by UE k with power p_k . Typically, the antenna terminals of UEs can support a maximum transmission power denoted by P_{max} , ensuring $0 \leq p_k \leq P_{max}, \forall k = 1, \dots, K$. It is important to note that the symbols $s_k, k = 1, \dots, K$ are generated independently and $\mathbf{n}_l$ denotes the independent receiver AWGN.

The receiver scheme adopted can be based on the second level of receiver cooperation, as investigated in [32]. It involves local CE and combining at the AP, along with simplified centralized decoding at the CPU, which computes the total average of the local estimates. Thus, the l th AP preprocesses the received signal in Equation (21) and calculates the local estimate of the data transmitted by UE k , denoted as $\hat{s}_{kl}$. This is achieved by utilizing a local combining vector $\mathbf{v}_{kl} \in \mathbb{C}^{N \times 1}$, in accordance with

$$\hat{s}_{kl} = \mathbf{v}_{kl}^H \mathbf{y}_l = \mathbf{v}_{kl}^H \mathbf{h}_{kl} s_k + \sum_{k'=1, k' \neq k}^K \mathbf{v}_{kl}^H \mathbf{h}_{k'l} s_{k'} + \mathbf{v}_{kl}^H \mathbf{n}_l. \quad (22)$$

The design of the local combining vector is crucial for mitigating the IUI, and one of the most common approaches employs the maximum ratio combining (MRC) technique [14], where

$$\mathbf{v}_{kl} = \hat{\mathbf{h}}_{kl}. \quad (23)$$

Subsequently, each AP's local estimate $\hat{s}_{kl}$, as represented in Equation (22), is transmitted to the supporting CPU. The CPU then consolidates all of the AP's local estimates to generate a final estimation of the UE data signal, $\hat{s}_k$. This is accomplished by averaging the local estimates [14,46], i.e.,

$$\hat{s}_k = \frac{1}{L} \sum_{l=1}^L \hat{s}_{kl}, \quad k = 1, \dots, K. \quad (24)$$

The attainable SE of UE k at the CPU is expressed as per [32]:

$$\begin{aligned} \text{SE}_k &= \left(1 - \frac{\tau_p}{\tau_c}\right) \log_2(1 + \text{SINR}_k) = \left(1 - \frac{\tau_p}{\tau_c}\right) \\ &\times \left(1 + \frac{p_k \left| \sum_{l=1}^L \mathbb{E} \{ \mathbf{v}_{kl}^H \mathbf{h}_{kl} \} \right|^2}{\sum_{k'=1, k' \neq k}^K p_{k'} \mathbb{E} \left\{ \left| \sum_{l=1}^L \mathbf{v}_{kl}^H \mathbf{h}_{k'l} \right|^2 \right\} + \sigma^2 \sum_{l=1}^L \mathbb{E} \{ \|\mathbf{v}_{kl}\|^2 \}} \right), \end{aligned} \quad (25)$$

where the effective $\text{SINR}_k = \frac{\text{DS}_k}{\text{IS}_k}$ represents the ratio between the desired signal (DS) and the interference signal (IS) for UE k . If MRC is employed, and only CEs vectors

are available, the SE achieved in Equation (25) can be computed using the closed-form expressions considered in [65], as

$$DS_k = p_k \left(\sum_{l=1}^L \text{tr}(\hat{\mathbf{R}}_{kl}) \right)^2, \quad (26)$$

and

$$\begin{aligned} IS_k = & p_k \sum_{l=1}^L \text{tr}(\mathbf{R}_{kl} \hat{\mathbf{R}}_{kl}) + \tau_p^2 \check{p}_k^2 \sum_{k' \in \mathcal{P}_k, k' \neq k} p_{k'} \left| \sum_{l=1}^L \text{tr}(\mathbf{R}_{k'l} \mathbf{R}_{kl} \Gamma_{t_{kl}}^{-1}) \right|^2 \\ & + \sum_{k'=1, k' \neq k}^K p_{k'} \sum_{l=1}^L \text{tr}(\mathbf{R}_{k'l} \hat{\mathbf{R}}_{kl}) + \sum_{l=1}^L \text{tr}(\hat{\mathbf{R}}_{kl}), \quad k = 1, \dots, K. \end{aligned} \quad (27)$$

4. Resource Allocation on Cell-Free

In CF mMIMO, various UEs undergo spatial multiplexing. Hence, the configurations of CF networks, which entail the deployment of spatially distributed APs, mirror the complexities and opportunities inherent in D-mMIMO. This likeness extends to the challenges surrounding hierarchical precoding and decoding techniques, as well as the varying levels of cooperation among processing units, as discussed in [66,67]. Consequently, similarly to conventional cell-centric mMIMO systems, the efficient support of such systems relies heavily on robust RA techniques. These techniques aim to optimize multiple network function metrics (NFMs), including parameters such as SE, PE, data rates, bit error rate, latency, and more.

4.1. Uplink Power Optimization

Among the critical resources, the power allocated from each AP's antenna to each UE in the DL, or conversely, for each UE in the UL, holds significance. This allocation can be regulated by power control algorithms designed to enhance the overall network performance [46,57]. While a straightforward approach may assume that all UEs transmit at full power, this is not the optimal strategy. Although such an assumption is often made in proposals for various detection schemes (e.g., [14,32]), it leads to power wastage and increased interference levels. Consequently, power control policies are pivotal in addressing the near-far effect and safeguarding APs from strong IUI. By doing so, they facilitate the optimization of a given NFM under power constraints, ensuring system scalability and low latency, even with a substantial growth in the number of UEs [16]. Consequently, significant research efforts have been invested in developing efficient power control algorithms that strike a balance between performance and computational complexity [14,49,56,58,68–92].

Power control schemes in mMIMO systems are typically managed by the CPU, and due to CH, the transmission coefficients may overlook the SSF. Consequently, these coefficients are solely tailored to the LSF characteristics [26,27]. In this context, the computation of transmission power for each UE and the subsequent power distribution to each AP by the CPU are adjusted based on the channel coherence time [68]. Essentially, these algorithms represent methods for solving an optimization problem, wherein the decision variables encompass the aforementioned power control coefficients. In these instances, constraints are often associated with the limited power budget of the BS in the DL, as well as the maximum transmission power that each terminal can accommodate in the UL. Additionally, the objective function (OF) is linked to an NFM that requires optimization.

In [14], an exhaustive comparative analysis between a CF and a centralized mMIMO system is conducted, assuming the utilization of the MRC technique at single-antenna APs based on local CE. A closed-form expression for the UL SE is derived to formulate the quasi-linear max-min fairness (MMF) power optimization problem. The solution relies on a second-order cone programming (SOCP) optimization approach utilizing an iterative bisection search method to determine the global optimal solution. In [69], a DL power control algorithm is proposed with the aim of maximizing the system's total PE, taking into

account HW and backhaul power consumption. Meanwhile, in [70], the authors explore the UL SE performance of a CF mMIMO system with a propagation channel modeled via the Ricean distribution. The optimization problem involves adapting power and AP-weighting receiver filter coefficients. Two sub-problems are solved: receiver filter coefficients through a generalized eigenvalue problem and power control through the bisection method with linear programming.

In [71], the same optimization problem is investigated with a zero-forcing (ZF) combining scheme at the APs. Additionally, in [49,72], the UL optimization problem with per-UE power constraints is addressed by designing optimal APs' receiver filter coefficients and UE power allocation. The UEs' data rates are approximated based on channel statistics, and as the optimization problem is not jointly convex in terms of both variables, the two problems are decoupled and iteratively solved. The design of receiver filter coefficients is formulated and solved at the CPU as a generalized eigenvalue problem, while geometric programming (GP) is employed to solve the UEs' power allocation problem, avoiding the bisection approach. This transforms the optimization problem into two decoupled single-objective (SO) optimization problems. In [73], a similar approach is implemented to solve the MMF problem, accounting for QoS constraints on specific groups of UEs. Building upon the work in [74], the iterative algorithm is examined in a CF mMIMO scenario with limited backhaul capacity. The same optimization problem is considered in [75] with optimal uniform quantization, while in [76], the system's total PE is optimized, subject to per-UE power and per-UE QoS constraints.

In [77], a mobile edge computing-based CF mMIMO network is studied, optimizing UEs' power in UL according to minimum transmission power (MTP) under power budget and latency constraints, concurrently considering the MMF. In [78], a joint power control and load balancing algorithm is proposed for UL CF mMIMO with MRC and ZF, optimizing under three different metrics: MTP, MMF in terms of QoS, and max-sum rate (MSR) under imperfect CSI. Further, in [79], power allocation policies for the UL and DL of the CF network are evaluated, with LSF-based scalable policies. The UL policy includes a parameter for controlling a trade-off between average performance and fairness, while the DL policy employs two parameters for the same purpose. In [80], a power allocation scheme is proposed for the UL of a UE-centric CF mMIMO system, enhancing average SE and fairness performance while reducing UL transmission power. Lastly, in [81], two algorithms for DL MSR optimization based on weighted MMSE and fractional programming (FrP) are developed, along with a new FrP-based algorithm for MMF.

In many of the aforementioned papers, the power allocation optimization problem is typically addressed through either sequential successive convex approximation (SCA), involving the resolution of a sequence of linear feasibility problems, or through the utilization of convex approximation coupled with GP. Both approaches heavily rely on SOCP, leading to high computational complexity and scalability issues, particularly in CF mMIMO networks. To mitigate these challenges and enhance efficiency, recent research has explored alternative optimization techniques. In [82], the non-convex UL power control problem is reformulated as a convex program. Although the equivalent problem is non-smooth, the authors leverage Nesterov's smoothing technique to approximate the original problem. This enables the use of an accelerated projected gradient (APG) to obtain the solution. Additionally, in [83], DL power allocation is optimized for maximizing PE, employing a first-order method for non-convex programming.

Alternative power optimization approaches may also incorporate deep learning (DeL). In [84], UL power optimization for MSR is performed using a heuristic sub-optimal scheme. The original problem is converted into a standard GP problem, and the authors use a deep convolutional neural network (DCNN) to incorporate LSF. The DCNN establishes a mapping between LSF coefficients and optimal power using quantized channels. Authors in [85] proposed a DeL-based power control algorithm, solving the DL MMF problem by modeling a deep neural network (DNN) with unsupervised training. This approach achieves comparable performance to optimization-based algorithms with significantly

faster run times. The DL MMF power optimization with maximum ratio transmission (MRT) is explored in [68], introducing a DNN and comparing it with a heuristic involving a non-convex iteration algorithm combined with the bisection method. In [86], a deep reinforcement learning (DRL) approach is considered for DL MSR optimization in CF mMIMO operating in the microwave domain.

Moreover, in [87,88], DNN and DeL are employed for MSR and MMF power allocation in the UL, taking into account pilot contamination and SF effects. In this scenario, the DeL method individually addresses each power optimization problem, resulting in two independent SO optimization problems. In [56], a similar problem is solved for MRT. Authors in [89] use an unsupervised low training complexity DeL approach for MMF, max product, and MRC SO optimization in the UL of a CF mMIMO system where optimal power allocations are not required to be known. In [90,91], a DNN is trained to optimize DL power allocation under MSR and proportional fairness metrics with MRT and regularized ZF (RZF) precoding. In [58], the authors propose three different optimization algorithms based on meta-heuristic (MH) approaches as alternative schemes to solve UL MMF power optimization in CF mMIMO with per-UE power constraint, local AP MRC, and average weighting at the CPU. These approaches are compared with exact algorithms such as bisection and GP in terms of accuracy and computational complexity. The study demonstrates that these algorithms are adaptive and capable of providing near-optimal solutions with affordable computational requirements. In [92], the authors address the UL power allocation in a CF mMIMO system by considering a bi-objective (BO) power optimization problem focused on the MMF and MSR metrics. By assigning different weights to each metric, they transform the BO optimization problem into an SO problem. Given that optimizing MMF and MSR results in a non-convex problem, the authors use the LSF coefficients as inputs for a twin delayed DRL deterministic policy gradient, which is subsequently solved through SCA.

This discussion is summarized in Table 1. Furthermore, Table 2 provides a comparative analysis between the power allocation techniques in CF mMIMO networks in terms of computational complexity.

Table 1. State-of-the-art research on UL and DL power optimization in CF mMIMO networks.

	Spectral Efficiency (SE)		
	Max-Sum Rate (MSR)	Max-Min Fairness (MMF)	Power Efficiency (PE)
Successive Convex Approximation (SCA) SO optimization	UL: GP-based [78] LSF-based [80] DL: Weighted MMSE and FrP-based [81]	UL: MRC-based bisection [14] Rician distribution bisection [70] ZF-based bisection [71] GP-based [49,72,78] QoS-constrained [73] Limited backhaul [74] Uniform quantization [75] LSF-based [80] MH-based [58] DL: LSF-based [79] FrP-based [81]	UL: MTP [78,80] DL: HW and backhaul [69] QoS-constrained [76]
Non-convex SO optimization		UL: APG-based [82]	DL: First-order method [83]
Deep Learning (DeL) SO optimization	UL: DNN-based [87,88] DL: DNN and MRT-based [56] DNN MRT/RZF [90,91]	UL: DNN-based [87,88] Unsupervised low training MRC-based [89] DL: DNN-based [85] DNN and MRT-based [56,68]	UL: GP and DCNN/LSF-based [84] DL: DRL-based [86]
BO optimization	UL: DRL/LSF and SCA-based [92]	UL: SCA MTP and latency-constrained [77]	

Table 2. Computational complexity comparison between the power optimization schemes in CF mMIMO networks.

Paper Reference	Optimization Technique	Computational Complexity
[14]	SOCP with iterative bisection search	High
[69]	Linear programming with bisection method	High
[70]	Generalized eigenvalue problem, bisection method	High
[71]	Generalized eigenvalue problem	Moderate
[72]	GP	Moderate
[73]	GP	Moderate
[74]	SCA	High
[75]	Convex optimization with uniform quantization	High
[76]	Convex optimization	High
[77]	Convex optimization	High
[78]	SCA	High
[79]	LSF-based scalable policies	Moderate
[80]	Convex optimization	Moderate
[81]	FrP	Moderate
[82]	Nesterov's smoothing technique, APG	Moderate
[83]	First-order method for non-convex programming	Moderate
[84]	DCNN with GP	Moderate
[85]	DNN	Low
[68]	Heuristic with non-convex iteration, DNN	High (heuristic), Low (DNN)
[86]	DRL	High
[87]	DeL and DNN	Low
[88]	DeL and DNN	Low
[89]	Unsupervised low training complexity DeL approach	Low
[90]	DNN	Low
[91]	DNN	Low
[58]	MH approaches	Variable
[92]	Twin delayed DRL deterministic policy gradient, SCA	High

4.2. Access Point Selection for Optimized Uplink User Allocation

Moreover, in the context of CF mMIMO networks, evaluating the efficacy of transmission and detection techniques often assumes full cooperation among APs in handling UE information signals. This assumption extends to the belief in extensive fronthaul link capacity between APs and CPUs, coupled with the assumption of infinite processing capabilities within the CPU. However, the network's characteristics and the distribution of UEs can lead certain APs to contribute significantly to IUI, thereby reducing signal-to-noise-and-interference ratios (SINRs) and SE at the CPU [69,93]. In response to these challenges, network engineers have been exploring an alternative solution known as UE-centric operation in the CF mMIMO context [18,51,52,54]. In this approach, a specific subset of APs is assigned to serve a particular UE. This strategy not only alleviates the CPU processing burden but also reduces fronthaul load and signaling requirements. Additionally, it mitigates the computational complexity of the AP processing unit and contributes to an overall reduction in network power consumption. Furthermore, this approach has the potential to enhance SINRs by limiting the interference term to only a fraction of UEs. Numerous studies have investigated the integration of APS schemes into signal transmission and detection techniques for CF mMIMO networks [69,78,87,93–111].

In [69], two DL APS schemes were introduced with the goal of enhancing total PE. One scheme relies on power control coefficients, involving high computational complexity, while the other is based on LSF coefficients. Similarly, in [94], an APS approach based

on ZF precoding and LSF is employed to improve MSR. The authors of [95] develop a comprehensive strategy that combines DL joint power allocation and APS to minimize the overall energy consumption of a CF mMIMO system, all while adhering to QoS constraints. Meanwhile, in [96], the CF mMIMO DL SE performance is studied through an iterative APS scheme paired with MMSE precoding and power allocation, showcasing improvements over conventional approaches. The authors of [97] propose a sequential DL APS approach that leverages LSF and calculates effective channel gain from all UEs to all APs, along with considering the channel quality of each UE. Additionally, in addressing the challenges of CH absence in CF mMIMO, ref. [93] introduces a novel UL APS scheme and a signal detection method, enhancing UEs' throughput and reducing the data load exchanged over fronthaul links.

In [98], it is demonstrated that an APS scheme effectively delivers satisfactory DL SE results, while ensuring load balance (LB) with substantial power reductions. Meanwhile, ref. [78] optimizes power control and LB in the UL of a CF network. In [99], a joint APS and power control scheme is implemented in a CF visible light communication network to enhance UE fairness and LB. The authors of [100] employ MaL to model a cluster-based APS algorithm for DL CF mMIMO, aiming at reducing capacity requirements and mitigating pilot contamination. In [101], an APS algorithm is developed to decrease fronthaul and complexity requirements for the UL of a CF mMIMO system with a Rician fading channel. On the other hand, ref. [102] tackles the UL APS problem using game theory, modeling the formation of an UE-centric AP service cluster as a local altruistic game. The authors of [103] prioritize the DL SE of UEs with poor channel conditions through the implementation of an APS using a linear assignment algorithm.

In [104], the authors introduce a graph neural network-based UL APS scheme tailored for CF mMIMO networks. This innovative approach demonstrates superior accuracy in predicting links between UEs and APs when compared to proximity-based APS schemes. Notably, it stands out by not necessitating the knowledge of the received signal strengths from all neighboring APs, which is a departure from APS schemes relying on LSF coefficients. A computationally more efficient alternative compared to MMSE-based APS methods is presented for UL in [105]. In this approach, the CPU utilizes CE to perform an APS scheme by assessing SINRs for each UE. Meanwhile, ref. [106] employs a DRL approach to dynamically select the APs serving each UE for DL based on its position. This methodology aims to explore the trade-off between QoS and power consumption. In [107], the authors implemented an APS scheme incorporating a full-pilot ZF combining approach. This strategy yields reasonably good SE while concurrently enhancing the system's PE.

In [108], a distance-based DL APS approach is synergized with an orthogonal assignment of sub-carriers among different UEs to enhance the PE and SE of a CF mMIMO-orthogonal frequency division multiplexing (OFDM) system. In [109], a DRL approach is employed to optimize the PE of a UL CF mMIMO system by determining the optimal AP–UE association while adhering to minimum rate constraints for all devices. A different approach is proposed in [87] that organizes the APs into cell-centric clusters connected to different cooperative CPUs. However, the UL APS scheme outlined in the paper allows for the association of each UE to a virtual cluster. This AP–UE association method aims at the MSR and offers a substantially lower backhaul load when compared to full CF approaches. In [110], the authors combine beamforming with an APS scheme for the DL of a mmWave CF mMIMO system. In [111], the authors aim to design AP–UE association, hybrid beamforming, and fronthaul compression in an mmWave CF mMIMO system for MSR and MMF enhancement.

This discussion is summarized in Table 3. Similar to the previous subsection, Table 4 provides a comparative analysis between the APS techniques in CF mMIMO networks in terms of computational complexity.

Table 3. State-of-the-art research on UL and DL APS schemes in CF mMIMO networks.

	Capacity Requirements	Load Balance (LB)	Spectral Efficiency (SE)	Power Efficiency (PE)
SO optimization	UL : Fronthaul [93,101] MMSE-based [105]	UL: Power control aided [78]	UL: Game theory-based [102] DL: ZF/LSF-based [94] Power control aided with MMSE [96] Sequential/LSF-based [97] Linear assignment-based [103] Joint beamforming for mmWave [110] mmWave-based [111]	DL: Power control aided with LSF-based [69] QoS-constrained [95]
Deep Learning (DeL) SO optimization	UL: Graph neural network-based [104] DL: Cluster-based [100]			UL: DRL/SE QoS-constrained [109] DL: QoS/DRL-based [106]
BO optimization		UL: Virtual clusters-based [87] DL: SOCP-based [98] Dual projected gradient SCA-based [99]	UL: ZF-based [107] DL: Distance/OFDM-based [108]	

Table 4. Computational complexity comparison between the APS schemes in CF mMIMO networks.

Paper Reference	Optimization Technique	Computational Complexity
[69]	DeL with APS (power/control coefficients, LSF)	High
[94]	ZF precoding, LSF-based APS	Moderate
[95]	DL joint power allocation, APS	High
[96]	Iterative APS, MMSE precoding, power allocation	High
[97]	Sequential DL APS with LSF, effective channel gain calculation	Moderate
[93]	UL APS, novel signal detection method	Moderate
[98]	APS for DL SE, LB	Moderate
[78]	UL power control, LB	Moderate
[99]	Joint APS and power control in visible light CF	Moderate
[100]	Cluster-based APS using MaL for DL	Moderate
[101]	APS for UL with Rician fading channel	Moderate
[102]	UL APS using game theory for AP service cluster formation	Moderate
[103]	DL SE prioritization with linear assignment APS	Low
[104]	Graph neural network-based UL APS	Low
[105]	CE-based APS with SINR assessment for UL	Moderate
[106]	DRL-based dynamic AP-UE association for DL	High
[107]	Full-pilot ZF combining APS for DL	Moderate
[108]	Distance-based DL APS with orthogonal sub-carrier assignment	Moderate
[109]	DRL for UL APS optimizing PE with rate constraints	High
[87]	Cell-centric clustering of APs, virtual cluster UE association	High
[110]	Beamforming combined with DL APS in mmWave	Moderate
[111]	AP-UE association, hybrid beamforming, fronthaul compression	Moderate

5. Radio Stripe Network Model

A significant challenge in the practical implementation of a mobile CF mMIMO network is the considerable demand for fronthaul and backhaul capacity. This challenge is aggravated by extensive signaling requirements and a high implementation cost associated with a dense network of long cables connecting APs to and between CPUs, as illustrated in Figure 1. As a result, the development of practical CF mMIMO systems that incorporate

decentralized signal processing algorithms and techniques capable of managing data in a more feasible manner becomes imperative [112–114].

The recently proposed RSs represent an evolutionary step from D-mMIMO, being adopted by Ericsson [16,115–138]. These systems are poised to play a pivotal role in B5G and 6G networks, where there is a demand for elevated SE and PE across the network. This will ultimately result in enhanced performance levels for UEs, manifesting in improved SINR and the introduction of novel services.

In contrast to conventional CF mMIMO concepts, where each AP is typically linked to the CPU via a dedicated fronthaul connection, RS networks adopt a different approach. In these networks, APs are strategically positioned and connected sequentially, sharing the same fronthaul link through a cable or stripe, effectively serving as a bus for data transfer, power supply, and synchronization among the APs. Moreover, the APs, equipped with multiple antenna elements operating coherently in phase, each containing a local processing unit (LPU), including power amplifiers, phase shifters, filters, modulators, an analog-to-digital converters (ADC) and a digital-to-analog converter (DAC). This enables sequential processing methods for received data [16]. Their installation is convenient, requiring a simple plug and play connection directly to an area processing unit (APU) or CPU, or, in the case of expansion, to the fronthaul network, as illustrated in Figure 2. The distributed functionality of RS networks enhances reliability and resilience, along with improved heat dissipation, thereby reducing the need and cost for maintenance and cooling systems compared to traditional CF mMIMO architectures [115]. Therefore, this concept has the potential to enhance the UEs' experience through various mechanisms [16]:

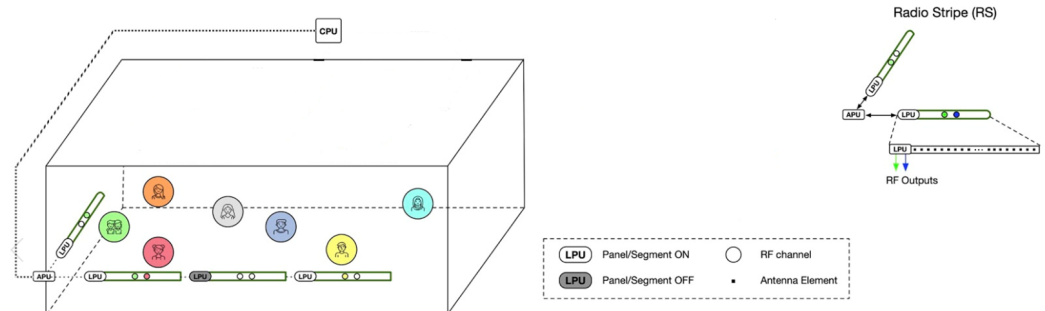


Figure 2. In the model of an RS network, each AP is equipped with a LPU that establishes a connection either to an APU or a CPU.

- Increasing macro-diversity to enable the cancellation of ICI and reducing the power transmission requirements per antenna;
- Employing massive antenna arrays to achieve gains in system capacity, throughput, PE, and SE;
- Reducing fronthaul overhead by adopting TDD operation, ensuring system scalability and distributed processing;
- Facilitating a more cost-effective deployment with increased robustness, resilience, and lower heat dissipation.

A practical sequential execution of the CF mMIMO network is achieved by implementing an RS network. This RS network consists of L multi-antenna APs, each comprising a linear array of N antennas (the RS network model involves a total of $M = L \times N$ antennas) [116]. Additionally, the assumption is made that there are K single-antenna UEs randomly distributed geographically within a square area covered by the RS network, all served simultaneously by the APs using the same time-frequency resources [16,115]. This enables the RS concept to emulate a practical implementation of the centralized CF mMIMO network, offering the same advantages with significantly reduced fronthaul requirements [116].

Figure 2 can be linked to small/moderate areas representative of B5G and 6G scenarios, such as airports, stadiums, and train carriages. To achieve this, for each AP $l = 1, \dots, L$

and UE $k = 1, \dots, K$, the channel, represented by $\mathbf{h}_{kl} \in \mathbb{C}^{N \times 1}$, and the spatial correlation matrix, denoted as $\mathbf{R}_{kl} \in \mathbb{C}^{N \times N}$, follow the definitions established previously. This network model aligns with the methodologies introduced in [14,32,116] and facilitates a meaningful comparison between cell-centric and CF mMIMO networks. The frame format adheres to the TDD protocol [16].

5.1. Channel State Information Estimation

Similar to Section 3.1, in this phase, τ_p mutually orthogonal pilot training signals, each with τ_p samples denoted as $\{\Phi_1, \dots, \Phi_{\tau_p}\}$, are transmitted in the UL from the UEs, with k ranging from 1 to K , to each AP with l ranging from 1 to L , within the same time-frequency block. While payload data transmission may consider the use of an APS scheme, it is crucial to accurately estimate all channel coefficients from each AP to each UE.

Pilot contamination is a phenomenon that may occur as a result of pilot reuse or the transmission of non-orthogonal pilot sequences, leading to mutual interference between signals transmitted by different UEs and observed at each AP. This, in turn, results in correlated CE. Pilot contamination becomes prominent when the number of UEs exceeds the count of mutually orthogonal pilot signals, i.e., $K \gg \tau_p$, significantly impacting the overall system performance. Consequently, it follows that $\tau_u \gg \tau_p$. The received signal at AP l can be expressed by Equation (16).

The CE vectors are obtained by despreading the signal received in Equation (16) based on Equation (17). Utilizing the MMSE estimator, the CE can be determined using Equations (18) and (19).

It is noteworthy that the CE and the corresponding error are statistically independent, adhering to the distributions $\hat{\mathbf{h}}_{kl} \sim \mathcal{N}_{\mathbb{C}}(\mathbf{0}, \hat{\mathbf{R}}_{kl})$ and $\tilde{\mathbf{h}}_{kl} = \mathbf{h}_{kl} - \hat{\mathbf{h}}_{kl} \sim \mathcal{N}_{\mathbb{C}}(\mathbf{0}, \tilde{\mathbf{R}}_{kl})$, respectively. The correlation matrices are defined by Equations (20) and (28)

$$\tilde{\mathbf{R}}_{kl} = \mathbf{R}_{kl} - \hat{\mathbf{R}}_{kl}. \quad (28)$$

5.2. Uplink and Downlink Payload Transmission

The baseband complex signal received at AP l in the UL, denoted as $\mathbf{y}_l \in \mathbb{C}^{N \times 1}$, encompasses the transmitted data from all K UEs, as articulated in [32,116]

$$\mathbf{y}_l = \mathbf{H}_l \mathbf{s}_l + \mathbf{n}_l. \quad (29)$$

Assume that $\mathbf{H}_l = [\mathbf{h}_{1l}^T, \dots, \mathbf{h}_{Kl}^T] \in \mathbb{C}^{N \times K}$ represents the UL channel matrix from AP l to all UEs, and defining the combined UL signal vector at AP l as $\mathbf{s}_l = [\mathbf{s}_{1l}, \dots, \mathbf{s}_{Kl}]^T \in \mathbb{C}^{K \times 1}$, where each element $s_{lk} \sim \mathcal{N}_{\mathbb{C}}(0, p_k)$ denotes the payload signal transmitted by UE k with UL power p_k . Then, the UL signal vector can alternatively be expressed as $\mathbf{s}_l \sim \mathcal{N}_{\mathbb{C}}(\mathbf{0}, \mathbf{Q})$, where

$$\mathbf{Q} = \begin{bmatrix} p_1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & p_k & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & p_K \end{bmatrix} \quad (30)$$

Furthermore, the independent receiver AWGN at AP l , $\mathbf{n}_l \in \mathbb{C}^{N \times 1}$, follows $\mathbf{n}_l \sim \mathcal{N}_{\mathbb{C}}(\mathbf{0}, \sigma^2 \mathbf{I}_N)$, where σ^2 represents its power. Equation (29) can be reformulated as

$$\mathbf{y}_l = \hat{\mathbf{H}}_l \mathbf{s}_l + \mathbf{w}_l. \quad (31)$$

Consequently,

$$\hat{\mathbf{H}}_l = \mathbf{H}_l - \tilde{\mathbf{H}}_l, \quad (32)$$

represents the matrix of MMSE CE vectors for the UL, and $\tilde{\mathbf{H}}_l$ denotes the matrix of CSI errors for the UL. Additionally, the term

$$\mathbf{w}_l = \tilde{\mathbf{H}}_l \mathbf{s}_l + \mathbf{n}_l, \quad (33)$$

is an UL vector encompassing the estimation errors of CSI and the terms associated with the AWGN, denoted as $\mathbf{w}_l \sim \mathcal{N}_{\mathbb{C}}(\mathbf{0}, \Sigma_l)$, where the correlation matrix is specified by

$$\Sigma_l = \sum_{k=1}^K p_k \tilde{\mathbf{R}}_{kl} + \sigma^2 \mathbf{I}_N. \quad (34)$$

In the DL, the signal received by a UE k , denoted as $y_k \in \mathbb{C}$, includes all the data transmitted by the APs, and can be expressed as

$$y_k = \mathbf{H}_k \mathbf{s}_k + n_k, \quad (35)$$

where $\mathbf{H}_k = [\mathbf{h}_{k1}, \dots, \mathbf{h}_{kL}] \in \mathbb{C}^{1 \times M}$ represents the DL channel matrix for UE k from all APs, while $\mathbf{s}_k = [\mathbf{s}_{k1}, \dots, \mathbf{s}_{kL}]^T \in \mathbb{C}^{M \times 1}$ is the corresponding DL signal vector at UE k , with its elements given as

$$\mathbf{s}_{kl} = \mathbf{c}_{kl} \zeta_{kl}. \quad (36)$$

Here, $\zeta_{kl} \sim \mathcal{N}_{\mathbb{C}}(0, \rho_{kl})$ represents the DL data signal intended for UE k , with ρ_{kl} denoting the DL signal power. This signal is assigned to a transmission precoding vector $\mathbf{c}_{kl} \in \mathbb{C}^{N \times 1}$ that determines the spatial directivity of the transmission. Typically, this precoding vector satisfies $\mathbb{E}\{\|\mathbf{c}_{kl}\|^2\} = 1$ [27]. Once again, $n_k \sim \mathcal{N}_{\mathbb{C}}(0, \sigma^2)$ denotes the independent receiver noise at UE k with power σ^2 . Equation (35) can be reformulated as

$$y_k = \hat{\mathbf{H}}_k \mathbf{s}_k + w_k, \quad (37)$$

where

$$\hat{\mathbf{H}}_k = \mathbf{H}_k - \tilde{\mathbf{H}}_k, \quad (38)$$

constitutes the DL counterparts of Equation (32). Additionally, the term

$$w_k = \tilde{\mathbf{H}}_k \mathbf{s}_k + n_k, \quad (39)$$

represents the DL counterpart of Equation (33), with a variance specified by the error statistics of the LSF coefficient

$$\Sigma_k = \sum_{l=1}^L \zeta_{kl} \tilde{\beta}_{kl} + \sigma^2. \quad (40)$$

An APS scheme can be implemented in both the UL and DL. In the UL channel, UEs' signals are transmitted to all APs, which collaborate sequentially through an SLP algorithm to estimate the original signal. The APS scheme can be incorporated into the equalization estimation. This integration can be represented by a Boolean matrix, $\mathbf{D} \in \mathbb{B}^{K \times M}$, where each element, D_{km} , indicates whether UE k is intended to be served by antenna element m from the APs, taking the values of 1 or 0 to signify inclusion or exclusion, respectively.

For better comprehension of the definition, the sub-matrix $\mathbf{D}_{\bar{l}} \in \mathbb{B}^{K \times N}$, is introduced. $\mathbf{D}_{\bar{l}}$ is defined as a sub-matrix of $\mathbf{D}$, given by $\mathbf{D} = [\mathbf{D}_{\bar{1}}, \dots, \mathbf{D}_{\bar{L}}]$. Furthermore, $\mathbf{D}_{\bar{l}}$ can be represented as $\mathbf{D}_{\bar{l}} = [\mathbf{D}_{\bar{l}1}, \dots, \mathbf{D}_{\bar{l}L}, \dots, \mathbf{D}_{\bar{l}N}]$, where $\mathbf{D}_{\bar{l}l} \in \mathbb{B}^{1 \times N}$. Similarly, following the same rationale, $\mathbf{D}_{\bar{k}} \in \mathbb{B}^{M \times 1}$, represents a specific row of $\mathbf{D}$, such that $\mathbf{D} = [\mathbf{D}_{\bar{1}}, \dots, \mathbf{D}_{\bar{K}}]^T$. Additionally, $\mathbf{D}_{\bar{k}} = [\mathbf{D}_{\bar{k}1}, \dots, \mathbf{D}_{\bar{k}L}, \dots, \mathbf{D}_{\bar{k}N}]^T$.

Hence, the received baseband complex signal in the UL at a specific AP l , denoted as $\mathbf{y}_l \in \mathbb{C}^{N \times 1}$, adheres to

$$\mathbf{y}_l = (\mathbf{D}_{\bar{l}}^T \odot \mathbf{H}_l) \mathbf{s}_l + \mathbf{n}_l, \quad (41)$$

where the symbol $\odot$ denotes the element-wise product of matrices, also referred to as the Hadamard product. Additionally, the signal received by a UE k in the DL, denoted as $y_k \in \mathbb{C}$, encompasses all the data transmitted by the corresponding set of APs

$$y_k = (\mathbf{D}_k^T \odot \mathbf{H}_k) \mathbf{s}_k + n_k. \quad (42)$$

The power allocated to each UE and AP throughout all phases of transmission is typically constrained by an upper limit, denoted as P_{max} . This upper limit is contingent upon the physical implementation of each UE's and AP's antenna terminal. Consequently, the UL and DL payload signals, s_k and s_{kl} , respectively, remain mutually independent and subject to power restrictions, where $0 \leq p_k \leq P_{max}$ and $0 \leq \rho_{kl} \leq P_{max}$.

Equations (41) and (42) can be rewritten as

$$\mathbf{y}_l = (\mathbf{D}_l^T \odot \hat{\mathbf{H}}_l) \mathbf{s}_l + \mathbf{w}_l, \quad (43)$$

and

$$y_k = (\mathbf{D}_k^T \odot \hat{\mathbf{H}}_k) \mathbf{s}_k + w_k, \quad (44)$$

where $\hat{\mathbf{H}}_l = \mathbf{H}_l - \tilde{\mathbf{H}}_l = [\hat{\mathbf{h}}_{1l}^T, \dots, \hat{\mathbf{h}}_{Kl}^T]$ and $\hat{\mathbf{H}}_k = \mathbf{H}_k - \tilde{\mathbf{H}}_k = [\hat{\mathbf{h}}_{k1}, \dots, \hat{\mathbf{h}}_{kL}]$. Additionally, $\mathbf{w}_l$ and w_k are defined by

$$\mathbf{w}_l = (\mathbf{D}_l^T \odot \tilde{\mathbf{H}}_l) \mathbf{s}_l + \mathbf{n}_l, \quad (45)$$

and

$$w_k = (\mathbf{D}_k^T \odot \tilde{\mathbf{H}}_k) \mathbf{s}_k + n_k \quad (46)$$

following $\mathbf{w}_l \sim \mathcal{N}_{\mathbb{C}}(\mathbf{0}, \boldsymbol{\Sigma}_l)$ and $w_k \sim \mathcal{N}_{\mathbb{C}}(0, \Sigma_k)$ given by

$$\boldsymbol{\Sigma}_l = \sum_{k=1}^K p_k (\mathbf{E}_{kl} \odot \tilde{\mathbf{R}}_{kl}) + \sigma^2 \mathbf{I}_N, \quad (47)$$

and

$$\Sigma_k = \sum_{l=1}^L \frac{\tilde{\zeta}_{kl}}{N} \mathbf{D}_{kl} [(\tilde{\beta}_{kl})]_N + \sigma^2. \quad (48)$$

where $\mathbf{E}_{kl} \in \mathbb{B}^{N \times N}$ is a Boolean matrix that signifies the channel spatial correlation characteristics to be considered. This determination is based on the individual antennas from AP l participating in the transmission and detection process of the signal from UE k in the UL. $\mathbf{E}_{kl}$ corresponds to $\mathbf{D}_{kl}$, with its 1 elements representing the antenna indexes from $\mathbf{D}_{kl}$ for UE k and AP l .

5.3. Uplink Payload Reception

Previous research in the realm of RSs has primarily concentrated on the development of SLP (specifically, distributed) algorithms for the UL, within the LPU over the fronthaul [115,116]. The primary objective of this focus has been to replicate the performance exhibited by the LMMSE-based detection scheme employed in the centralized implementations of the CF mMIMO concept [32,55].

Hence, for sequential CF mMIMO networks like the RS topology, alternative detection schemes can rely on a general class of SLP algorithms, as demonstrated in [115,116]. The SLP algorithm enables the acquisition of the signal's estimation vector for each AP l across the sequential network, denoted as $\hat{\mathbf{s}}_l = [\hat{s}_{1l}, \dots, \hat{s}_{Kl}]^T$, where $\hat{s}_{lk}$ represents the individual estimates for each UE k . The sequential algorithm commences with the computation of the signal's estimation vector for AP 1 after receiving $\mathbf{y}_1$, i.e., $\hat{\mathbf{s}}_1$. Subsequently, this information is transmitted to AP 2, which conducts its own estimation, $\hat{\mathbf{s}}_2$. Importantly, this estimation is not solely based on $\mathbf{y}_2$ but also incorporates information embedded in $\hat{\mathbf{s}}_1$. Thus, in line with its name, the fundamental concept of the SLP is that each AP l along the network,

upon receiving the signal's soft estimation vector from AP $l-1$, denoted as $\hat{\mathbf{s}}_{l-1}$, performs its own soft estimation of signal $\mathbf{s}_l$, i.e., $\hat{\mathbf{s}}_l$. Subsequently, this information is forwarded to AP $l+1$. This iterative process continues until AP L is reached, forwarding the final signal vector estimate, $\hat{\mathbf{s}}_L$, to the CPU.

In AP 1, the computation of the signal's soft estimation vector is carried out as follows:

$$\hat{\mathbf{s}}_1 = \mathbf{B}_1 \mathbf{y}_1, \quad (49)$$

where $\mathbf{B}_1 \in \mathbb{C}^{K \times N}$ represents the matrix that contains the local receiver combining vectors from AP 1 for each UE k , and it may be based on various designs. The signal estimate in Equation (49) is transmitted to AP 2, initiating the SLP algorithm as outlined below: for AP $l \in \{2, \dots, L\}$, upon receipt of the signal's soft estimation vector from AP $l-1$, denoted as $\hat{\mathbf{s}}_{l-1}$, the algorithm proceeds to compute its own soft estimate by following the process

$$\hat{\mathbf{s}}_l = \mathbf{A}_l \hat{\mathbf{s}}_{l-1} + \mathbf{B}_l \mathbf{y}_l. \quad (50)$$

Here, $\mathbf{A}_l \in \mathbb{C}^{K \times K}$ represents a receiver combining matrix that enables local detection to utilize the soft estimates computed from the previous AP, denoted as $\hat{\mathbf{s}}_{l-1}$, while $\mathbf{B}_l \in \mathbb{C}^{K \times N}$ depends on the information provided by the locally received signal, i.e., $\mathbf{y}_l$. Assuming that the initial signal estimate, i.e., $\hat{\mathbf{s}}_0$, is a null vector, Equation (50) can be generalized for $l \in \{1, \dots, L\}$, as discussed in [116]

$$\hat{\mathbf{s}}_l = \tilde{\mathbf{B}}_l \mathbf{z}_l, \quad (51)$$

where, $\mathbf{z}_l = [\mathbf{y}_1^H, \dots, \mathbf{y}_l^H]^H \in \mathbb{C}^{lN \times 1}$ represents the augmented received signal at AP l , and the term $\tilde{\mathbf{B}}_l \in \mathbb{C}^{K \times lN}$ denotes the augmented receiver matrix combining. This matrix is defined as

$$\tilde{\mathbf{B}}_l = \begin{cases} [\mathbf{A}_l \tilde{\mathbf{B}}_{l-1} & \mathbf{B}_l], & \text{if } l > 1 \\ \mathbf{B}_1, & \text{if } l = 1. \end{cases} \quad (52)$$

Equation (52) can be reformulated as $\tilde{\mathbf{B}}_l = [\tilde{\mathbf{B}}_{l1}, \tilde{\mathbf{B}}_{l2}, \dots, \tilde{\mathbf{B}}_{ll}]$, where

$$\begin{cases} \tilde{\mathbf{B}}_{lv} = \mathbf{A}_l \mathbf{A}_{l-1} \cdots \mathbf{A}_{v+1} \mathbf{B}_v, & 1 \leq v < l \\ \tilde{\mathbf{B}}_{ll} = \mathbf{B}_l. \end{cases} \quad (53)$$

The authors in [115,116,119,120] conduct a comprehensive exploration of alternative SLP algorithms, examining different choices for both the receiver combining matrices, $\mathbf{A}_l$ and $\mathbf{B}_l$, aimed at enhancing the performance of the sequential MRC method. Specifically, in [116], the UL SLP algorithm, referred to as OSLP, demonstrates optimized accuracy in data estimates on the CPU. While the proof of the CPU propositions is not provided, its receiver combining matrices are presented as

$$\begin{cases} \mathbf{A}_l = \mathbf{I}_K - \mathbf{T}_l \hat{\mathbf{H}}_l \\ \mathbf{B}_l = \mathbf{T}_l, \end{cases} \quad (54)$$

where

$$\begin{cases} \mathbf{T}_l = \mathbf{P}_{l-1} \hat{\mathbf{H}}_l^H (\boldsymbol{\Sigma}_l + \hat{\mathbf{H}}_l \mathbf{P}_{l-1} \hat{\mathbf{H}}_l^H)^{-1} \\ \mathbf{P}_{l-1} = (\mathbf{I}_K - \mathbf{T}_{l-1} \hat{\mathbf{H}}_{l-1}) \mathbf{P}_{l-2}. \end{cases} \quad (55)$$

and $\mathbf{P}_0 = \mathbf{Q}$ from Equation (30). In the context of sequential MRC, the matrices are specified as

$$\begin{cases} \mathbf{A}_l = \mathbf{I}_K \\ \mathbf{B}_l = \hat{\mathbf{H}}_l^H. \end{cases} \quad (56)$$

As evident from Equations (54) to (56), the MRC scheme relies on the match filtered (MF) operation, presenting significantly lower computational complexity compared to the OSLP scheme, which is grounded in MMSE processing, as discussed in [116].

Upon the completion of computations by the last AP in the RS (i.e., $l = L$), resulting in the final estimate $\hat{\mathbf{s}}_L$, the estimate is transmitted to the CPU for the ultimate decoding process. Along the RS network, the attainable SE of UE k in AP l is expressed as

$$\text{SE}_{kl} = \left(1 - \frac{\tau_p}{\tau_c}\right) \mathbb{E}\{\log_2(1 + \text{SINR}_{kl})\}, \quad (57)$$

where the effective SINR is given by

$$\text{SINR}_{kl} = \frac{p_k \left| \mathbf{B}_{lk}^H \hat{\mathbf{H}}_{kl} \right|^2}{\sum_{k'=1, k' \neq k}^K p_{k'} \left| \mathbf{B}_{lk} \hat{\mathbf{H}}_{k'l} \right|^2 + \mathbf{B}_{lk}^H \mathbf{K}_l \mathbf{B}_{lk}}, \quad (58)$$

where $\mathbf{B}_{lk} \in \mathbb{C}^{IN \times 1}$ is defined such that $\bar{\mathbf{B}}_l = [\mathbf{B}_{l1}, \dots, \mathbf{B}_{lK}]^T \in \mathbb{C}^{K \times IN}$, $\hat{\mathbf{H}}_{kl} = [\hat{\mathbf{h}}_{k1}, \dots, \hat{\mathbf{h}}_{kl}]^T \in \mathbb{C}^{IN \times 1}$, and the additional term $\mathbf{K}_l \in \mathbb{C}^{IN \times IN}$ represents the correlation matrix of the augmented error estimation plus AWGN, given by

$$\mathbf{K}_l = \begin{bmatrix} \Sigma_1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \Sigma_l \end{bmatrix} \quad (59)$$

With an APS scheme, the CE matrices are modified based on $\mathbf{D}$, according to the following expression, $\hat{\mathbf{H}}_{kl} = [\mathbf{D}_{k1} \odot \hat{\mathbf{h}}_{k1}, \dots, \mathbf{D}_{kl} \odot \hat{\mathbf{h}}_{kl}]^T$.

6. Developments on Radio Stripe Technology

In recent years, there has been a growing body of research dedicated to rendering the RS network a practical embodiment of CF. In the study by [16], the authors successfully demonstrate the advantages of CF mMIMO while addressing the practical deployment challenges associated with fronthaul capacity in this architecture. The paper provides a comprehensive overview of the RS concept, covering system characteristics such as network operation, RA, and practical deployment issues. Subsequent research efforts focus on developing sequential processing algorithms for UL and DL to be implemented in the APs over the fronthaul. Motivated by findings in [32], subsequent works attempt to adapt the MMSE, combining it to the distributed and sequential nature of the RS network. In [115], a distributed normalized LMMSE (NLMMSE) equalization technique is employed at each AP in the UL, enabling interference suppression while maintaining low fronthaul requirements. The AP locally transmits soft signal estimates of the desired signal, local CSI, and error statistics to the next AP in the RS sequence until reaching the last AP. In [116], a sequential linear processing (SLP) algorithm, known as optimal sequential linear processing (OSLP), is proposed for UL RS communications and is compared to the standard sequential MRC. The former is proven to be optimal in both maximizing SE and minimizing mean square error (MSE). This approach achieves performance comparable to the optimal centralized implementation based on LMMSE combining proposed in [32,55] across all SINRs. However, it does so in a distributed manner, thereby significantly reducing fronthaul requirements usually observed in CF mMIMO networks. The works in [62,63] were further extended to RS in [117], where team MMSE precoding is introduced that generalizes classical centralized MMSE precoding to arbitrary patterns of CSI. The work in [138] provides an investigation into the potential of B5G and 6G mMIMO systems, characterized by high antenna density in communication infrastructures, such as RS.

However, various use cases are also under investigation for RSs. In [118], the authors leverage energy beamforming to develop an RF wireless energy transfer solution, addressing the energy harvesting demands of multiple UEs within an indoor RS mMIMO system. They derived optimal and sub-optimal precoders based on the MRT technique, aiming at maximizing the power transfer at the RS while utilizing information on the power transfer efficiency of the energy harvesting circuits at the UEs. In [119], a cooperative RZF detection for RS networks is proposed, derived from MMSE processing, capable of achieving performance similar to centralized MMSE with low fronthaul capacity requirements. In [120], a novel UL detection scheme named quasi-LMMSE is introduced, utilizing only the MRC fronthaul signals. In [121], the received signal strength in an industrial Internet of things (IoT) context with mMIMO is studied. The authors compared the macro-diversity and signal spatial diversity performance of traditional mMIMO with different D-mMIMO setups, such as RS, and found that D-mMIMO can provide higher average channel gains. In [122], the outage and coverage probabilities in the UL and DL of an RS network are analyzed. The study demonstrated good system performance when the number of APs exceeded the number of UEs. In [123], the maximization of per-UE UL SE in an RS with limited capacity is investigated, employing a novel arrangement of APs and utilizing a compare-and-forward strategy to enable UL clustering cooperation, while in [137] a similar study is performed with a novel MMSE algorithm that leads to optimal results, minimizing MSE. In [124,125], new designs of low-pass filters for use in RS networks are addressed. In [133], the authors enable joint positioning and synchronization in the UL channel at sub-6 GHz bands by including the clock and phase offset of the UEs and deriving the maximum likelihood (ML) estimator. The authors in [134], under MSR metric, employ a joint precoding and fronthaul compression scheme leveraging the sequential nature of the RS network. In [136], the quality of the signal transmitted in the UL in an RS-aided wireless communication system is improved by low-density parity check (LDPC) codification. Finally, in [126], the operation of an RS network in the UL mmWave band is explored.

As in early CF mMIMO RA approaches, efficient power allocation or APS schemes play a pivotal role in supporting UL communications in RS-based systems. In the study by [139], a random APS approach is implemented to enhance the PE of the UL and DL RS network. In [135], an APS scheme is introduced to improve UL PE. Some investigations have focused on power allocation strategies to improve network SE [128]. In [129], a BO power optimization is conducted in the UL of a RS network employing OSLP, considering both MMF and MSR metrics. In related work, [131] introduces a centralized APS scheme for the UL of an RS network. This scheme incorporates two sequential equalization techniques: the OSLP and sequential MRC. The goal is to concurrently enhance network SE and ensure a balanced distribution of the load among the APs (i.e., LB). The work in [127] integrates RS deployments into wireless networks across sub-6 GHz and mmWave bands by deriving an approximation of the average UL UE channel and, consequently, the achievable SE.

Moreover, to augment system performance and enhance flexibility, the consideration of multi-objective (MO) optimization [140–143] for RA problems in the context of RS scenarios is recommended. This approach involves the simultaneous consideration of various NFM, including but not limited to, the MMF, MSR, and MTP, as explored in [130]. Exploring this avenue further, the adoption of tailored MO programming with MHs [144–147], emerges as a compelling alternative. This approach is capable of delivering high-quality RA solutions with a significantly rationalized computational effort.

The research on RSs is summarized in Table 5.

Table 5. State-of-the-art research on RS networks.

	Equalization or Precoding	RF Wireless Energy Transfer	IoT and mmWave	Coverage and Codification	Network Design	Resource Allocation (RA)
Uplink (UL)	NLMMSE-based [115] OSLP-based [116] RZF-based [119] Quasi-LMMSE-based [120] Clustered-based [123] Cluster-MMSE-based [137]	MRT-based [118]	Spatial Diversity Performance [121] Exploration [126] Integration [127]	Outage Probabilities [122] LDPC codification [136]	Comparison with CF [16] Comparison with LIS [138] Low-pass [124,125] Joint Positioning and synchronization with ML [133]	APS to improve PE [135,139] SO power optimization [128] BO power optimization [129] BO APS to improve SE/LB [131] MO power optimization [130]
Downlink (DL)	Team MMSE-based [117] Joint precoding and fronthaul compression [134]			Outage Probabilities [122]	Comparison with CF [16] Low-pass [124,125]	APS to improve PE [139]

7. Research Challenges, Directions, and Open Issues

We have explored the CF and RS technologies along with state-of-the-art research on RA algorithms suitable for these networks. These hold great potential for the future of wireless communications, offering enhanced connectivity, capacity, and coverage. The major KPI trade-offs between both technologies is summarized in Table 6.

Table 6. KPIs of CF and RS mMIMO technologies.

Metric	CF	RS
SE	High, improves with the number of antennas and APs; scalable	High, with potential improvements using RA
Deployment Complexity	Complex, requires multiple distributed APs	Relatively simpler due to linear arrangement of APs in stripes
Interference Management	Better interference management due to distributed nature	Effective interference management due to sequentially connected APs
Coverage	Wide coverage with uniform UE distribution	Suitable for medium/small scenarios, enhanced by the linear distribution of APs
CH	Weaker than cellular mMIMO, relies on distributed APs	Improved due to the structured deployment of APs
PE	High, with proper power control strategies	High, especially with optimized power allocation
Scalability	Scalable by adding more APs	Scalable, facilitated by the stripe architecture
Latency	Low, but depends on efficient fronthaul and LPU	Medium, with potential improvements from streamlined connectivity of APs
Cost	Potentially higher due to more HW and complex deployment	Lower due to simpler and more linear deployment

Despite their promising potential, several research challenges, future directions, and open issues must be addressed. One of the primary research challenges is scalability and complexity, as the required coordination among these units to ensure seamless connectivity can be computationally intensive. Additionally, the algorithms needed for RA in a distributed system are inherently complex, necessitating the development of efficient algorithms capable of real-time operation. PE poses its own set of challenges. The distributed nature of these systems can lead to higher overall power consumption. This can be addressed through efficient RA and HW. Interference management to improve SE is another critical challenge. With an increasing number of APs and UEs, effective precoding/equalization techniques for DL and UL communications are necessary. The constraints of backhaul and fronthaul links are also significant to ensure low latency and real-time communication between the APs and the APU/CPU. High-capacity backhaul and fronthaul links are required to connect distributed APs to the core network. Ensuring

low-latency communication between APs and central processing units is critical for supporting real-time applications. This is alleviated in RS networks; however, it can become a bottleneck.

Several research directions are being explored to address these challenges. We have explored throughout the paper several RA techniques aimed at improving the KPIs. Additionally, advanced signal processing techniques coupled with enhanced CE methods are being developed to improve signal quality and reduce interference. MaL and AI are also being leveraged to create adaptive algorithms that can dynamically adjust to changing network conditions and drive predictive maintenance strategies. Exploring new network topologies is another promising research direction, which is the main purpose of the RS architecture.

Despite these advances, several issues remain open. Standardization of protocols and interfaces for the CF and RS technologies is crucial to ensure interoperability among equipment from different vendors, which requires compliance with international regulations. Security and privacy are critical concerns, requiring robust measures to protect UE data and ensure secure communication in distributed networks. Real-world implementation of such networks also requires field trials to validate theoretical models and algorithms under real-world conditions. Finally, the economic viability needs to be assessed and efficient strategies need to support the deployment and maintenance of these technologies.

8. Conclusions

In this paper, we offer a comprehensive overview of the fundamental principles governing both CF and RS networks, while also examining the recent advancements in these technologies. It provides a detailed exposition of the operational stages within these networks, delineating the processes of UL pilot transmission, CE, as well as data transmission and reception between APs and UEs. Such elucidation, along with the exploration of both traditional cellular networks and distributed system models, and the examination of crucial elements such as mMIMO systems, correlated fading models, and channel characteristics, offers a nuanced contextualization of current technologies. This sets the stage for the innovative methodologies unveiled in both B5G and 6G communication standards. Moreover, this paper serves as a survey of the optimization concepts and techniques supporting RA in both CF and RS networks, delving into state-of-the-art works capable of providing a robust foundation for comprehending the intricacies of designing practical UL power control and AP-UE RA techniques within CF and RS networks.

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Abbreviations

The following abbreviations are used in this manuscript:

CF	Cell-Free
RS	Radio Stripe
mMIMO	Massive Multiple-Input-Multiple-Output
CE	Channel Estimation
UL	Uplink
DL	Downlink
RA	Resource Allocation
APS	Access Point Selection
6G	Sixth Generation
KPI	Key Performance Indicator
SE	Spectral Efficiency
PE	Power Efficiency
FeMBB	Further Enhanced Mobile Broadband
umMTC	Ultra-Massive Machine-Type Communications
eURLLC	Enhanced Ultra-Reliable and Low-Latency Communications
LDHMC	Long-Distance and High Mobility Communications
ELPC	Extremely Low-Power Communications
AI	Artificial Intelligence
THz	Terahertz
QoS	Quality of Service
MaL	Machine Learning
UE	User Equipment
HW	Hardware
LIS	Large Intelligent Surface
AP	Access Point
BS	Base Station
FR1	Frequency Range 1
FR2	Frequency Range 2
TDD	Time-Division Duplex
CSI	Channel State Information
3GPP	Third Generation Partnership Project
ICI	Inter-Cell Interference
CH	Channel Hardening
FP	Favorable Propagation
DFT	Discrete Fourier Transform
AWGN	Additive White Gaussian Noise
nLoS	Non-Line-of-Sight
SSF	Small-Scale Fading
LSF	Large-Scale Fading
PL	Path-Loss
LoS	Line-of-Sight
RF	Radio Frequency
SF	Shadow Fading
D-mMIMO	Distributed mMIMO
C-RAN	Cloud Radio Access Network
CoMP-JT	Coordination Multipoint with Joint Transmission
DAS	Distributed Antenna System
CPU	Central Processing Unit
mmWave	Millimeter Wave
IUI	Inter-User Interference
LMMSE	Local Minimum Mean Square Error
MRC	Maximum Ratio Combining

DS	Desired Signal
IS	Interference Signal
NFM	Network Function Metric
OF	Objective Function
MMF	Max-Min Fairness
NFM	Network Function Metric
OF	Objective Function
MMF	Max-Min Fairness
SOCP	Second-Order Cone Programming
ZF	Zero-Forcing
GP	Geometric Programming
SO	Single-Objective
MTP	Minimum Transmission Power
MSR	Max-Sum Rate
FrP	Fractional Programming
SCA	Successive Convex Approximation
APG	Accelerated Projected Gradient
DeL	Deep Learning
DCNN	Deep Convolutional Neural Network
DNN	Deep Neural Network
MRT	Maximum Ratio Transmission
DRL	Deep Reinforcement Learning
RZF	Regularized ZF
BO	Bi-Objective
MH	Meta-Heuristic
SINR	Signal-to-Noise-and-Interference Ratio
LB	Load Balance
OFDM	Orthogonal Frequency Division Multiplexing
LPU	Local Processing Unit
ADC	Analog-to-Digital Converter
DAC	Digital-to-Analog Converter
APU	Area Processing Unit
NLMMSE	Normalized LMMSE
SLP	Sequential Linear Processing
OSLP	Optimal Sequential Linear Processing
MSE	Mean Square Error
IoT	Internet of Things
MF	Match Filtered
ML	Maximum Likelihood
LDPC	Low-Density Parity Check
MO	Multi-Objective

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