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Review

A Review of Energy Efficiency and Power Control Schemes in Ultra-Dense Cell-Free Massive MIMO Systems for Sustainable 6G Wireless Communication

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Abstract: The traditional multiple input multiple output (MIMO) systems cannot provide very high Spectral Efficiency (SE), Energy Efficiency (EE), and link reliability, which are critical to guaranteeing the desired Quality of Experience (QoE) in 5G and beyond 5G wireless networks. To bridge this gap, ultra-dense cell-free massive MIMO (UD CF-mMIMO) systems are exploited to boost cell-edge performance and provide ultra-low latency in emerging wireless communication systems. This paper attempts to provide critical insights on high EE operation and power control schemes for maximizing the performance of UD CF-mMIMO systems. First, the recent advances in UD CF-mMIMO systems and the associated models are elaborated. The power consumption model, power consumption parts, and energy maximization techniques are discussed extensively. Further, the various power control optimization techniques are discussed comprehensively. Key findings from this study indicate an unprecedented growth in high-rate demands, leading to a significant increase in energy consumption. Additionally, substantial gains in EE require efficient utilization of optimal energy maximization techniques, green design, and dense deployment of massive antenna arrays. Overall, this review provides an elaborate discussion of the research gaps and proposes several research directions, critical challenges, and useful recommendations for future works in wireless communication systems.

Keywords: cell-free massive mimo; ultra-dense CF-mMIMO; energy harvesting; energy efficiency; spectral efficiency; power control; sleep mode; resource allocation; sustainable wireless networks

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1. Introduction

The prevalence of massive devices and mobile applications has recently gained widespread popularity in the wireless communication domain. The dramatic rate variations and inter-cell interference inherent in classical cell-based structures impose a heavy burden on the existing wireless network infrastructure [1]. As a result, ultra-dense cell-free massive multiple input multiple output (UD CF-mMIMO) has been identified as a candidate wireless networking technology to cater to the continuous data traffic surge, remedy the cell-edge performance issues, and guarantee unprecedented wireless network link reliability [2]. However, the transitioning towards tetherless connectivity for a fully mobile-networked society, achieving multiple orders of Energy Efficiency (EE) gains and quality throughput, poses an increasingly important design criterion.

The real-time requirements of connected devices and capacity demands of the current wireless network infrastructure are increasing rapidly. The landscape of upcoming wireless networks is envisaged to support pervasive interconnectivity, high transmission rates, ultra-reliability, and low latency, spurring novel information and communication technologies (ICT) and revolutionary ultra-dense (UD) wireless infrastructure [3]. The envisioned next-generation wireless communication systems will integrate virtually everything into the internet while accommodating novel technologies like virtual reality [4,5], machine-to-machine (M2M) communications [6–8], vehicle-to-everything (V2X) [9], and device-to-device (D2D) communications [10].

Essentially, the next-generation wireless networks will rely on the availability of higher frequency bands, which brings more opportunities for multi-gigabit throughput and extreme capacity [11–14]. Ultra-dense networks (where the density of the base stations (BSs) is much higher than that of the network users) and/or massive multiple input multiple output (mMIMO) (where large antenna arrays enhance the BSs) have been identified as enabling technology to satisfy the vast requirements of next-generation wireless networks [2]. However, the service-quality variations and cell-edge issues inherent in the traditional cellular network architecture pose a significant bottleneck for the mobile network operators [1,15].

Cell-free massive multiple input multiple output (CF-mMIMO), a practical incarnation of distributed mMIMO, has become an intensive research topic in industry and academia. CF-mMIMO can potentially mitigate significant pathloss variations and cell-edge performance issues inherent in conventional cellular networks [16–21]. Despite the enormous merits of CF-mMIMO, the outcry for environment-friendly designs and greener networking solutions is alarming [22]. Adopting a distributed antenna array in CF-mMIMO systems could dramatically increase the power consumption and the overall energy emissions of wireless communication systems [23].

Consequently, the geometric outburst of digital signal processing (DSP) power consumption, prohibitive radio-frequency (RF) circuit power costs, and energy costs of data processing units have become a critical concern for mobile network operators [24]. As such, Energy Efficiency (EE), expressed in bits/joule, has emerged as a dominant performance index for benchmarking wireless communication systems [25]. Depicted in Figure 1 is a typical illustration of the next-generation communication system. In this configuration, a dearth of user equipment (UE) is jointly served by a large chunk of arbitrarily allocated access points (APs), all connected to a central processing unit (CPU) that handles complex signal processing [10,26].

Gracia-Morales et al. [27] proposed an insightful switch on/off algorithm to minimize the global carbon footprint emanating from cellular network equipment. Ahmed et al. [28] characterized the network capacity, energy efficiency, and design constraints of UD infrastructure. Similarly, Dai and Yu [29] proposed the implementation of precoding techniques to improve the EE performance of CF-mMIMO. Nguyen et al. [30] investigated the uplink EE of CF-mMIMO by introducing a novel closed-form algorithm with a zero-forcing (ZF) precoder to resolve a multi-objective total EE maximization problem. In another related study, Hamdi and Qaraqe [31] considered the feasibility of incorporating energy harvesting and energy exchange capabilities into CF-mMIMO networks.

Power control in CF-mMIMO is of particular interest and a significant figure of merit to optimize the network performance and realize uniform quality of service (QoS) for all users, including those at the cell-edge [32]. Moreover, power control techniques are essential to deal with interference and pilot contamination issues inherent in CF architectures [33]. Results from existing reports on the actual performance of CF-mMIMO with power control optimization techniques, reveal that proper power allocation can greatly improve the net throughput, max-min fairness, spectral efficiency (SE), and EE of CF-mMIMO systems [34–38]. More precisely, Ngo et al. [39] demonstrated that max-min power control could moderately improve the lowest user throughput. Andrea et al. [40] illustrated a deep learning-based power control approach, which is capable of addressing the sum-rate and minimum-rate maximization problem in CF-mMIMO. The results reported in [34] indicate that the EE performance of CF-mMIMO can be enhanced significantly with proper power control. The findings of the work [41] revealed that insightful power allocation algorithms could effectively optimize the sum SE of CF-mMIMO systems.

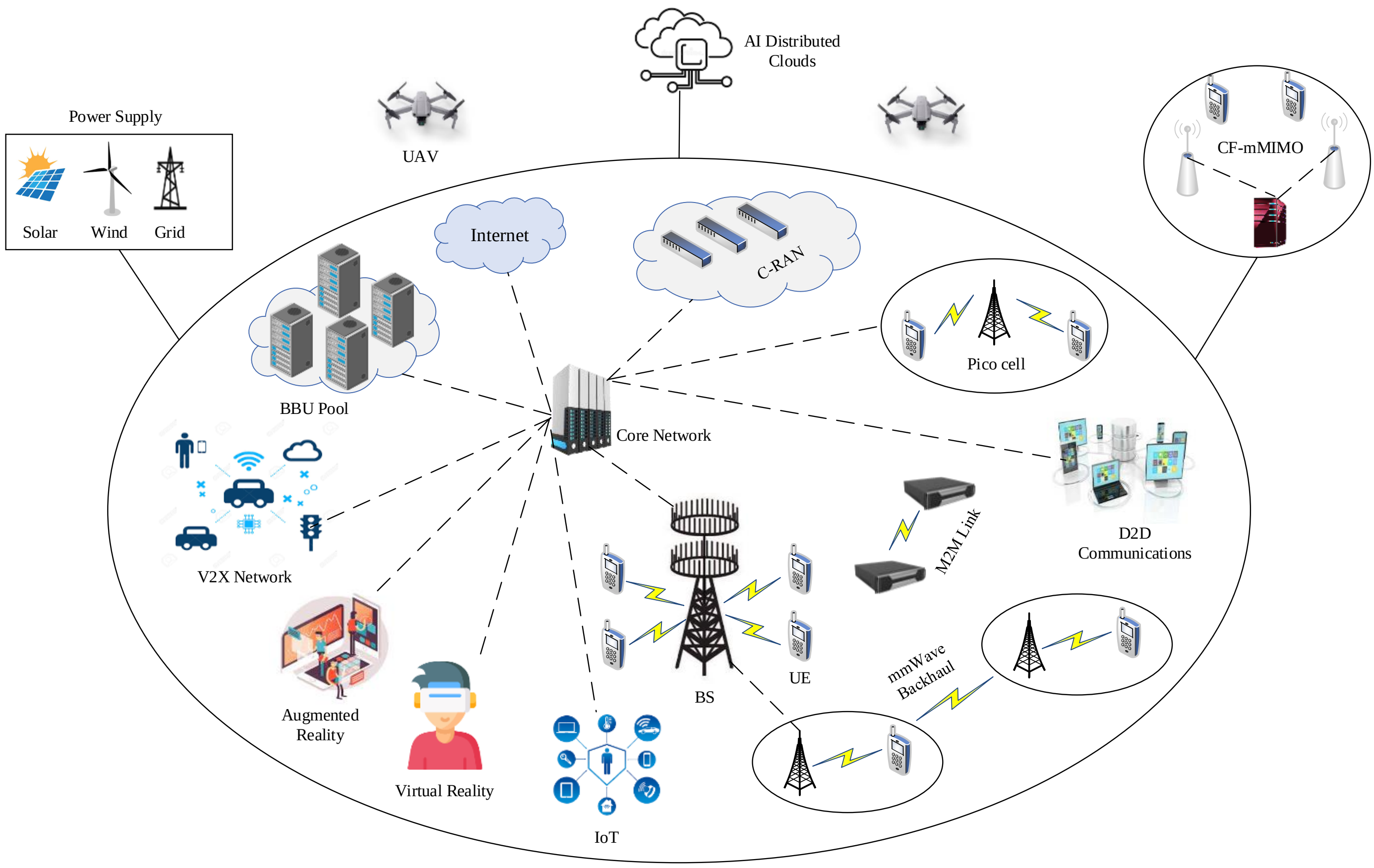

Figure 1. Illustration of a typical next-generation communication system.

Nonetheless, the existing works of literature on CF-mMIMO systems lack research attempts that jointly optimize EE and power control. In light of the above, this paper aims to bridge this gap by considering green networking solutions and sustainable power allocation strategies in UD CF-mMIMO systems. In particular, the paper attempts to identify contemporary research trends, unearth key research challenges, and guide future research in this domain. A concise roadmap of this study is presented in Figure 2. The noteworthy contributions of the review paper are outlined as follows:

- The fundamental structure of CF-mMIMO and its corresponding system model is described.
- A panoramic view of the power consumption model and power consumption parts is highlighted.
- A comprehensive analysis of selected green communication techniques is discussed.
- An exhaustive study of current trends in power control techniques for CF-mMIMO systems is presented.
- Critical open research issues are identified, and future research directions for energy-efficient power control schemes in CF-mMIMO systems are elaborated.

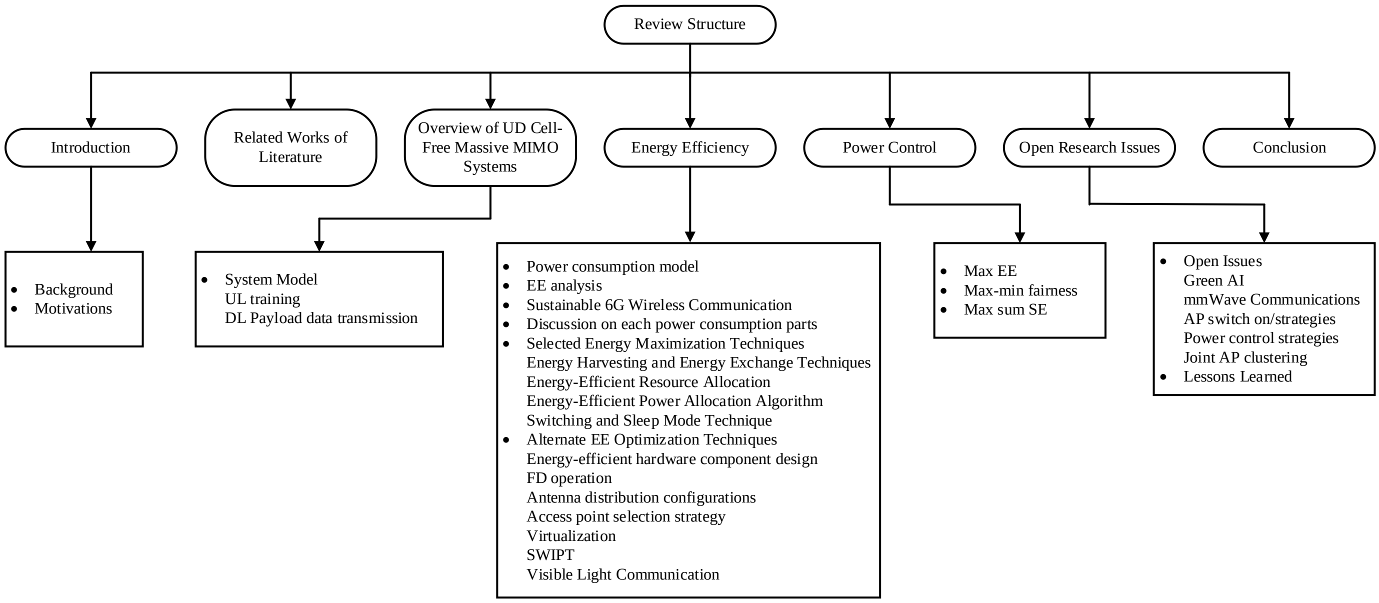

Figure 2. A comprehensive roadmap of the study.

The structure of the paper is as follows: Section 2, "Related Work", discusses prior works on energy-efficient power control schemes in emerging wireless communication networks. Section 3, "Overview of Ultra-Dense Cell-Free Massive MIMO Systems", summarizes the foundational background on CF-mMIMO systems and the associated system model, including the Uplink (UL) training and Downlink (DL) payload data transmission. Further, the power consumption model, power consumption parts, and an exhaustive analysis of selected EE maximization techniques are presented in Section 4, "Energy Efficiency". Similarly, insightful power allocation strategies for performance maximization are discussed in Section 5, "Power Control". Section 6, "Open Research Issues", provides a clear path for future investigations in wireless communication. Finally, a concise conclusion is drawn in Section 7, "Conclusion".

2. Related Work

The need to minimize the global carbon footprint and address interference issues associated with wireless communication networks has gained significant, widespread research interest in the past few years. Many innovative green networking techniques, EE maximization schemes, interference detection and mitigation techniques, and connectivity management strategies have been proposed [42–44]. The schemes are designed to facilitate efficient wireless networks to meet the growing traffic demand and guarantee the continuous evolution of wireless systems. Specifically, in [45], Tang et al. characterized the EE of simultaneous wireless information and power transfer (SWIPT)-aided non-orthogonal multiple access networks. As a step further, Alageli et al. [46] considered the distinctive combination of CF-mMIMO and SWIPT for energy-efficient wireless communication networks.

As reported by Jin et al. [47], a novel strategy to maximize the sum of SE and total EE by properly allocating DL data power control coefficients and pilot is proposed. Alonzo et al. [38] examined the EE of CF and user-centric (UC) networks with millimeter (mm)-Wave. Hamdi and Qaraqe [48] provide essential design insights for greening wireless networks. Their proposed design was achieved by incorporating energy cooperation and a management approach for CF-mMIMO systems. Wang et al. [49] proposed an insightful AP selection technique and an optimal power allocation algorithm to maximize the total EE of CF-mMIMO. Furthermore, a computationally efficient convex conic feasibility checking problem is proposed in [50] to solve the problem of max-min power control in CF-mMIMO networks.

Nikbakht and Lozano [51] proposed a fractional power control policy to maximize the UL performance of CF-mMIMO systems. Interestingly, Zhao et al. [52] advocated using an optimized DL power control algorithm to jointly maximize the SE of 95% of users and the experience of high-priority users in wireless networks. Lai et al. [53] introduced a novel artificial fish school algorithm to maximize the mean rate of users while realizing the target of max-min power control. Mai et al. [54] explored the possibility of minimizing the effect of pilot contamination and ultimately improving the performance of UL CF-mMIMO systems using a data power control algorithm and a joint pilot design. Following a similar approach, Li et al. [55] formulated a novel pilot assignment algorithm in weighted counting to mitigate the so-called pilot contamination effect in CF wireless networks.

Nevertheless, detailed characterization of energy-efficient wireless communication and power control schemes is integral for designing and optimizing CF-mMIMO networks. Accordingly, this article explores the contemporary perspectives of energy-efficient power control techniques and highlights promising directions for future research in emerging wireless communication systems. Table 1 features the scope and drawbacks of some related research attempts and the authors' contribution to bridging the research gaps in the current review.

Table 1. Limitations of some related works.

Ref.	Year	Focus and Coverage	Limitations	This Contribution
[2]	2021	The survey provides a holistic overview of up-to-date works on CF-mMIMO. The work serves as a comprehensive roadmap to open up new frontiers on CF-mMIMO systems.	■ Challenges with EE are not clearly outlined. ■ Power maximization techniques are not discussed.	■ Joint optimization of EE and power control for CF-mMIMO is presented. ■ Exciting research trends for future works are presented.
[27]	2020	The work characterized the performance of AP switch-mode techniques to maximize the EE of CF-mmWave mMIMO networks. Unlike prior studies, the survey takes into consideration non-uniform spatial traffic densities.	■ Sophisticated power control techniques are not elaborated.	■ The work provides insight into various power allocation strategies dimensioned to complicated setups.
[33]	2018	The work analyzed the performance of a pilot power control technique to minimize the channel estimation error and ultimately mitigate the effect of pilot contamination.	■ Challenges with EE are not clearly outlined.	■ A detailed outline of unresolved EE challenges is presented.
[36]	2020	The work presents an exhaustive analysis of the impact of channel ageing and pilot contamination on the performance of CF-mMIMO systems. The study also proposes a practical fractional power control scheme to alleviate the effects of inter-user interference.	■ Power control is limited to the fractional power control method. ■ EE and green networking strategies are not accounted for appropriately.	■ The work presents sophisticated power control schemes. ■ An exhaustive analysis of EE techniques for green wireless communication is presented.
[37]	2021	The work proposes an unsupervised deep learning-based approach to address the challenge of max-min user fairness in CF networks.	■ The proposed power control algorithm is centered on simple network setups comprising a few users and APs.	■ Power allocation strategies dimensioned to complicated configurations with excess supply of APs are presented.

Table 1. *Cont.*

Ref.	Year	Focus and Coverage	Limitations	This Contribution
[56]	2018	The work compares the performance of CF and UC approaches in wireless networks operating at mmWave frequencies. The work also presents power control algorithms to maximize the system's global EE.	▪ Although a baseline for future work is presented, the evaluation of performance metrics is not clearly outlined. ▪ Energy models and power consumption parts are not discussed.	▪ A holistic overview of the power consumption model, the corresponding EE, and power consumption parts is presented.
[57]	2020	Provides important design insights for green wireless communications by characterizing the EE per unit area of CF-mMIMO systems while accounting for the irregular spatial randomness of multiple-antenna APs.	▪ Power Optimization techniques are not presented. ▪ Open research issues and future research directions are not discussed in depth.	▪ Joint optimization of EE and power control for CF-mMIMO is presented. ▪ A wide range of challenging research problems are discussed.
[58]	2021	Presents optimization techniques to maximize the SE and power control of CF-mMIMO systems encompassing UL and DL transmission.	▪ Energy models and power consumption parts are not accounted for accordingly. ▪ Power optimization is limited to the neighborhood field optimization ensemble method.	▪ The parts of the power consumption model, associated EE, and power consumption are presented. ▪ A robust discussion on several power optimization schemes is provided.
[59]	2021	Examined the performance of three different transmit power control (TPC) algorithms to improve the uplink (UL) EE of CF-mMIMO and ultimately achieve an optimum SE-EE trade-off for CF systems.	▪ Energy models and power consumption parts are not accounted for comprehensively. ▪ Open research issues and future research directions are not discussed in depth.	▪ Essential insights into the energy model and power consumption parts are provided. ▪ A range of challenging research problems are discussed.
[60]	2020	The work proposes two novel optimization techniques to solve the downlink (DL) power consumption problem of CF-mMIMO concerning antenna power and the user's DL rate constraints.	▪ Future research directions are not outlined.	▪ Lines of research requiring further investigation are reported.

3. Overview of Ultra-Dense Cell-Free Massive MIMO Systems

In the last decade, the geometric outburst of various innovative communication technologies has been overwhelming. Primarily, mMIMO network architecture has evolved over the years to support the explosive increase in wireless data traffic. In the regime of large-scale antenna arrays at the BSs and by exploiting spatial multiplexing, spatial diversity, and advanced beamforming, a large number of User Equipment (UE) can be served with the same time/frequency resources [3,61]. However, large service-quality variations and cell-edge performance issues constitute a significant setback for the effective deployment of cellular network infrastructure [1]. Thus, UD CF-mMIMO has appeared as a promising network paradigm to cater to the continuous data traffic surge and alleviate the mediocre cell-edge problems inherent in cellular networks [62,63]. In these networks, an excess number of geographically allocated Access Points (APs) coordinated by a Central Processing Unit (CPU) coherently serve a smaller number of UEs distributed across a wide serving area [64].

CF-mMIMO is essentially a practical embodiment of mMIMO and network MIMO, where cooperation between low-complexity APs deployed in a distributed manner helps to potentially minimize the effects of intercell interference and offer considerable gains in coverage probability [16]. As in cellular networks, CF-mMIMO reaps the benefits of channel hardening and favorable propagation through simple signal processing [65]. Moreover, compared with Small-Cells (SCs) and co-located systems, CF-mMIMO promises multifold improvement in SE, EE, and 95% likely per-user throughput [66]. Figure 3 illustrates the fundamental structure of a typical CF-mMIMO network. It comprises the CPU and the associated APs linked via a fronthaul network to the CPU without the intervening cells.

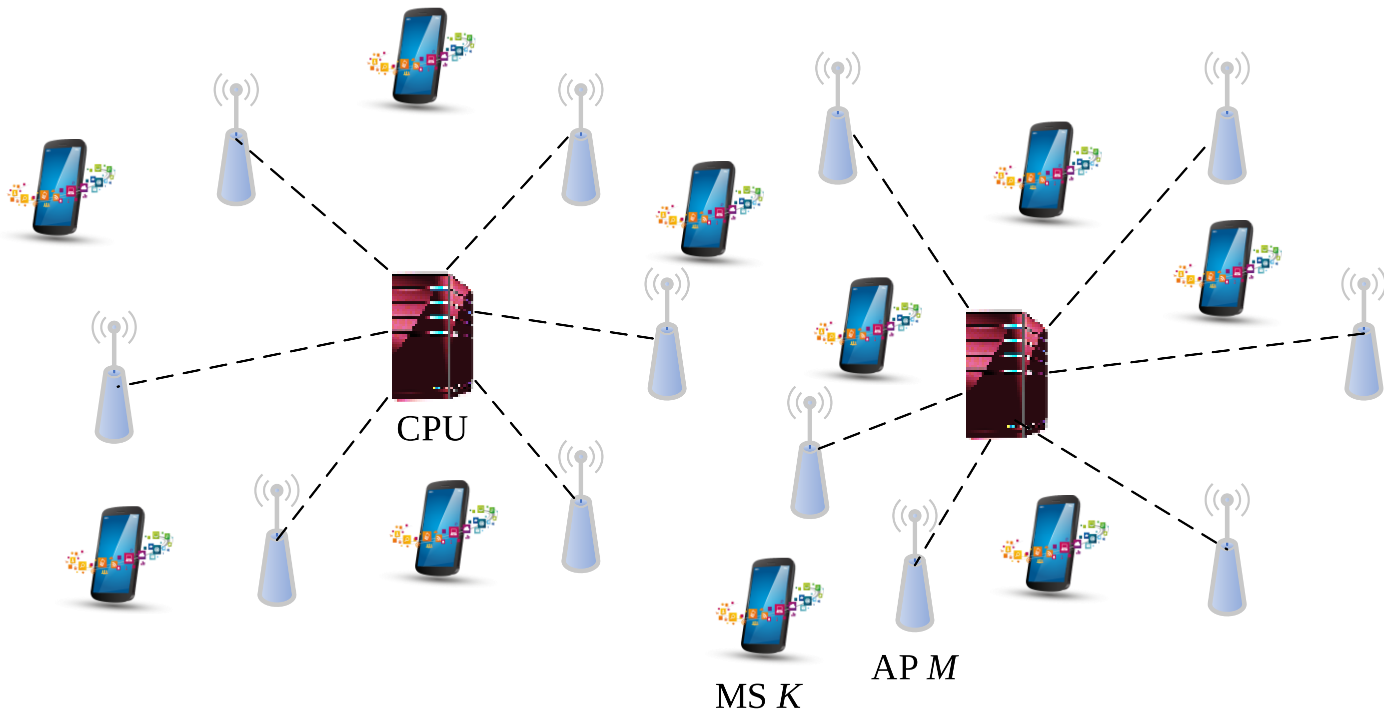

Figure 3. A Typical Architecture of a Cell-Free Massive MIMO (CF-mMIMO) Network.

3.1. System Model

A CF-mMIMO system operated in time division duplex (TDD) mode is investigated. Let M specify the number of randomly deployed single-antenna APs simultaneously serving k single-antenna UEs in the same time/frequency block. All APs are linked via a fronthaul network to a CPU, wherein network information is exchanged. Let h_{mk} reflect the channel between the mth AP and the kth UE. The channel model is defined as (1)

$$h_{mk} = \sqrt{\beta_{mk}} d_{mk} \tag{1}$$

where β_{mk} accounts for the large-scale fading and d_{mk} accounts for the small-scale fading. It is assumed that d_{mk} are independent identically distributed (i.i.d) random variables, $d_{mk} \sim \mathcal{CN}(0,\ 1)$ for $m = 1, \ldots, M$, $k = 1, \ldots, K$. What is more, concerning frequency, β_{mk} coefficients are assumed to be constant and known as a priori at any moment. In this context, two communication protocols—UL training and DL payload data transmission—are analyzed.

3.1.1. Uplink Training

For each coherence interval, let $\tau_{u,p}$ reflect the length of UL training duration and let $\sqrt{\tau_{u,p}}\psi_k \in \mathbb{C}^{\tau_{u,p}\times 1}$ reflect the pilot sequence forwarded by the kth user, $k = 1, \ldots, K$. Further, we assume that these assigned pilot sequences are mutually orthonormal. $\psi_k^D \psi_{k'} = 0$ for $k' \neq k$, and $\psi_k{}^2 = 1$, which necessitates that $\tau_{u,p} \geq K$. The mth AP receives a pilot signal defined by (2)

$$\boldsymbol{x}_{up,m} = \sqrt{\tau_{u,p}\rho_{u,p}} \sum_{k=1}^{K} h_{mk}\psi_k + \boldsymbol{z}_{up,m}, \tag{2}$$

where $\rho_{u,p}$ accounts for the normalized transmit signal-to-noise ratio (SNR) and $\boldsymbol{z}_{up,m} \sim \mathcal{CN}\left(0,\ N\boldsymbol{I}_{\tau_{u,p}}\right)$ accounts for the additive noise. The received pilot at the mth AP is processed as (3)

$$\check{x}_{up,mk} = \psi_k^D \boldsymbol{x}_{up,m} = \sqrt{\tau_{u,p}\rho_{u,p}} h_{mk} + \psi_k^D \boldsymbol{z}_{up,m} \tag{3}$$

By adopting the minimum mean squared error (MMSE) technique, the channel h_{mk} is estimated. The channel estimation of h_{mk} is expressed as (4)

$$\hat{h}_{mk} = \frac{\mathbb{E}\left\{\check{x}^*_{up,mk}\right\}}{\mathbb{E}\left\{\left|\check{x}_{up,mk}\right|^2\right\}} \check{x}_{up,mk} = c_{mk}\check{x}_{up,mk} \tag{4}$$

where c_{mk} is reflected by (5), and the associated channel estimation error is reflected by (6)

$$c_{mk} \triangleq \frac{\sqrt{\tau_{u,p}\rho_{u,p}}\beta_{mk}}{\tau_{u,p}\rho_{u,p}\beta_{mk} + 1} \tag{5}$$

$$\widetilde{h}_{mk} \triangleq h_{mk} - \hat{h}_{mk} \tag{6}$$

3.1.2. Downlink Payload Data Transmission

In this phase, conjugate beamforming (CB) is employed. The transmitted signal from the mth AP to the K users is expressed as (7)

$$w_m = \sqrt{\rho_d} \sum_{k=1}^{K} \sqrt{\eta_{mk}} \hat{h}^*_{mk} v_k, \tag{7}$$

where ρ_d specifies the normalized transmit SNR corresponding to the data symbol and v_k specifies the symbol assigned to the kth UE, satisfying $\mathbb{E}\left\{|v_k|^2\right\} = 1$. Moreover, by exploiting $m = 1, \ldots, M$, $k = 1, \ldots, K$, and η_{mk} power control coefficients, the average power constraint $\mathbb{E}\left\{|w_m|^2\right\} \leq \rho_d$ is satisfied. Thus, the power constraint can be remodeled as (8)

$$\textstyle\sum_{k=1}^{K} \eta_{mk}\phi_{mk} \leq 1, \text{ for all m}, \tag{8}$$

where ϕ_{mk} reflects the variance of the channel estimate and is given by (9)

$$\phi_{mk} \triangleq \mathbb{E}\left\{\left|\hat{h}_{mk}\right|^2\right\} = \sqrt{\tau_{u,p}\rho_{u,p}}\beta_{mk}c_{mk} \tag{9}$$

The received data signal at the kth UE is defined as (10)

$$y_{d,k} = \sum_{m=1}^{M} h_{mk}w_m + z_{d,k} = \sqrt{\rho_d} \sum_{k'=1}^{K} a_{kk'}v_{k'} + z_{d,k} \tag{10}$$

where $z_{d,k} \in \mathcal{CN}\ (0, 1)$ and $a_{kk'} \triangleq \sum_{m=1}^{M} \sqrt{\eta_{mk'}} h_{mk}\hat{h}^*_{mk'}$, $k' = 1, \ldots, K$.

4. Energy Efficiency

The demand for green communication is exacerbated by the proliferation of data-intensive applications, increased operational costs, capital investment, and power consumption [67–69]. Reasonably, Energy Efficiency (EE), considered a critical performance criterion, has attracted more and more research attention in recent times. The goal is to minimize the ecological and environmental concerns resulting from the mobile communication industry [70]. Numerous energy-efficient strategies, resource allocation algorithms, and optimal power control strategies have been proposed [34,49]. As a result, it is paramount to characterize this meaningful and appropriate design index extensively. This context sheds more light on the EE metric. As a starting point, the corresponding power consumption model and an insightful formulation of the total achievable EE of the CF-mMIMO network are highlighted clearly.

4.1. Power Consumption Model

According to recent reports [23,34], the total power consumption is defined as (11)

$$P_{total} = \sum_{m=1}^{M} P_{ac,m} + \sum_{m=1}^{M} P_{b,m}, \tag{11}$$

where $P_{ac,m}$ accounts for the amplifier and circuit power consumption at the mth AP and $P_{b,m}$ accounts for the backhaul link power consumption associated with the mth AP. The power consumption $P_{ac,m}$ is obtained as (12)

$$P_{ac,m} = (\sigma_m)^{-1} \rho_d N_0 \left(N \sum_{k=1}^{K} \eta_{mk} \phi_{mk} \right) + N P_{tc,m}, \tag{12}$$

where $0 < \sigma_m \leq 1$ depicts the efficiency of the power amplifier, N_0 depicts the noise power, and $P_{tc,m}$ depicts the power needed to run the circuit units of each antenna at the mth AP. As a further advance, the backhaul power consumption $P_{b,m}$ can be modeled as (13)

$$P_{b,m} = P_{0,m} + B S_e P_{bt,m}(\eta_{mk}) \tag{13}$$

where $P_{0,m}$ reflects the fixed power consumption value of each backhaul link, B reflects the transmission bandwidth, and $P_{bt,m}$ specifies the traffic-dependent power. By substituting the values of $P_{ac,m}$ and $P_{b,m}$ into (11), the total power consumption P_{total} can be remodeled as (14)

$$P_{total} = \rho_d N_0 \sum_{m=1}^{M} (\sigma_m)^{-1} \left(N \sum_{k=1}^{K} \eta_{mk} \phi_{mk} \right) + \sum_{m=1}^{M} (N P_{tc,m} + P_{0,m}) + B S_e \left(\sum_{m=1}^{M} P_{bt,m}(\eta_{mk}) \right) \tag{14}$$

4.2. Spectral Efficiency

The total achievable EE, measured in bit/joule, is defined as the ratio of the sum throughput (bit/s) and the total consumed power (watt) in the system and is defined as (15)

$$E_e(\eta_{mk}) = \frac{B S_e(\eta_{mk})}{P_{total}} \left(\frac{bit}{joule} \right) \tag{15}$$

where S_e is the sum of Spectral Efficiency (SE). Going forward, it is instructive to provide insights into the concept of SE which is a critical performance metric to be considered in keeping pace with an ever-increasing number of wireless data services and high-rate expectations. UD CF-mMIMO is envisioned to provide tremendous gains in SE through efficient utilization of massive and dense antenna arrays, insightful power optimization algorithms, and novel approaches to receiver filter coefficient design [10,14]. To put it simply, some key enabling technologies for 6G are gaining widespread popularity thanks to their ability to potentially improve and optimize SE through coherent transceiver processing. SE is measured in bits/second/hertz and is established as (16)

$$SE = \frac{Channel\ throughput\ (bit/s)}{Channel\ bandwidth\ (Hz)} \tag{16}$$

4.3. Discussions on Each Power Consumption Parts

This section briefly analyzes each power consumption part in the network [71].

(a) Circuit power: The deployment of large-scale antenna arrays, as in CF-mMIMO, significantly increases the power consumption of wireless networks owing to an abundance of antenna circuit elements [72]. The circuit power, resulting from the energy dissipated by the circuit elements such as analog devices and residually lossy factors in BSs, grows in tandem with the number of transmit antennas. Consequently, as the size of the hardware of the system grows large, the total circuit power dissipated increases.
(b) Signal processing power: Signal processing power dissipation is increasingly becoming a prime challenge to researchers, due to the greater complexity of signal processing algorithms and architectures per requirement. Advanced wireless communication systems, such as CF-mMIMO, require sophisticated signal processing units to code, precode, and decode symbols at both transmission ends. Although manifold benefits are realized, the total power consumption resulting from signal processing remains a significant issue to be addressed.
(c) Signal transmission power: The optimized data speed and simultaneous transmission of multiple signals in modern wireless communication systems necessitate even higher transmission power to maximize SNR, operating capacity, and coverage area. Besides, the power allocated to the transmitter during networking signals corresponds to the number of distributed users and antenna elements. Thus, signal transmission power has become a big deal in designing energy-efficient network architectures. The power consumption resulting from the signal transmission can be derived mathematically as $P_T = P_a/\eta$, where P_a specifies the average transmit power of the BS, and η specifies the efficiency of the average transmit power.
(d) The system fixed power: In addition to achieving tetherless connectivity and quality performance, minimizing the static energy (stable power consumption) caused by the hardware components of UD infrastructures, especially when performing different types of communication processes is critical.

4.4. Selected Energy Maximization Techniques

The problem of minimizing the high-power consumption of wireless communication systems while satisfying the target users' quality of service demands remains the focal point of many research works in recent times [73–76]. In order to tackle this fundamental issue and ensure the realization of an energy-efficient network, umpteen green networking approaches and novel strategies have been developed. In particular, energy-efficient resource allocation schemes, low-complexity power allocation algorithms, energy harvesting and energy exchange techniques, and hardware conditioning, amongst several other strategies, have been deployed [48,77–79]. Indeed, it is of practical interest to provide an up-to-date review of current trends in green wireless communications to guide future research efforts. In this context, an exhaustive analysis of the fundamental structure and recent advances in selected EE maximization techniques indexed in high-impact scientific research databases are presented. The key aspects considered are outlined as follows.

4.4.1. Energy Harvesting and Energy Exchange Techniques

Energy harvesting has emerged as a springboard to the realization of green wireless communications [80]. The basic idea underpinning energy harvesting is adopting renewable energy resources to complement existing grid-powered network architectures, which would probably guarantee sustainable and environmentally friendly networking solutions. Thus, telecom equipment manufacturers may incorporate energy bought from the electrical grid and preferentially independent energy harvesting sources to power a set of distributed APs [81]. Interestingly, novel algorithms based on Simultaneous Wireless Information and Power Transfer (SWIPT) have been formulated to maximize energy harvesting [82]. The potential of renewable energy sources to supply the energy demands of mobile communication networks while delivering equivalent information, as in the case of non-renewable energy sources, has also been primarily characterized. Available results indicate that the operational cost and greenhouse gas mitigation are substantially optimized [69,83,84]. As a result, the integration of renewable energy sources such as solar photovoltaic, biomass, wind, hydropower, ocean power, and geothermal, alongside widely used energy supply (hydrocarbon, diesel generator), is deemed ideal to offset the power consumption cost and maximize system EE, particularly for geographical regions lacking mature network infrastructures [85].

In the same vein, CF-mMIMO can be enabled with energy exchange capabilities via a smart grid infrastructure to minimize network operational costs and carbon footprints [48]. By exploiting the power cooperation between APs, extra available energy can be transferred from APs with low price/power requirements to APs with high price/power requirements. Thus, efficiently managing the energy supplied from different sources and compensating for the intermittency of renewable energy sources [31]. Although energy harvesting and exchange capabilities have appeared as preferred candidates for energy savings, several unresolved practical issues persist. Specifically, achieving economically justifiable configurations, ensuring data security, preserving fault tolerance without service disruption, and minimizing power dissipation losses in scenarios with solar photovoltaics, are significant shortcomings in deploying energy harvesting techniques. In addition, the cooperation between two APs through energy exchange results in a power loss [86,87]. Figure 4 illustrates the architecture of a CF-mMIMO network with per-AP renewable energy resources. In addition, Table 2 provides essential insights into the development of optimal energy harvesting and energy exchange techniques for energy-efficient wireless communication systems.

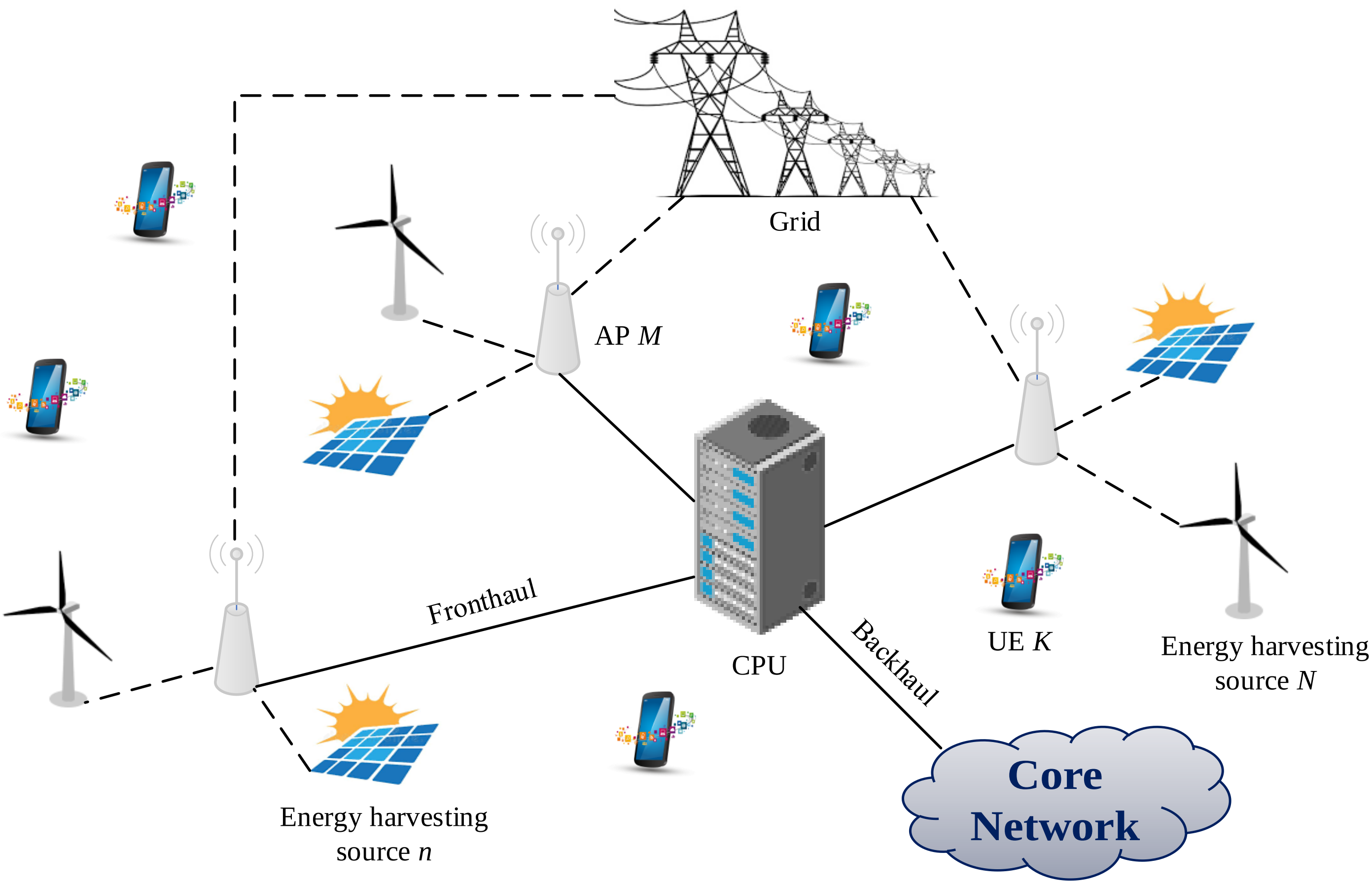

Figure 4. Renewable Energy-Powered Cell-Free Massive MIMO Network.

Table 2. Recent advances in energy harvesting and energy exchange techniques for energy-efficient wireless communication.

Ref.	Focus and Coverage	Key Findings	Remarks	Year
[31]	The work provided an extension to the scheme presented in [88]. The work proposed a novel power allocation and cooperation technique to manage energy exchange in CF-mMIMO networks.	Compared to traditional systems, the EE of CF-mMIMO systems is considerably maximized.	ML-based power cooperation techniques alongside energy harvesting sources may be incorporated for CF-mMIMO.	2020
[48]	The work considered the performance of a CF-mMIMO network with energy exchange capabilities powered by the grid and an energy harvesting source.	The proposed energy management approach significantly reduces consumed grid power EE compared to systems without cooperation.	More improvement is required to compensate for the intermittency of renewable energy in CF-mMIMO.	2019
[80]	Introduced a novel RF energy harvesting framework that exploits the distinctive benefits presented by CF-mMIMO, unmanned aerial vehicles (UAVs) [89], and reconfigurable intelligent surfaces (RIS) for the internet of things (IoT) devices.	Compared to the scheme in [90], a substantial increase in energy harvesting is achieved.	One critical aspect for improved energy harvesting is the height and deployment position of the RISs and UAV APs.	2021
[81]	The work proposed using energy harvested from renewable energy sources to power all the BSs in a two-tier hybrid heterogeneous network. A distributed user association algorithm is introduced to palliate the effects of renewable deployment on the user association.	The throughput of the proposed system is substantially optimized owing to larger bandwidths.	The adverse effects of these emerging techniques on user association are still largely understudied and require more work.	2016
[82]	Characterized the performance of a SWIPT-assisted CF-mMIMO network that coherently serves both energy harvesting and non-energy harvesting users.	A reasonable trade-off exists between the achievable spectral and EE, the energy assigned for UL pilot transmission, and the harvested energy.	The development of the joint AP clustering technique and the deployment of limited-capacity fronthaul links between the CPU and the APs was not considered.	2021
[86]	The work provided significant insight into the performance of a wirelessly powered CF IoT coupled with energy harvesting technology.	A robust improvement in EE is achieved with the proposed optimization technique.	Comprehensive power optimization algorithms are crucial to achieving significant gains in EE.	2020

4.4.2. Energy-Efficient Resource Allocation

With an attendant rise in the greenhouse effect and energy shortage, energy-efficient resource allocation is a significant criterion to solve the problem of EE in next-generation wireless networks [91]. Resource allocation entails intelligently assigning the limited available resources such as pilot training, transmit power, and spatial transmission resources among users to maximize performance and minimize complexity in hardware design costs. More precisely, network resources are adjusted adaptively and synchronously to achieve the highest possible performance [92]. Resource allocation can be modeled as a design utility optimization problem that simultaneously maximizes the power allocation, user selection, bandwidth allocation, number of antennas, subcarrier, and time. If the resource allocation scheme is optimized, the optimization algorithm can efficiently allocate the time for data transmission and energy harvesting and optimally schedule antennas to enable UEs to create high-quality links and ultimately enhance EE [1]. Numerous computationally efficient and low-complexity resource allocation techniques have been proposed for energy-efficient wireless communications [93–95]. Table 3 presents an exhaustive analysis of recent advances in resource allocation for wireless communication architectures.

Table 3. Recent advances in resource allocation schemes for energy-efficient wireless communication.

Ref.	Focus and Coverage	Key Findings	Remarks	Year
[96]	The work advocated using a green resource allocation technique that jointly maximizes the bandwidth and transmits power at the APs for DL CF-mMIMO.	Results were obtained to validate the effectiveness of the proposed scheme and the moderate EE-AP trade-off.	With an ever-evolving wireless communication network, the trade-off between the quantity of APs and the EE is suboptimal for practical applications.	2017
[97]	The work comprehensively surveyed energy-efficient resource allocation schemes for mMIMO networks. Besides, an evaluation of the SE-EE trade-off alongside a large-scale fading-based EE approximation is presented.	The proposed algorithm is shown to be computationally efficient with fast convergence.	The circuit power consumption model primarily impacts the achievable EE.	2018
[98]	The work characterized the performance of an mMIMO non-orthogonal multiple access (NOMA) system integrated with wireless power transfer. The work introduced an insightful joint power, antenna selection, time, and subcarrier resource allocation technique for EE maximization.	Compared to benchmark schemes, the proposed algorithm achieves superior EE performance with better convergence.	It can also be extended to more practical and complicated setups	2021
[77]	In resolving the EE problem of an mMIMO system coupled with wireless power transfer, a resource allocation scheme that optimizes the power and time allocation, antenna selection, and beamforming design is analyzed.	Simulation results demonstrate the effectiveness of the proposed scheme over existing schemes.	More work is required to address the detrimental effect of imperfect channel state information on the system performance.	2021
[99]	The work proposed an efficient EE maximization scheme for UC CF-mMIMO using power allocation with instantaneous channel state information and different resource block allocation techniques.	The proposed technique is shown to outperform that with statistical information in terms of EE.	The proposed solution is a promising technological enabler for EE maximization in 5G-and-beyond networks.	2022
[100]	Joint optimization of the offloading rate, transmission power, and user's offloading data bits for secure and efficient mMIMO-mobile edge computing systems is presented.	Aside from ensuring heightened information security, the total EE is also maximized (about 30%).	The correspondence provides a secure and efficient framework to handle vigorous computational tasks.	2020

4.4.3. Energy-Efficient Power Allocation Algorithm

As a design goal of green mobile networks, it is critical to formulate novel and comprehensive power allocation algorithms, which are considered an essential index to prolong the lifetime of network terminals, and achieve EE maximization in mMIMO systems [101]. Appropriately dividing power between the UEs to optimize utility functions is referred to as power allocation [2]. Herein, an AP can arbitrarily cut down on their powers to avoid unnecessary interference and high-power consumption. In the last decade, low-complexity power allocation algorithms and optimization frameworks have been proposed to minimize energy consumption in wireless networks significantly. While striking a balance between optimality and computational complexity remains a prime challenge, numerous energy-efficient algorithms with faster convergence and better performance have been developed [102–104]. Table 4 summarizes recent works on power allocation algorithms for green wireless communication.

Table 4. Recent advances in power allocation techniques for energy-efficient wireless communication.

Ref.	Focus and Coverage	Key Findings	Remarks	Year
[22]	The work introduced two low-complexity optimization algorithms to tackle a mixed-integer second-order cone program (SOCP) to minimize power consumption in CF-mMIMO.	Results were obtained to validate the effectiveness of the proposed approach in reducing power consumption instead of solely minimizing the transmit power.	The global optimum solution outperforms the proposed algorithms in energy savings (about 20%).	2020
[105]	The work formulated a novel path-following approximation algorithm to handle the non-convexity of the proposed resource optimization problem to improve the total EE.	The proposed algorithm converges very quickly and can substantially maximize the total EE.	A significant increase in APs beyond some optimal points results in a steady decrease in the total EE.	2019
[30]	Proposed an insightful power allocation algorithm alongside a ZF precoding design to minimize high power consumption in CF-mMIMO systems.	Compared to the case without power control, the proposed process provides a robust enhancement in EE.	The system's performance is significantly impacted when the transmit power is high.	2017
[59]	The work provided a comparative analysis of various TPC algorithms under ZF reception, intending to maximize the UL EE while satisfying the target SE.	The max-min EE algorithm outperforms other TPC algorithms at a target SE, mainly when the number of single-antenna APs is massive.	Performance characterization under varying UEs, APs, and antennas per AP is not accounted for.	2021
[106]	Proposed an insightful accelerated projected gradient-based power allocation algorithm as an alternative to the conventional SOCP-based approaches deemed computationally inefficient for practical CF-mMIMO networks.	However, the proposed scheme obtained EE performance similar to the existing SOCP-based approach, with a much faster run time.	The degradation of the total EE when extending the system scale, i.e., increasing the number of users, is one paramount factor limiting real-time implementation.	2022
[107]	To address the computational complexity and high run time challenge of SOCP-based methods, two low-complexity and highly efficient techniques, namely proximal gradient and accelerated proximal gradient-based approaches, are analyzed for CF-mMIMO systems.	Compared with the conventional SOCP-based approaches, the proposed methods achieve the same EE performance with a much shorter run time.	As the number of users and the inter-user interference grows, the total EE decreases.	2022

4.4.4. Switching and Sleep Mode Techniques

In a bid to substantially increase the network EE and yield significant energy allowances to the telecom network operators at low implementation cost, switching and sleep mode strategies have appeared as an innovative paradigm for energy-efficient system design and energy savings, particularly in low-traffic scenarios [27]. As alluded to earlier, the APs are responsible for the highest proportion of energy consumed in wireless technology. Intuitively, incorporating AP switching and sleep mode techniques in the upcoming wireless networks is considered elementary and has attracted considerable research attention recently [27,108,109]. The architecture in Figure 5 presents a diagrammatic illustration of a sleep mode scenario in CF-mMIMO. In such approaches, a low-power state in the hardware is implemented. Some resources are either astutely turned off during "off-peak" hours or operated in low-energy consumption states. Lightly loaded APs can be dynamically turned on/off in correspondence with the traffic load/order of priority of APs within the network architecture [110].

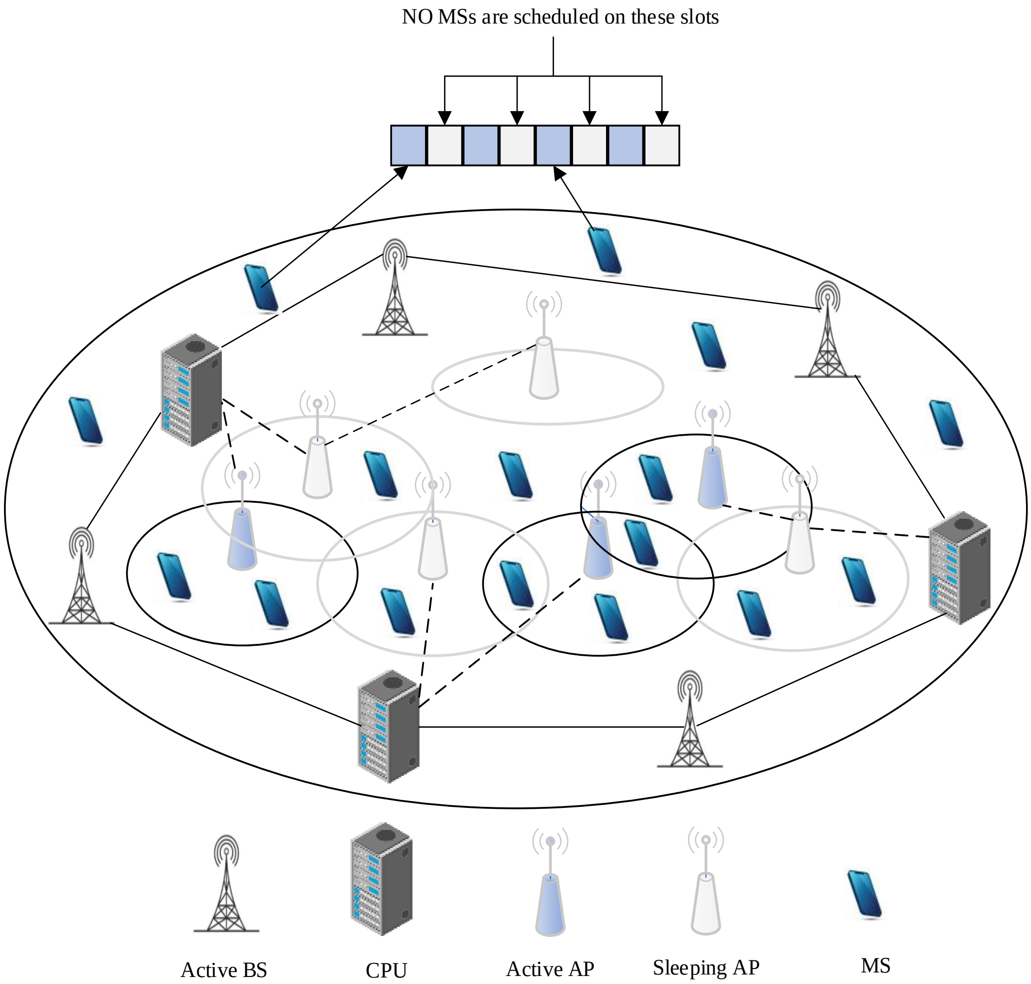

Figure 5. Sleep Mode Scenario in Cell-Free Massive MIMO.

Switching on and off APs must be modulated over the variations in traffic patterns on a daily or weekly basis. Hence, traffic load in the network can be monitored. Then, the particular energy-saving algorithm may decide to turn off/switch to the deep idle mode or turn on specific components in the network, thus avoiding unnecessary power consumption. Some hardware components that can be switched between low-power mode and awake mode include the entire AP, signal processing unit, power amplifiers, cooling equipment, etc. As a complement to the use of sleep modes, green user association techniques, cell breathing, and self-organizing networks are crucial enablers [111]. While energy saving can be realized by adopting switching and sleep mode techniques, the QoS is primarily impacted due to reduced system capacity [79]. A summary of recent advances in AP switching and sleep mode techniques is presented in Table 5.

Table 5. Recent advances in switching and sleep mode for energy-efficient wireless communication.

Ref.	Focus and Coverage	Key Findings	Remarks	Year
[79]	Provided an exhaustive analysis of the performance of AP switches on/off strategies for UD CF-mmWave mMIMO systems, designed to adaptively turn on/off APs, per the priority of APs deployed in the system.	Compared to conventional schemes, a considerable boost in EE is obtained.	Sophisticated power control strategies are not adopted.	2021
[27]	Enhanced perspective on AP switches on/off strategies by proposing a green AP sleep mode scheme following the goodness-of-fit test for CF-mmWave mMIMO systems.	Results have shown that in cases with non-uniform spatial traffic distribution, insightful goodness-of-fit-dependent AP switch on/off techniques can improve the achievable EE.	Deploying more reactive AP switch on/off strategies integrated with hybrid analogue-digital precoding frameworks is a rich area for further study.	2020
[108]	The work presented a comprehensive survey of energy efficiency techniques for 5G radio access networks, emphasizing mMIMO and sleep modes (advanced idle modes), amongst others.	From a practical viewpoint, sleep modes are considered an innovative energy-saving-based solution with numerous potentials.	A clear roadmap toward sustainable communication systems is provided.	2022
[110]	Characterized the performance of various AP switch on/off techniques dimensioned to selectively turn on/off some of the APs in relation to the traffic load in the system.	It suffices that properly designed switch on/off techniques can significantly maximize the achievable EE.	The scheme could still be exploited for more sophisticated AP switch on/off techniques, scalability aspects, and more complex power control techniques.	2020
[112]	The work considered the performance of a random AP sleep mode architecture for greening radio stripe-based CF-mMIMO systems.	Compared to similar configurations of CF-mMIMO networks, the proposed algorithm is shown to substantially increase the achievable EE of radio stripe technology.	Investigative studies on finite-capacity fronthaul links between the CPU and the APs as well as non-uniform long-term user distributions were not presented.	2021

4.5. Alternate Energy Efficiency Optimization Techniques

The emerging sophistication in mobile and wireless networks and the tremendous growth in the number of subscribers has accentuated energy consumption. Thus, capping power consumption while achieving reliability and performance objectives has also sky-rocketed research efforts in the wireless ecosystem [69]. In addition to the EE improvement techniques delineated in this contribution, numerous innovative approaches for greener wireless technology and greater power savings are being extensively researched. A few of the prominent strategies include green transmission techniques [113], energy-efficient component design [114], AP assignment algorithms [115], antenna distribution configurations [116], full-duplex (FD) operation [117], virtualization [118], SWIPT [119], and software-defined networking (SDN) [120]. The following provides important insights into developing novel strategies for energy-efficient wireless communication. Additionally, Table 6 summarizes the recent advances in alternate EE optimization strategies.

Table 6. Recent advances in alternate EE techniques for green wireless communication.

Ref.	Alternate Optimization	Focus and Coverage	Key Findings	Remarks	Year
[34]	AP selection scheme	Proposed an insightful power allocation algorithm alongside AP selection schemes to minimize power consumption resulting from backhaul links.	The total EE is significantly maximized, particularly for an enormous count of APs.	Achieving computationally efficient schemes remains a rich area for further investigation.	2018
[116]	Antenna distribution configuration	The work examined the performance of different antenna distribution designs, applying TPC.	It was shown that semi-distributed deployment could improve spectral and EE, particularly when the number of UEs grows.	For various usage scenarios, sophisticated TPC techniques are required to improve the EE further.	2021
[121]	AP selection scheme	Introduced a joint power allocation and AP selection scheme to achieve energy savings in CF-mMIMO networks.	It provided a significant reduction in the total power consumed.	The proposed approach is a promising technological enabler for improved wireless networks.	2020
[122]	Energy-efficient virtualization	The work advocated using an optical network-supported model to enhance the performance of network function virtualization (NFV) towards energy savings.	38% of the total power consumption is saved, as revealed by the mixed-integer linear programming model.	Further results verification is needed to analyze the impact of core network virtual machines inter-traffic on green NFV.	2019
[123]	Energy-efficient hardware component design	The work adopted well established distortion models to analyze the detrimental effect of hardware impairment (HI) on CF-mMIMO systems.	Results indicate that low-quality hardware can be utilized for CF deployment.	Specialized models to minimize the impact of HI at the UE were not considered	2017
[124]	Energy-efficient hardware component design	The work provided a comparative analysis of low-resolution ZF and maximum ratio combining receivers for energy-efficient CF-mMIMO networks.	From an EE point of view, ZF provides superior performance with a large chunk of quantization bits.	No reference is made to CF-mMIMO configurations with mixed-analogue-to-digital converters under Rician fading.	2020
[125]	FD operation	The work characterized the unique interplay between FD operation and CF-mMIMO systems to optimize the spectral and EE of wireless networks.	It suffices that a significant gain in spectral and EE is achievable with the proposed model as opposed to SC and co-located mMIMO.	Although the proposed model outperforms the baseline ones, the EE diminishes in scenarios with a massive number of APs.	2020
[126]	FD operation	Exploited the distinctive gains presented by FD communications to achieve improved energy-efficient CF-mMIMO networks.	However, the weighted sum EE obtained is similar to the centralized approach, with higher computational efficiency.	Unfortunately, residual interference suppression at APs is insufficient to realize optimized SE.	2022

Table 6. *Cont.*

Ref.	Alternate Optimization	Focus and Coverage	Key Findings	Remarks	Year
[127]	Frequency division duplexing (FDD)	Improved the feedback overhead and channel state information concerns of FDD-based CF-mMIMO systems.	The simulation results show that 15% of transmission power is saved. Thus, EE is optimized.	To effectively deploy the systems in a real environment, novel algorithms and insights are required to address other serious concerns of FDD systems.	2018
[128]	SWIPT	The work considered the performance of a CF-mMIMO network incorporated with SWIPT technology while adopting a UC AP selection technique.	A robust improvement in EE alongside a superior trade-off between SE and EE is obtained.	Satisfying the SE requirements of users is a top priority, and the slight loss in SE is non-negligible.	2021
[129]	SDN	The work characterized the performance of energy management and monitoring application infrastructure integrated with the SDN framework to reduce energy consumption.	The proposed solution can potentially minimize energy consumption in upcoming mobile networks.	Although the real-time implementation of the proposed model is presented, optimization techniques are needed to realize minimized energy consumption.	2017

4.5.1. Energy-Efficient Hardware Component Design

Considering the large amount of energy consumed by hardware components, it is essential to utilize components with higher energy-efficient features. For instance, power amplifiers widely deployed in wireless communication to optimize the signal level over the communication medium are shown to dissipate more than 80% of the input energy as heat [111]. Moreover, from an EE perspective, the static energy and the signal transmit energy consumed by hardware components are grossly unsatisfactory [71]. Adopting well-established models that satisfy certain EE requirements by minimizing energy consumption in such systems is preferable. While certain hardware replacement can be financially burdensome and economically unjustifiable, special consideration of both economic and operational features are critical to achieving a substantial amount of energy savings [130].

4.5.2. Full Duplex Operation

Full duplex (FD) wireless systems have been identified as a critical technology for the 5G and beyond 5G wireless networks, given the exponential demand for ubiquitous and untethered connectivity [131]. By enabling coherent transmission of UL and DL data on the same time-frequency resource, capacity enhancement in terms of SE and EE can be actualized for traditional wireless communication systems. Interestingly, advanced self-interference suppression mechanisms for FD technology have now been implemented in real-time, thereby making FD an attractive solution for future wireless networks [132]. Thus, it is of practical interest to exploit the possible gains in EE of FD and CF-mMIMO to reach even higher EE and greater carbon footprint minimization [133]. The system model for an FD CF-mMIMO network is presented in Figure 6.

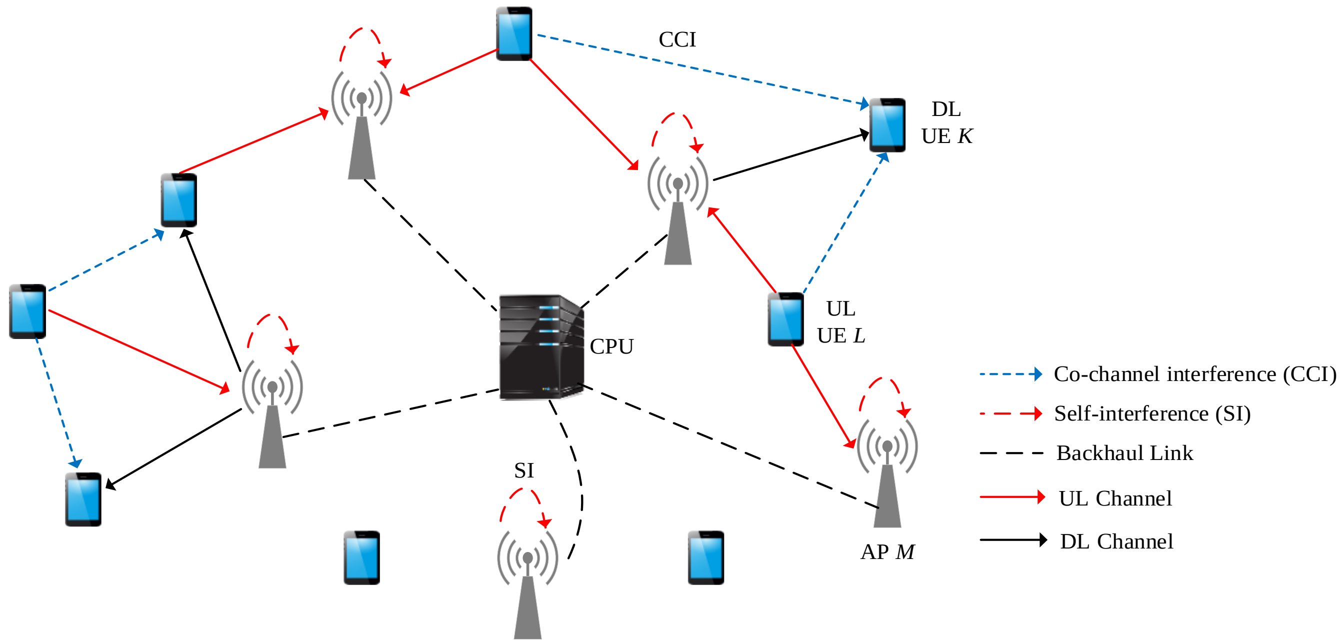

Figure 6. Full-Duplex Cell-Free Massive MIMO Communication.

4.5.3. Antenna Distribution Configurations

A promising approach to improve network coverage and achieve significant power-saving along with cost-effective networks consists of deploying distributed antenna systems [134]. As revealed by measurement-based evaluations [135], optimally deploying antennas of distributed antenna systems can result in reduced total radiated power level, less energy consumption, and enhanced SE. In the CF-mMIMO network, many distributed antennas cooperate in providing robust connections to users with optimized EE, which is a paramount index for implementation in a real environment. Many investigations on various antenna distribution setups and optimal positioning of distributed antennas are currently being explored for network capacity enhancement and greener communications [136–139].

4.5.4. Access Point Selection Strategy

In practice, reducing the effect of backhaul power consumption has been a very sought-after way of maximizing EE [140]. One of the significant research areas to improve energy usage in backhaul links and reach considerable energy savings is the energy-efficient AP selection technique [141]. The selection strategy addresses this problem by adaptively selecting a subset of APs to serve each user. More precisely, only some APs in the proximity of a given user jointly cooperate in serving it, thus ensuring efficient resource utilization [142]. The beneficial combination of both power allocation schemes and AP selection strategies helps to handle the complexity of the problem and its feasibility [121]. This method is thus a promising trend to satisfy the given QoS constraints for all users while increasing the total EE.

4.5.5. Virtualization

With a huge growing concern about the attendant rise in energy consumption, virtualization has been proposed as a prominent approach to consolidate other EE techniques and achieve performance maximization [122]. In this case, it is possible to minimize the number of dedicated hardware and software components, such that functions are separated from their underlying hardware and forwarded into software-based mobile functions while being made available on-demand [143]. As a further advance, network function virtualization can be incorporated with optical network-supported frameworks to achieve significant gains in agility, scalability, and reduced power consumption [144]. To this end, research efforts are targeting green virtualization frameworks that can contribute to reduced energy usage in wireless communication systems.

4.5.6. Simultaneous Wireless Information and Power Transfer

Recently, notable research activities geared towards addressing the energy scarcity problem in wireless networks through the reclamation of energy have gained traction. The emergence of simultaneous wireless information and power transfer (SWIPT), spurred by ever-increasing connected devices and high energy consumption has provided an insightful alternative to reach the green design target of mobile network operators and enhances the sustainable development of wireless communication systems [45]. In this case, part of the energy carried by wireless devices can be harvested and utilized to relay power and information across the wireless network. Essentially, radio frequency signals are exploited for superposing information and power transfer [82]. This technique can be effectively applied to energy-constrained relays to provide the much-needed flexibility for harvesting energy [46]. The concept of SWIPT has attracted a great deal of research attention in both academia and industry, to overcome the trade-off between rate and energy, eavesdropping, and practical implementation of transmit beamforming.

4.5.7. Visible Light Communication

A new paradigm of radio frequency-based technology, visible light communication (VLC), otherwise known as optical wireless communication, is envisaged to revolutionize the future of next-generation wireless standards [145–148]. Experimental and analytical investigations have demonstrated the potential of VLC to support large data rates and ultra-wide bandwidth with remarkable optimization in EE [149,150]. VLC seeks to harness the potential of LED luminaires through efficient modulation of the visible light spectrum for high-speed data communication. By exploiting the EE and unprecedented enhancement of LED technologies, VLC can serve as a complement to the existing network infrastructures, while providing improved EE as well as added security/privacy [151]. VLC, although in its infancy, is a potential access option to reach highspeed sustainable wireless frontiers, and is an interesting area requiring further elucidation [152].

Key findings from Table 2 indicate a robust improvement in EE due to a drastic minimization of grid power consumption and greenhouse emissions compared to systems without cooperation. Although the architecture suffers from the discredit of intermittency, infrastructure challenges, and huge initial capital investment. Future development in this domain comprises the application of Machine Learning (ML) in power cooperation modeling, intricate power optimization algorithms, and reliable energy storage systems.

From Table 3, aside from ensuring substantial energy savings, green resource allocation techniques provide a reliable and cost-effective starting point in the pursuit of sustainable next-generation wireless communication systems. Moreover, as demonstrated in Table 3, researchers have demonstrated impressive strides in this domain. The various literature reviewed can be extended to more practical and advanced configurations.

Table 4 indicates tremendous progress in terms of insightful power allocation algorithms with robust computational efficiency and a much faster run time. More so, the total EE is trending upwards in cases with low-complexity optimization algorithms, as opposed to cases without power control schemes.

From a practical viewpoint, the investigative studies delineated in Table 5 illustrate that switching and sleep mode techniques are innovative energy-based solutions with numerous potential applications. Effective AP switching and properly designed sleep mode techniques are shown to substantially enhance the achievable EE of wireless networks. As seen in Table 5, using sophisticated AP switch on/off strategies is not without contention. Nonetheless, the state-of-the-art provides a clear roadmap towards realizing a future with clean energy.

Alternate energy maximization schemes are evolving to consolidate the existing green innovative techniques for optimal performance. Key findings shown in Table 6 indicate that an adequate supply of green networking solutions geared toward addressing the attendant rise in energy consumption have been proposed. Most notable amongst them is the energy-efficient hardware component design, FD operation, SWIPT, AP selection scheme, and antenna distribution configuration, which is shown to substantially minimize energy consumption in mobile networks. Although the transition will be harder to achieve and requires further elucidation/verification, the approaches under consideration are promising technological enablers in achieving the desired goals of energy sustainability.

4.6. Sustainable 6G Wireless Systems

One of the design goals of the commercialized 5G mobile system standard is to support massive connectivity, guarantee low latency, deliver a completely immersive experience, and robust security, and exhibit even more heterogeneity [3,153–155]. However, with the exponential growth of data-centric and automated systems, novel synthesis of future services such as multi-sensory data fusion and massive man-machine interfaces, and the escalating demands for tetherless connectivity in a fully mobile-networked society, 5G networks will be insufficient to fulfill the wireless networks' demand of the future [14]. 6G wireless standards are currently being developed and are envisioned to overcome the laggings of 5G networks. 6G wireless systems will support innovative applications and address new challenges in wireless connectivity. Like its predecessors, 6G technology will provide substantially higher capacity, ultra-low latency and ubiquitous instant communications, and very high-data-rate connectivity per device [10,156]. The 6G system is expected to exploit higher frequencies than 5G networks, to facilitate the integration of maritime, aerial, and terrestrial communications into a sophisticated network with improved access to cutting-edge technologies such as holographic beamforming [157–160], fog/edge computing [161], tactile Internet [162], quantum communications [163], intelligent reflecting surface (IRS) [164,165], backscatter communication [166,167], artificial intelligence (AI)/machine learning (ML) [168,169], and 3-dimensional (3D) networking [170,171]. Besides a laudable increase in delivering much more data at faster rates, tackling sustainable wireless communication development issues will pose serious concerns in the 6G era. The issue of sustainability has become imperative, owing to the exponential increase in greenhouse emissions, deterioration of the environment, and climate change resulting from massive energy consumption from dense wireless devices [171,172]. Thus, to achieve commercial success in 6G, stringent green requirements and sustainable development goals should form the core requirements.

5. Power Control

The transmit power constitutes one of the primary radio resources for a wireless network and should be managed appropriately [22]. Power control encompasses the procedure of intelligently controlling the power of a transmitter to improve the Quality of Service (QoS) of all the users. During the UL transmission phase, the K users are required to select suitable transmit powers $0 \leq p_k \leq p_{max}$, $k = 1, \ldots, K$, while the M APs are required to forward their transmit powers $0 \leq \rho_m \leq \rho_{max}$, $m = 1, \ldots, M$ during DL transmission phase [2]. Power control is of prime importance in CF-mMIMO to optimize the power of the desired received signal, reduce pilot contamination, manage the generated interference, and offer considerable improvement in the QoS to the UEs [33,52].

In addition, power control can help to limit the total power consumption in a CF-mMIMO network [56]. Thus, selecting appropriate power control algorithms is critical to maximizing the overall efficiency of the wireless network. It is worth noting that power control algorithms can be dynamically deployed to solve specific system-wide utility functions [173]. Some of the most common utility functions—max EE, max-min fairness, and max sum SE—are discussed extensively in the next section. Tables 7–11 present a concise summary of recent advances in power control algorithms (geometric programming (GP), successive convex approximation (SCA), fractional power control, Second-Order Cone

Program (SOCP), and ML-based power optimization schemes), respectively. Essentially, these schemes are dimensioned to maximize the common utility optimization problems.

5.1. Max Energy Efficiency

One of the major concerns for designing a wireless network is optimizing energy consumption while satisfying performance and reliability objectives [174]. Specifically, to pave the way for the practical implementation of CF-mMIMO alongside other emerging technologies, it is vital to prioritize total energy maximization, i.e., how much energy can be saved during the communication process [3]. A possible approach to minimize energy consumption is to deploy insightful power optimization algorithms [175]. Choi et al. [59] characterized the EE maximization problem in a CF-mMIMO network using ZF reception. The problem was solved effectively by exploiting three different Transmit Power Control (TPC) algorithms with a sub-optimal trade-off in SE.

Bashar et al. [176] considered the EE maximization problem under multiple constraints. Since the problem is non-convex, an alternate approach that decomposed the original problem into two sub-problems, receiver filter coefficient design and power allocation, was exploited. Results indicate that the receiver filter coefficient design was formulated as a generalized eigenvalue problem. In contrast, a heuristic sub-optimal model and a Successive Convex Approximation (SCA) scheme were deployed to solve the power allocation problem. Nguyen et al. [30] proposed a novel SCA scheme with a ZF precoding design to achieve energy savings in CF-mMIMO under the per-UE and per-AP power constraints. The EE maximization problem was addressed after exploiting a sequence of SOCP. It is worth noting that novel algorithms and insights are rapidly emerging for maximizing the EE utility function [177].

5.2. Max-Min Fairness

CF-mMIMO is essentially a practical embodiment of mMIMO and network MIMO, where joint cooperation between low-complexity APs deployed in a distributed manner help to minimize the effects of intercell interference and offers improved QoS over the wide serving area [178]. Max-min fairness is deployed in these systems to optimize the SE performance of all users in the network, particularly those with the worst channel condition, thus ensuring uniform service for mobile subscribers [64]. It is interesting to note that max-min fairness is equivalent to finding the maximum possible value of the Signal-to-interference-plus noise ratio (SINR) among all the UEs [66]. Max-min fairness problems can either be convex [179] or non-convex [180]. An optimal solution can be obtained in the former using insightful algorithms such as GP, convex optimization, bisection search, and SOCP [181].

An alternate optimization can be exploited in the latter to find a local optimum [182]. A weighted power control algorithm to solve the problem of max-min fairness in UL CF-mMIMO with ZF receiver was proposed in [183]. The weighted algorithm offered considerable gains in the achievable UL per-user rate and improved QoS. Zhou et al. [179] characterized the performance of an optimum DL beamforming technique for CF-mMIMO. A max-min optimization problem is introduced to enhance the minimum SINR among all users.

Moreover, a low-complexity approach to address the max-min fairness problem in UL CF-mMIMO was proposed in [184]. The original problem is decomposed into two sub-problems and solved using a generalized eigenvalue problem and an accelerated projected gradient approach, combined with a smoothing technique. The meta-heuristics approach was exploited in [185] to solve the max-min fairness optimization problem under linear maximum ratio combining at APs and per-UE power constraints. Although ML-based models can be adapted to improve computational efficiency, their solutions are suboptimal compared to classical optimization techniques [186]. A feedforward neural network was proposed in [187] to solve the problem of max-min fairness in CF wireless networks.

5.3. Max-Sum Spectral Efficiency

With the attendant rise in mobile subscriptions and the demand for extremely high data rates in wireless networks, it is of paramount importance to maximize the overall SE performance of the network [188]. While the SE achieved by each user can be individually optimized, the overall system performance could be impacted by a dearth of UEs in the worst conditions [178]. Thus, the max sum SE problem has appeared as a preferred candidate over the max-min SE fairness problem to reach a substantially larger SE. The problem mentioned above is usually non-convex. Thus, it is difficult to arrive at the optimal solution [1]. However, insightful algorithms have been developed to achieve a local optimum. The sum SE optimization problem for CF-mMIMO was studied in [189]. Novel fractional programming and weighted minimum mean square error algorithms were employed to find the global optimum solution with reduced complexity.

In a related study, Nguyen et al. [190] considered the sum SE minimization problem. Since the problem is nondeterministic polynomial time (NP)-hard, an insightful successive approach was adopted to solve the problem. The SCA scheme was also exploited in [191] to solve the sum SE minimization problem. The algorithm was reformulated as a SOCP to obtain the local optimum solution. ML-based models may also be applied to provide performance enhancement [192]. A deep neural network (DNN) optimization scheme was analyzed in [35] to find better solutions to the sum SE problem. Last, Andrea et al. [40] proposed an artificial neural network (ANN) to address the sum SE problem in a CF-mMIMO network.

The respective Tables 7–11 on power control techniques covering the GP, SCA, fractional power control, SOCP, and ML-based schemes suggest that insightful power allocation algorithms and low-complexity frameworks are needed to facilitate realistic deployment of next-generation wireless networks. Obviously, with ever-evolving wireless network standards, it is critical to optimize the power of the desired received signal, manage the prevailing interference, minimize the effect of pilot contamination, and optimize the overall SE and energy consumption, while satisfying performance and reliability objectives. The power control techniques under consideration have emerged as new participants to match these requirements. Compared to distributed power allocation techniques and other benchmark schemes, the ML-based approach is shown to provide a robust improvement in system performance with optimal complexity and processing time.

Table 7. Recent advances in GP power control technique.

Ref.	Focus and Coverage	Key Findings	Remarks	Year
[176]	The work exploited the unique interplay between a heuristic sub-optimal scheme and an SCA approach to reformulate a power allocation problem. The problem is designed for EE maximization of UL CF-mMIMO into a standard GP problem.	The work compared to the equal power allocation scheme; the EE is considerably maximized with the proposed algorithms.	Unfortunately, a modest part of the max-min SE is sacrificed.	2019
[182]	Bashar et al. proposed to solve the max-min optimization problem for user fairness maximization by exploiting the choice of receiver coefficient and power allocation. The original problem is decoupled into two sub-problems, in which GP and the generalized eigenvalue problem are iteratively solved.	Results manifest that a three-fold increase in system rate is obtainable with the proposed technique.	The DL rate of the users was not considered.	2018

Table 7. *Cont.*

Ref.	Focus and Coverage	Key Findings	Remarks	Year
[193]	The work examined a QoS problem to enable real-time users to meet the QoS constraints in CF-mMIMO. A standard GP is adopted to solve the user power allocation problem, which decomposes the original problem.	The proposed scheme provides a substantial improvement in 90% likely throughput compared to a simple benchmark scheme.	More advanced strategies with superior convergence are required.	2018
[194]	The work provided a comprehensive rate analysis for UL and DL CF-mMIMO networks over spatially correlated Rayleigh channels. A GP approach is introduced to characterize the objective function for UL rate analysis.	Simulation results validate the superiority of the proposed max-min fairness algorithms, which can be decoupled as GP and SOCP.	The impact of channel correlation is detrimental to the system's performance.	2020
[195]	The work investigated the max-min problem of a CF-mMIMO system concerning the effect of quantization. While an eigenvalue problem is adopted to design the receiver filter, the GP approach is employed to solve the power allocation problem.	Numerical results confirm the effectiveness of the proposed algorithm in improving system performance compared to existing algorithms.	The algorithm can be further optimized, using even more sophisticated approaches.	2019

Table 8. Recent advances in the SCA power control technique.

Ref.	Focus and Coverage	Key Findings	Remarks	Year
[190]	The work proposed jointly optimizing the power control and load balancing in UL CF-mMIMO networks under different objectives. These include power minimization, min QoS, and sum SE maximization. In order to solve the power control optimization, an SCA scheme is applied to convert the sum SE maximization problem into the form of GP.	The proposed scheme significantly outperforms full-set joint transmission and maximum SNR association, particularly in high QoS scenarios.	Compared to the BS-users association method, the proposed linear receiver framework is becoming more influential.	2018
[191]	The work characterized the performance of CF-mMIMO with non-ideal hardware transceivers using two insightful power allocation algorithms, namely mixed QoS and max-total-SE algorithms.	Both algorithms are shown to maximize the total SE and satisfactorily satisfy their target users' QoS constraints.	The SE is significantly degraded when the target UE coincides with the receiver.	2020
[196]	The work evaluated the performance of a DL CF-mMIMO system to optimize the target users' signal-to-interference-plus-noise ratio (SINR). An SCA optimization algorithm alongside a CB precoder is proposed.	The results obtained validate the effectiveness of the proposed algorithm in minimizing the sum of DL transmission power and meeting each users' SINR constraints.	More advanced strategies with superior convergence are required.	2018

Table 8. *Cont.*

Ref.	Focus and Coverage	Key Findings	Remarks	Year
[197]	The work performed a thorough analysis of the effect of the spatial distribution of APs on the performance of CF-mMIMO. Further, several DL power control policies are developed.	However, the SCA policy is shown to outperform other schemes with high complexity.	In scenarios where a subset of all APs serves a given user and where coordination is absent, the SE begins to degrade.	2019
[198]	The work proposed to optimize the performance of federated learning frameworks using CF-mMIMO systems. An online SCA algorithm is deployed to solve the formulated optimization problem.	Results indicate that CF-mMIMO provides a significant gain in the training time of federated learning frameworks compared with other benchmark schemes.	CF-mMIMO is a promising technological enabler for improved federated learning in a wireless environment.	2020

Table 9. Recent advances in fractional power control technique.

Ref.	Focus and Coverage	Key Findings	Remarks	Year
[199]	The work proposed an insightful UL fractional power control and DL power allocation scheme based on large-scale quantities for performance maximization in CF-mMIMO.	The scheme is shown to optimize neither specific indices such as a weighted sum nor guarantee favoring individual users.	Learning-based frameworks are promising solutions to achieving superior trade-offs between performance and scalability.	2020
[17]	In addition to an initial access algorithm, two pilot assignment techniques, and a partial large-scale fading decoding technique, a fractional power control policy is introduced to solve the challenge of scalable massive access implementation in CF-mMIMO.	Simulation results validate the effectiveness of the proposed scheme compared to the state-of-the-art.	The proposed framework can be applied to cases with a larger class of fading distributions and multi-antenna UEs.	2021
[36]	The work examined the effect of channel ageing and pilot contamination on the performance of CF-mMIMO networks. In addition, the study adopted a fractional power control technique to minimize inter-user interference.	Compared to the full power transmission technique, the performance of fractional power control in scenarios with channel ageing is unsatisfactory.	In scenarios with severe channel ageing, advanced strategies more robust to channel ageing are required.	2020
[51]	The work characterized the performance of a fully distributed fractional power control policy for the UL of CF networks.	The proposed power control obtains fairly satisfactory performance compared to the max-min solution.	The effect of noise on the system was not accounted for accordingly. The scheme is also limited to UL CF wireless networks.	2019
[200]	The study performed a thorough investigation to determine the impact of fractional power control on the DL performance of mMIMO systems.	The results indicate a robust improvement in the cell border throughput, coupled with moderate performance optimization in cases with extreme pilot contamination.	To facilitate realistic deployments, introducing additional pilot contamination mitigation mechanisms is paramount.	2019

Table 10. Recent advances in SOCP power control technique.

Ref.	Focus and Coverage	Key Findings	Remarks	Year
[22]	The work evaluated the performance of energy-efficient load balancing as well as power allocation schemes for large-scale networks. Due to the non-convexity of the optimization problem, a mixed SOCP is exploited to provide a globally optimal solution.	Power consumption is significantly reduced. Moreover, the proposed algorithms are sufficient to handle AP activation and power allocation in large CF networks.	The developed algorithms are sub-optimal and consume even higher energy compared to the global optimum.	2020
[32]	The work proposed a joint optimization of power allocation and load balancing in CF-mMIMO. The optimization framework, which is non-convex, is solved using a mixed SOCP.	A significant energy saving is achieved compared to reducing the transmit power and keeping all APs turned on.	The obtained solution is sub-optimal in a real-time environment.	2020
[73]	The work performed a detailed analysis of two power minimization algorithms based on the QoS constraints of each user. With the precoders employing (CB and ZF), the power minimization problems are reformulated as a SOCP.	In the regime of low QoS SE, CB is shown to achieve significant power savings over the ZF precoder.	The benefits of the CB precoder vanish as the QoS SE increases.	2019
[201]	Characterized the total EE of a TDD CF-mMIMO system under backhaul and hardware power consumption to maximize EE. A power optimization algorithm is formulated, which is approximately solved by a SOCP.	The proposed algorithm significantly maximizes the EE compared to the case without power allocation.	As the number of APs grows large, the total EE is substantially degraded due to backhaul power consumption.	2017
[202]	The work proposed to maximize the scalability and EE of IoT systems using CF-mMIMO. A neural network is utilized in place of a SOCP problem to allocate power.	It suffices that considerable gains in SE and EE are achieved with the proposed algorithm as opposed to the full transmission technique.	The proposed algorithm, though sub-optimal, allows for scalability, which is crucial for IoT systems.	2021

Table 11. Recent advances in machine learning-based power control techniques.

Ref.	Focus and Coverage	Key Findings	Remarks	Year
[40]	The work exploited a deep learning approach to solve the sum-rate and minimum rate maximization problem in the UL of a CF-mMIMO system.	While a near-optimal performance is obtained, the effect of pilot contamination on the learning capabilities of the ANN is shown to be quite modest.	In the presence of shadowing, the learning capabilities of the ANN are significantly impacted.	2019
[187]	The work proposed to exploit the potential of feedforward neural networks with unsupervised learning to scale up power control implementation in UL CF-mMIMO systems.	The unsupervised neural network ensures superior performance while vastly satisfying distinct signals to interference objectives.	However, when large-scale channel gains are employed as inputs, the approximations become tighter, with a longer learning stage.	2019
[192]	The work proposed a low-complexity large-scale fading-deep learning-based power control scheme to perform sum-rate maximization in limited-fronthaul CF-mMIMO.	Results reveal a considerable boost in throughput, owing to the mapping derived from deep convolutional neural networks.	The practicality of the proposed scheme is validated through extensive simulation results and is a rich area for future research.	2020

Table 11. *Cont.*

Ref.	Focus and Coverage	Key Findings	Remarks	Year
[203]	The work introduced a deep learning framework to perform power allocation in the DL CF-mMIMO system using the max-min fairness approach.	A properly trained feed-forward DNN is shown to outperform the conventional distributed power allocation technique in terms of complexity and processing time.	More work is needed to bridge the gap between the decentralized and centralized approaches.	2019
[204]	The work considered an innovative DNN to overcome the nondeterministic polynomial-hard problem in CF-mMIMO with low time complexity.	It suffices that the DNN approach exhibits a performance close to the widely deployed heuristic concerning the bisection algorithm.	The study can be further extended to the mmWave domain with more advanced channel models.	2020

6. Open Research Issues

The open research issues require further research to pave the way for seamless wireless connectivity, greener wireless networks, and sustainable evolution of wireless communications. The lines of research that need to be addressed in future work are summarized as follows:

(a) Green Artificial Intelligence (GAI): One possible approach toward sustainable wireless communication is the integration of Artificial Intelligence (AI) to drive the design and optimization of learning-based models for maximized SE and EE indices [108]. Although groundbreaking advancements led by insightful ML solutions have been realized [205], the research in this line of interest is still in its infancy and requires further effort. Exploring yet undiscovered ML architectures that prioritize computational efficiency and energy consumption towards improved operating conditions may be interesting. More precisely, ML paradigms with faster convergence, high computational processing capabilities, and optimized energy consumption during the training and exploitation phases are needed.

(b) mmWave frequency spectrum: The distinctive interplay of CF-mMIMO alongside the rapidly emerging mmWave frequency bands is expected to reap mutual benefits from higher macro-diversity due to the coherent distributed transmission across APs [206]. However, mmWave propagation is characterized mainly by severe penetration, path, and diffraction losses, which continue to roadblock the successful coexistence of these enabling technologies [207]. Therefore, it is essential to address critical challenges in mmWave communications while analyzing the impact of the state-of-the-art on the achievable EE of CF-mMIMO systems.

(c) Sophisticated AP switch on/off strategies: Several AP switch on/off strategies for CF-mMIMO networks designed to switch BSs into sleep mode adaptively have been proposed in the literature [27]. Substantial energy allowances to the network operators can be achieved at the expense of the system capacity [79]. Further investigations on more reactive AP switch on/off techniques, the authenticity of the models, and their implementation issues constitute an attractive future research direction.

(d) Intricate power control strategies: The widespread popularity of complex scenarios in CF-mMIMO, such as user assignment and joint AP selection, calls for the design of innovative power control strategies to get better results in such complex configurations [208]. Besides, sophisticated power control techniques are urgently needed to manage scenarios where conventional approaches might be sub-optimal or time-consuming. Also, the evaluation of advanced pilot assignment techniques to contain pilot contamination may be considered in future studies.

(e) Joint AP clustering: In a typical CF-mMIMO configuration, a dearth of UE is jointly served by a large chunk of arbitrarily allocated APs, all linked to a CPU via a fronthaul network. The QoS will be impacted when the limited capacity fronthaul link becomes saturated [209]. Aiming at the practical implementation of CF-mMIMO alongside other emerging technologies such as SWIPT, joint AP clustering has appeared as an innovative paradigm to minimize the pressure on the fronthaul networks [141]. Nonetheless, performance degradation, amongst other challenges, must be tackled in this domain to satisfy future massive connectivity in a realistic environment.

Lessons Learned

In this section, a concise elucidation of key findings and lessons learned from this review is presented. These lessons, which encompass a broad range of investigative analysis and evaluation, would provide a reliable framework to open up new frontiers in the wireless communication domain.

Lesson One: The demand for increased mobility and coverage, microsecond latency communications, and ultra-high data rates have skyrocketed recently and continue to grow at a breakneck pace. Wireless networks are currently being upgraded beyond 5G systems to match the fast-paced development of revolutionary applications, wireless services demands, and smart social needs. While the current 5G architecture is designed to provide ubiquitous wireless connectivity and gives lower latency substantially, the technology is faced with rising technical requirements such as improved QoS, higher system capacity, and data speed. 6G wireless standards, with significantly more modest features than 5G, are envisioned to meet these requirements and support innovative applications through the deployment of the unexplored spectrum, UD CF-mMIMO networks, energy-efficient transmission techniques, and key disruptive technologies in conjunction with advanced AI techniques.

Lesson Two: Averting the energy crunch resulting from the deployment of novel paradigms of wireless communication remains a prime challenge. With the drive towards tetherless connectivity and capacity enhancement, network operators and standardization bodies are exploring cutting-edge technologies to address the requirements of rate-demanding and innovative services without tangible recourse to the environmental and ecological implications of these technologies. At present, the design and development of sustainable/green communication technologies are even more compelling, driven by global concerns for implicit consumption of energy, ecological imbalance, the strain on natural resources, and health, safety, and environmental challenges. Thus, EE becomes a key element in the standardization of beyond 5G and 6G wireless communication systems.

Lesson Three: As alluded to earlier, next-generation wireless networks are gaining widespread popularity and significant traction in the wireless industry and academia. Consequently, there is an urgent need to develop insightful energy-efficient frameworks and techniques to match up with such evolvement. Following the development and novel approaches to sustainable wireless network design, investigative analysis of the performance of several EE maximization techniques, such as energy harvesting and energy exchange techniques, energy-efficient resource allocation, and switching and sleep mode techniques, is presented. While a significant amount of environmental benefits/energy savings can be obtained with the proposed technologies, it is noteworthy that sustainable 6G communication is a relatively subjective concept. More precisely, the state-of-the-art is largely connected with the transmission mechanisms, component conditioning, specific configuration, and physical topology of the communication system.

Lesson Four: Intuitively, energy-efficient resource allocation, switching and sleep mode techniques, and energy harvesting techniques are promising landscapes for achieving sustainable communication systems. By intelligently assigning the limited resources among users, maximizing the fixed energy consumption in lightly loaded APs, and incorporating energy harvesting technologies in emerging wireless communication architectures, energy consumption can be significantly maximized. Additionally, energy-efficient hardware component design, FD operation, antenna distribution configuration, SWIPT, AP selection strategies, and VLC are also increasingly evolving green communication techniques with large potential for energy saving. However, to maximize the prospects of the EE maximization techniques, an excess count of unresolved issues ranging from techno-economic feasibility to unrealistic assumptions need to be carefully tackled.

Lesson Five: Even though various enabling technologies to achieve the desired goals of sustainable 6G communication systems have been proposed, the issue of cost-efficiency and economic justification of selected EE maximization techniques have been ignored. Specific hardware design solutions covering major architectural modifications can be financially burdensome. Moreover, deploying energy-efficient techniques with novel infrastructural requirements may consume higher energy than the existing system resulting in a cost-efficiency issue. For instance, large initial capital investment is required to reliably utilize renewable energy resources. Thus, technically feasible models, as well as minimized-cost solutions, are critical to achieving sustainable wireless communication systems.

Lesson Six: It is observed that next-generation wireless technology, in conjunction with UD CF-mMIMO, can provide substantial improvement in both the SE and throughput of wireless communication systems. Unfortunately, adopting a distributed antenna array in UD CF-mMIMO systems may dramatically increase the power consumption and the overall energy emissions of wireless communication systems. Indeed, the conflict of simultaneously optimizing the SE and EE of UD CF-mMIMO systems remains one of the prime concerns for network operators. Since both of these two-design metrics are critical for future wireless communication networks, obtaining a suitable balance between EE and SE is imperative.

Lesson Seven: Power control is an indispensable candidate technique offering a tremendous improvement in the QoS of all users. Power control is also of great necessity to minimize the effects of pilot contamination and manage the associated interference. Interestingly, insightful power allocation algorithms such as GP, SCA, SOCP, fractional power control, and ML-based power allocation schemes can be effectively deployed to resolve common utility optimization problems (max EE, max-min fairness, and max-sum SE) and achieve optimal performance.

7. Conclusions

This work has provided an extensive overview of the concepts and techniques proposed for energy-efficient power control in ultra-dense cell-free massive MIMO (UD CF-mMIMO) systems. An elaborate introduction to the technical foundations and mathematical system model of CF-mMIMO is presented. Next, a comprehensive evaluation of the power consumption model, energy efficiency (EE), and power consumption parts are provided. Further, standard EE-maximization techniques for the state-of-the-art, including energy-efficient resource allocation schemes, energy harvesting and exchange techniques, switching and sleep mode techniques, and virtualization, are discussed comprehensively. Additionally, a review of recent advances in energy-efficient power control in UD CF-mMIMO systems was highlighted. Different power allocation schemes, such as geometric programming (GP), successive convex approximation (SCA), Second-Order Cone Program (SOCP), fractional power control, and ML-based power control, target max EE, max sum SE, and max-min fairness in wireless networks are discussed elaborately. Finally, critical insights on the open issues and critical challenges in guaranteeing sustainable wireless communication are delineated. Key findings from the survey thread evidence that an ever-increasing number of users and high-rate demands are accompanied by a substantial increase in energy consumption. While significant gains in EE have been realized through efficient utilization of energy maximization techniques and dense deployment of antenna arrays, the concept of energy sustainability and green design expectations remains. Future work would examine the design and characterization of optimal energy-efficient power control schemes in UD CF-mMIMO networks for application in the envisioned 6G wireless communication systems.

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Abbreviations

3D	3-Dimensional
5G	Fifth-Generation
AI	Artificial Intelligence
ANN	Artificial Neural Network
AP	Access Point
BS	Base Station
CB	Conjugate Beamforming
CCI	Co-channel Interference
CF-mMIMO	Cell-Free Massive MIMO
CPU	Central Processing Unit
DL	Downlink
DNN	Deep Neural Network
DSP	Digital Signal Processing
D2D	Device-to-Device
EE	Energy Efficiency
FD	Full-Duplex
FDD	Frequency Division Duplexing
GP	Geometric Programming
HI	Hardware Impairment
ICT	Information and Communication Technology
i.i.d	Independent Identically Distributed
IoT	Internet of Things
IRS	Intelligent Reflecting Surface
ML	Machine Learning
mm	Millimeter
M2M	Machine-to-Machine
NFV	Network Function Virtualization
NOMA	Non-Orthogonal Multiple Access
NP	Nondeterministic Polynomial Time
QoS	Quality-of-Service
RF	Radio-frequency
RIS	Reconfigurable Intelligent Surfaces
SC	Small-Cell
SCA	Successive Convex Approximation
SDN	Software Defined Networking
SE	Spectral Efficiency
SI	Self-Interference
SNR	Signal-to-noise ratio
SINR	Signal-to-interference-plus noise ratio
SOCP	Second-Order Cone Program
SWIPT	Simultaneous Wireless Information and Power Transfer
TDD	Time Division Duplex
TPC	Transmit Power Control

UAV	Unmanned Aerial Vehicle
UC	User-Centric
UD	Ultra-Dense
UE	User Equipment
UL	Uplink
V2X	Vehicle-to-Everything
VLC	Visible Light Communication
ZF	Zero-Forcing

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