

REVIEWS

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Application of cell-free massive MIMO in 5G and beyond 5G wireless networks: a survey



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Abstract

In recent times, the rapid growth in mobile subscriptions and the associated demand for high data rates fuels the need for a robust wireless network design to meet the required capacity and coverage. Deploying massive numbers of cellular base stations (BSs) over a geographic area to fulfill high-capacity demands and broad network coverage is quite challenging due to inter-cell interference and significant rate variations. Cell-free massive MIMO (CF-mMIMO), a key enabler for 5G and 6G wireless networks, has been identified as an innovative technology to address this problem. In CF-mMIMO, many irregularly scattered single access points (APs) are linked to a central processing unit (CPU) via a backhaul network that coherently serves a limited number of mobile stations (MSs) to achieve high energy efficiency (EE) and spectral gains. This paper presents key areas of applications of CF-mMIMO in the ubiquitous 5G, and the envisioned 6G wireless networks. First, a foundational background on massive MIMO solutions-cellular massive MIMO, network MIMO, and CF-mMIMO is presented, focusing on the application areas and associated challenges. Additionally, CF-mMIMO architectures, design considerations, and system modeling are discussed extensively. Furthermore, the key areas of application of CF-mMIMO such as simultaneous wireless information and power transfer (SWIPT), channel hardening, hardware efficiency, power control, non-orthogonal multiple access (NOMA), spectral efficiency (SE), and EE are discussed exhaustively. Finally, the research directions, open issues, and lessons learned to stimulate cutting-edge research in this emerging domain of wireless communications are highlighted.

Keywords: Cell-free massive MIMO, 5G and B5G wireless networks, Channel estimation, Hardware impairments, NOMA, SWIPT, Energy efficiency, Outage probability

Introduction

The exponential growth of wireless network service users worldwide orchestrates the need to deploy novel enabling technologies to satisfy billions of data-hungry applications [1]. In recent times, the emergence of the Internet of Things (IoT) has ushered in new-age internet-enabled smartphones and machine-to-machine communications (M2M) for the growing mobile users [2]. However, the current network infrastructure is already overstretched, and there is a need for novel technologies to improve the



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existing wireless network architecture [3]. From managing security and privacy challenges, network spectrum issues, traffic spikes, complex network configuration, prohibitive operating costs, network failure, to hardware compatibility issues and more, the ubiquitous fifth-generation (5G) wireless network architecture needs to be enhanced to accommodate these growing concerns optimally [4, 5]. Recently, key enabling technologies for the envisioned beyond 5G and 6G wireless systems have been proposed [6–9]. Interestingly, these enablers include cell-free massive MIMO (CF-mMIMO) technology [10–12], mmWave communication [13–15], terahertz communication [16–18], quantum communication [19, 20], directional beamforming [21], reconfigurable intelligent surfaces (RIS) [22–24], and more.

The concept of CF-mMIMO introduced in [25] presents a promising alternative to guarantee high quality of service (QoS) to all UEs. CF-mMIMO leverages the idea of small-cells (SC), massive MIMO, and user-based joint transmission coordinated multi-point (JT-CoMP) [26] to deal with inter-cell interference [27]. Additionally, CF-mMIMO provides massive macro-diversity to mitigate path loss [28] via minimizing the adverse effects of spatially correlated fading and shadowing [29]. In this case, several ubiquitous access points (APs) with single or multiple antennas jointly serve a smaller number of distributed UEs over the coverage area in time-division duplex (TDD) mode [30]. CF-mMIMO has been described as an embodiment of network MIMO and is regarded as an alternative network MIMO [31]. Compared to the fully distributed SC system and massive cellular MIMO, CF-mMIMO has improved performance under several practical conditions, including but not limited to favorable propagation and channel hardening with spatially well-separated UEs and APs. This results in increased macro-diversity gain from the low distance between UEs and APs [3, 32, 33].

Currently, there is a growing interest in the implementation of sustainable and greener CF-mMIMO systems [34] to boost the energy efficiency (EE) [35, 36] of wireless systems, offset the power consumption cost [37], and minimize the environmental impacts of wireless systems [38]. Several optimization techniques, EE-saving algorithms, and robust power control models [39, 40], such as energy cooperation [41], reconfigurable intelligent surface (RIS) [23, 42, 43], and more, have been explored. Combining CF-mMIMO and simultaneous wireless information and power transfer (SWIPT) technique is considered to drive energy-limited user devices and improve the EE of next-generation wireless networks [44–46]. Given that several APs and several users are involved in a CF system [47], the deployment cost and energy consumption may rise, and more energy resources [48, 49] would be required. In order to realize CF-mMIMO in practice, carrier frequency and sampling rate offsets, In-phase/quadrature-phase (I/Q) imbalance, phase noise, and analog-to-digital converter distortions need to be examined [50, 51]. Toward this end, this paper provides an extensive survey on the areas of application of CF-mMIMO in next-generation wireless communication systems. A comprehensive layout of the paper is presented in Fig. 1. Furthermore, different massive MIMO-based solutions, massive cellular MIMO, and network MIMO are examined critically. The design and system configurations, system modeling, application scenarios, potentials, and associated challenges of CF-mMIMO are discussed extensively. Additionally, open research issues, lessons learned, and future research directions are outlined.

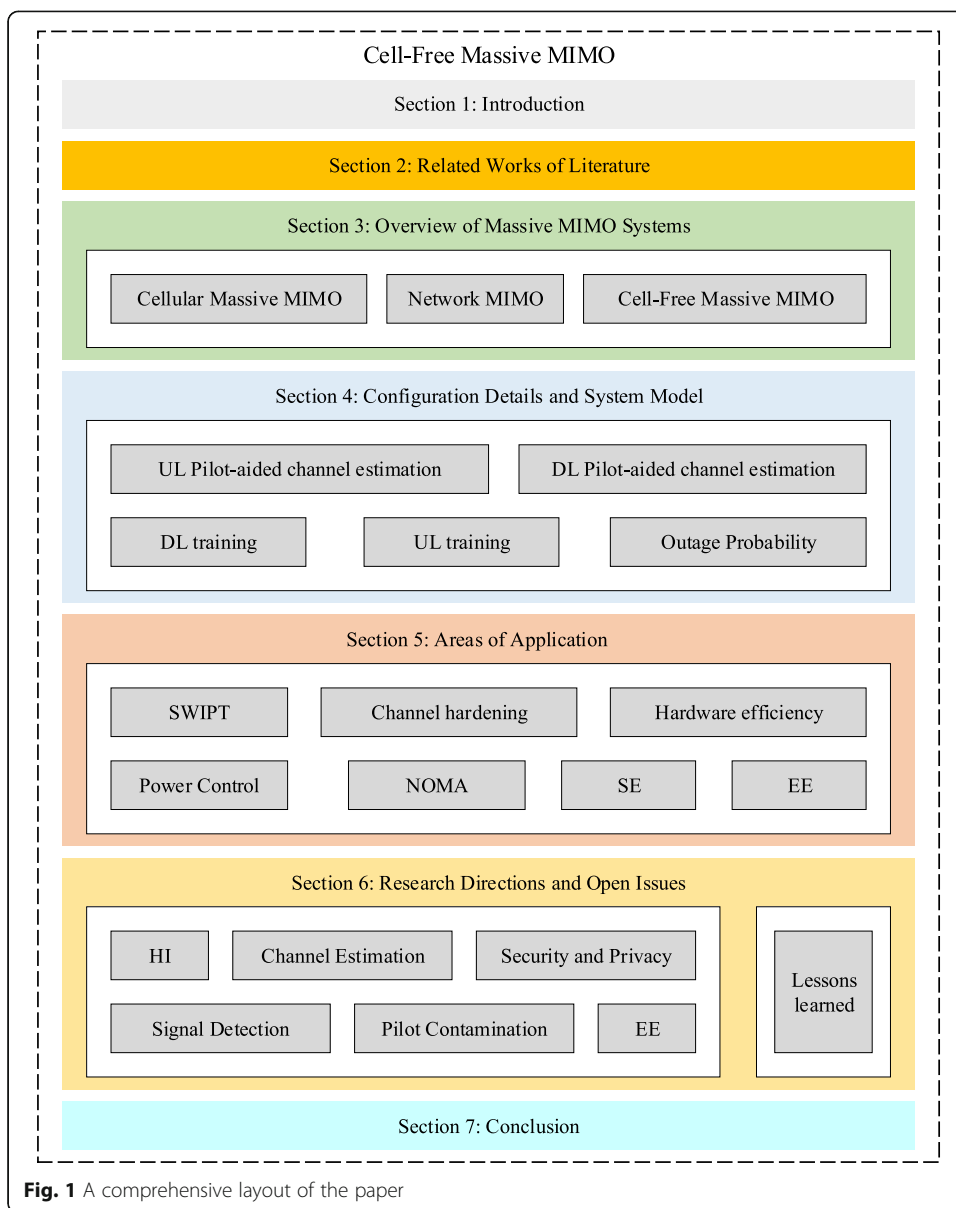


Fig. 1 A comprehensive layout of the paper

This survey is focused on applying CF-mMIMO in 5G and beyond 5G (B5G) wireless networks. The key highlights of the survey are outlined as follows.

1. We present a background on the evolution of CF-mMIMO in emerging wireless communication systems.
2. We present an overview of cellular massive MIMO, network massive MIMO, and CF massive MIMO, highlighting their areas of application, strengths, limitations, and performance comparison of these architectures with reference to key design metrics, interference management, channel hardening, and SE, among others.
3. We examine the configuration details and system modeling of CF-mMIMO, emphasizing the uplink/downlink (UL/DL) pilot-aided channel estimation, UL/DL training, channel hardening, and outage probability.

4. We highlight key areas of application of CF-mMIMO such as in SWIPT, power control, NOMA, SE, and EE.
5. We present key research findings and current trends in CF-mMIMO, highlighting their focus, coverage, prospects, and limitations.
6. We highlight open research issues, future research directions, and key take-away lessons on CF-mMIMO deployment in 5G and B5G wireless networks.

The rest of this paper is organized as follows. The literature review is presented in the “[Related work](#)” section. A comprehensive description of the traditional MIMO architecture, massive cellular MIMO, network MIMO, and CF-mMIMO is presented in the “[Overview of massive MIMO systems](#)” section. The “[System model of cell-free massive MIMO](#)” section offers a detailed account of the CF-mMIMO system modeling and configuration. The application of CF massive MIMO in channel hardening, NOMA, EE, and more are discussed in the “[Areas of application of cell-free massive MIMO](#)” section. Open research issues and lessons learned are highlighted in “[Open research issues and lessons learned](#)” section. Finally, the “[Conclusions](#)” section gives a concise conclusion to the paper.

Related work

Cell-free massive MIMO has attracted considerable research interest in the past decade, and it is currently regarded as a key 5G and beyond 5G physical layer technology [52–55]. The authors in [56] provide an in-depth exposition into simulation platforms and insightful schemes for emerging 5G interfaces. An extensive overview of several solutions for 5G infrastructures including, but not limited to massive MIMO, millimeter-wave (mmWave), NOMA, and also the latest achievements on simulator capabilities, are clearly outlined. Also, artificial intelligence (AI)-based discontinuous reception (DRX) technique for greening 5G enabled devices have been proposed in [57]. The proposed mechanism significantly outperforms the conventional long-term evolution (LTE)-DRX technique in efficient energy savings. In recent times, the use of deep learning techniques to perform power control in wireless communication networks has been studied in [58–60]. Reference [61] advocate using deep neural networks to perform joint beamforming and interference coordination at mmWave.

Additionally, the authors in [62] consider incorporating channel hardening in CF-mMIMO using stochastic geometry and evaluated the potential constraints to its practical implementation. It suffices that the channel hardening effect is more noticeable in massive cellular MIMO than in CF-mMIMO and depends mainly on the number of antennas per AP and the pathloss exponent of the propagation environment [63]. Fortunately, the authors [64] have shown that significant improvement in channel hardening is achievable with the normalized conjugate beamforming (NCB) precoder compared to the conjugate beamforming (CB) scheme. The works [65–67] characterized the coexistence of CF-mMIMO and SWIPT utilizing the Poisson point process (PPP) model.

Furthermore, an insight into the achievable harvested energy, channel variations due to fading and path loss, and UL/DL rates in closed form are considered [68, 69]. The detrimental effects of pilot contamination on the performance of CF-mMIMO are highlighted in [70, 1]. The authors in [53] proposed allocating pilot power for each user in the network to palliate this defect. Interestingly, interference management and

joint user association aimed at minimizing cell-edge effects are studied [70]. References [11, 71] have reported novel scalable and distributed algorithms used for initial access and cooperation cluster formation in CF-mMIMO. The authors also proposed scalable signal-to-leakage-and-noise ratio precoding to address the scalability issues in CF-mMIMO. Currently, federated learning (FL) frameworks are introduced in [72, 73], and FL optimization techniques have been presented in [74–76]. A detailed account recapitulating the impact of hardware impairments (HI) on the performance of CF-mMIMO is characterized [48]. By employing a hardware scaling law, the impact of HI on APs is shown to vanish asymptotically. The authors in [77] analyzed the UL and DL CF-mMIMO performance under the classical HI model to gain further insights.

Most of the literature provides valuable information on massive MIMO deployment in 5G wireless networks. Though some of these papers present several aspects of CF-mMIMO, there is no detailed study on CF-mMIMO systems that captures entirely cellular massive MIMO, network MIMO, and CF-mMIMO system modeling, architecture, strengths and limitation, and applications in terms of SWIPT, channel hardening, hardware efficiency, power control, NOMA, SE, and EE. To this end, the need for a comprehensive paper covering the aspects mentioned above of CF-mMIMO is vitally important. Therefore, the current paper presents an extensive survey on CF-mMIMO as a candidate enabler for 5G and B5G wireless networks. Specifically, the limitations of some selected literature are outlined, and the contributions of the current paper are highlighted, as presented in Table 1.

Overview of massive MIMO systems

The concept of massive MIMO has received considerable attention due to its deployment to meet the demands of wireless capacity and higher data rates [89]. Massive MIMO offers improved spectral and energy efficiency and adopts optimal signal processing schemes [90]. Moreover, massive MIMO can spatially multiplex many user equipment (UE) by using many phase-coherent transmitting/receiving antennas, thus suppressing inter-cell and intra-cell interference [91, 92]. These unique features have revitalized studies leading to the discoveries of several massive MIMO solutions [93]. Massive MIMO technology, empowered with several antennas at each cell site, offers tremendous improvements in the radiated EE, power efficiency, and SE compared to the traditional MIMO systems [94, 95]. Moreover, by operating in either a centralized or distributed fashion, favorable propagation facilitates the realization of near-optimal linear processing [96]. Motivated by the benefits mentioned above, various massive MIMO-based solutions significantly gained traction in academia and industry [97]. A brief discussion on cellular mMIMO, network MIMO, and CF-mMIMO focusing on their architectures, strengths, and applications are presented in the following subsections.

Cellular massive MIMO

Massive MIMO time-division duplex (mMIMO-TDD) systems have been reported to boost the throughput of wireless networks [83, 86]. Since the multiple antennas used in mMIMO-TDD are much smarter, it presents a practical means to outperform partial multiuser MIMO (MU-MIMO) systems. BS antennas could be substantially larger than

Table 1 Limitations of some related works

Ref.	Focus and coverage	Limitations	Contributions
[78]	The work quantifies the improvement of CF-mMIMO over cellular massive MIMO in EE using max-min power control and CB.	<ul style="list-style-type: none"> Optimization techniques not presented. Channel estimation not clearly outlined. 	<ul style="list-style-type: none"> This paper outlines useful techniques to improve the overall EE of CF-mMIMO. This paper examines the most recent research trends and future directions on EE in CF-mMIMO.
[79]	The authors examine the performance of CF-mMIMO systems with limited fronthaul capacity.	<ul style="list-style-type: none"> A perfect hardware transceiver that is not satisfied in practice is considered. 	<ul style="list-style-type: none"> An extensive analysis of transceiver HI, most recent research trends on the performance of CF-mMIMO systems with limited fronthaul capacity are presented.
[80]	This paper analyzes the UL SE of CF massive MIMO with multiple antennas at the APs and users, zero-forcing (ZF) combining, and data power controls.	<ul style="list-style-type: none"> Challenges with the use of multi-antenna are not clearly outlined. Security and privacy issues of multi-antenna users are not discussed elaborately. 	<ul style="list-style-type: none"> Presents a detailed outline of the application of CF-mMIMO in improving the SE. Security and privacy issues of wireless networks are clearly outlined. Also, UL SE of CF-mMIMO with multiple antennas at the APs and users are broached.
[81]	The authors propose an ANN-based UL power control technique to assess power allocation in a CF-mMIMO network to maximize the sum rate or the min rate.	<ul style="list-style-type: none"> Applications of power control in CF-mMIMO not clearly outlined. Power optimization techniques are limited to just a deep learning approach. 	<ul style="list-style-type: none"> Presents a robust discussion on the application of power control in CF-mMIMO. Power optimization techniques such as alternative optimization, second-order cone program (SOCP), and machine learning (ML)-based approaches are discussed [82].
[83]	The work considers maximizing the total EE of CF massive MIMO using a well-established DL power consumption model. Additionally, AP selection schemes are covered to minimize the power consumption caused by the backhaul links.	<ul style="list-style-type: none"> Channel estimation not clearly outlined. Open research issues and future research directions are not discussed elaborately. 	<ul style="list-style-type: none"> This paper examines the most recent research trends and future directions in CF-mMIMO. A robust discussion on AP selection schemes aimed at minimizing power consumption is presented.
[84]	The authors examine a generalized UL CF-mMIMO in the presence of radio frequency (RF) impairments and ADC imperfections. Also, the study provides novel insights on implementing low-quality transceiver RF chains and low-resolution ADCs.	<ul style="list-style-type: none"> Technical propositions to minimize hardware costs in practical systems are limited. Signal detection is not clearly outlined. 	<ul style="list-style-type: none"> Instructive insights to optimize the system's performance in practical scenarios are clearly discussed. Sophisticated signal detection techniques such as ML, deep learning-based techniques, and sphere decoder are highlighted.
[69]	The work characterizes the coexistence and underlying issues of SWIPT and CF massive MIMO.	<ul style="list-style-type: none"> Open research issues and future research directions in CF-mMIMO are not discussed clearly. 	<ul style="list-style-type: none"> Research activities capturing the most recent research trends and lessons learned related to SWIPT in CF massive MIMO are outlined.
[85]	The work presents the UL performance of CF-mMIMO systems with multiple antennas and least-square (LS) estimators considering the effects of spatially correlated fading channels.	<ul style="list-style-type: none"> The security and privacy threats to multi-antenna users are not considered. Pilot contamination effects were not discussed. 	<ul style="list-style-type: none"> Security and privacy issues of wireless networks are captured. Future research directions and lessons learned are outlined. This paper also provides a holistic review of pilot contamination and the UL performance of CF massive MIMO systems.
[86]	The paper considers using an NCB scheme in CFm-MIMO subject to short-term average power constraints. The work also considers the effects of channel estimation errors and pilot contamination.	<ul style="list-style-type: none"> Although future works are outlined, they are not discussed comprehensively. Power control algorithms are not developed. 	<ul style="list-style-type: none"> Future directions in the areas of channel estimation and pilot contamination are reported. Advanced power optimization techniques such as geometric programming (GP), SOCP, and

Table 1 Limitations of some related works (Continued)

Ref.	Focus and coverage	Limitations	Contributions
[62]	The work investigates the feasibility of observing channel hardening in CF massive MIMO using stochastic geometry.	<ul style="list-style-type: none"> The practical application of the proposed model is totally is not elaborated. 	<p>ML-based approaches are highlighted.</p> <ul style="list-style-type: none"> This paper discusses the application of CF-mMIMO in EE, SE, and SWIPT. Additionally, the research focus and directions related to channel hardening in CF-mMIMO systems are outlined.
[87]	This survey focuses on integrating CF massive MIMO systems with a power-domain NOMA technique.	<ul style="list-style-type: none"> Open research issues are not discussed. Signal detection was not discussed in this paper. 	<ul style="list-style-type: none"> Up-to-date review of past findings, most recent research activities, and lessons learned are outlined. This paper discusses the current research trends on NOMA in CF-mMIMO systems.
[88]	This survey focuses on the EE of limited-backhaul CF massive MIMO. The authors introduced an efficient solution to address the EE maximization problem.	<ul style="list-style-type: none"> The open research issues and future research directions are not clearly outlined. Practical implementation of CF-mMIMO is not covered. 	<ul style="list-style-type: none"> This paper provides a holistic discussion on EE and outlines key findings, current research trends, and future research directions in EE of CF-mMIMO systems.

the number of transmitter terminals. Recently, the attractive features of cellular networks, including exploiting channel reciprocity, especially as more antennas do not necessarily lead to a corresponding increase in the feedback overhead, have been investigated. The traditional cell-size shrinking technique is eliminated via the installation of extra antennas to existing cell sites. Furthermore, UL and DL transmit powers are considerably reduced due to increased antenna aperture and coherent combining. Nonetheless, cellular networks face significant challenges, including estimating the criticality of coherent channels, bandwidth, and interference limitations. Additionally, the substantial cost associated with a large number of transmitting/receive chains and power amplifiers is a major setback. An illustrative description of a typical cellular massive MIMO system is given in Fig. 2. The mobile station (MS) is connected to a central base station (BS) in each cell.

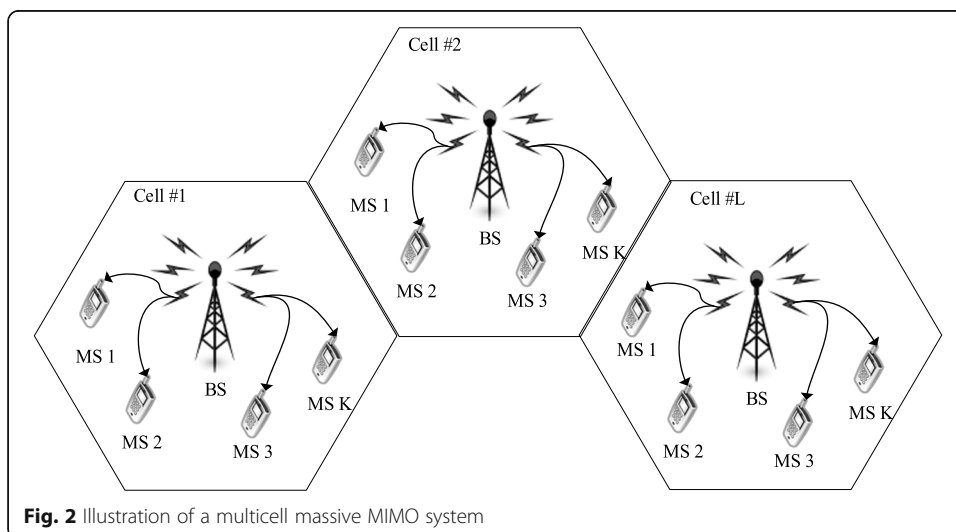


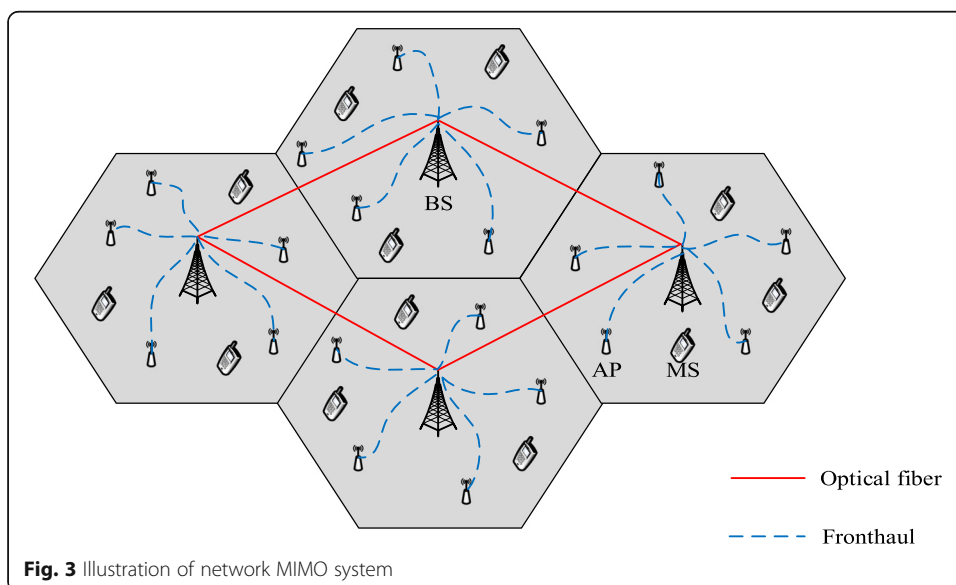
Fig. 2 Illustration of a multicell massive MIMO system

Network MIMO

Network MIMO system, which allows for coordination of a set of APs that jointly serve all users in the network, has often been hailed as an exciting alternative to achieving the capacity limit of cellular networks [98, 99]. Network MIMO or multicell MIMO signaling is considered a potential physical layer technique for 5G wireless networks. A plethora of interfering transmitters share user messages in a network MIMO system and enable joint precoding to be performed. Additionally, network MIMO could be referred to as cooperative communications used to improve the interference-limited performance of cellular networks. Specifically, by jointly designing the DL beams to multiplex multiple users spatially, intra-cluster interference can be eliminated. This concept has recently been introduced under a new network structure named CF massive MIMO [3]. It is considered a key enabling technology for 5G and beyond 5G wireless systems. Besides, the cell-edge problem inherent in cellular massive MIMO is eliminated, and all antennas jointly serve all users (UEs). Figure 3 presents the architecture of a typical network MIMO system.

Cell-free massive MIMO

The cellular topology has been the traditional way of covering the subscribers in a given geographical area with wireless network service for many decades. Each BS serves a given set of UEs using highly directional beamforming techniques [94]. This network topology has shown desirable performance gains, spectral efficiency, and energy efficiency [100–102]. However, the technology inevitably limits further performance improvements due to inter-cell interference, high QoS variations, and hand-offs [78, 103]. In order to address this problem, a viable option is to eliminate the inherent cell characteristics and take a considerable number of distributed APs densely deployed over a given coverage area to serve a smaller number of UEs optimally [53]. This novel communication architecture is described as cell-free massive MIMO, and it has been



identified as a candidate enabling technology for future wireless communication systems [83, 104].

Currently, key disruptive technologies have been deployed to cater to throughput, coverage, EE, and ubiquity requirements of next-generation wireless networks. In particular, having multiple antennas at the APs for several users has been observed as a promising technique to boost the multiplexing gain and enhance the SE in CF massive MIMO [55, 80]. Recently, power domain-centric NOMA integrated with CF-mMIMO emerged as a viable solution to address the conflicting demands on high SE, EE, high reliability with user-fairness, increased connectivity, and reduced latency in 5G wireless networks [105–107]. In CF-mMIMO, the number of simultaneously served users can be increased by supporting the users to utilize the same time-frequency resource effectively and invoking superposition-coded transmission and successive interference cancellation (SIC) decoding [108–110].

Cell-free massive MIMO leverages a distributed antenna system's unique features, coordinates beamforming, joint transmission, and scheduling to provide multiuser interference suppression and achieve stronger diversity gains. Moreover, due to the well-designed network topology, CF-mMIMO allows for favorable propagation and high quality of service throughout the coverage area [25, 52, 103, 111]. Compared to conventional cellular networks, some of the fascinating features of CF networks include uniform signal-to-noise ratio (SNR) with smaller variations, improved interference management, increased SNR due to coherent transmission [12], high EE, high SE, low latency, low complex linear processing, minimal power consumption, flexible and cost-efficient deployment, and high reliability, among others [9, 103]. Figure 4 presents a pictorial representation of a CF-mMIMO network, and Table 2 presents a performance comparison among cellular massive MIMO, network MIMO, and CF-mMIMO. According to its performance level, several critical performance metrics are selected, and each metric has been weighted (in percentage), as discussed in Section 5 of the current paper. Last, a pictorial comparison of cellular mMIMO and CF-mMIMO is shown in Fig. 5. For the cellular condition, hundreds and even thousands of BS antennas are

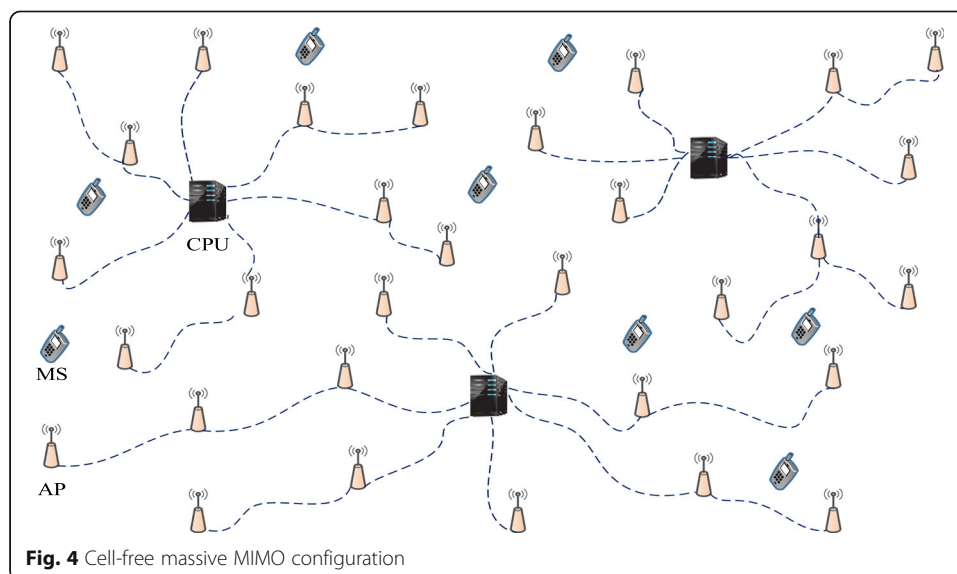


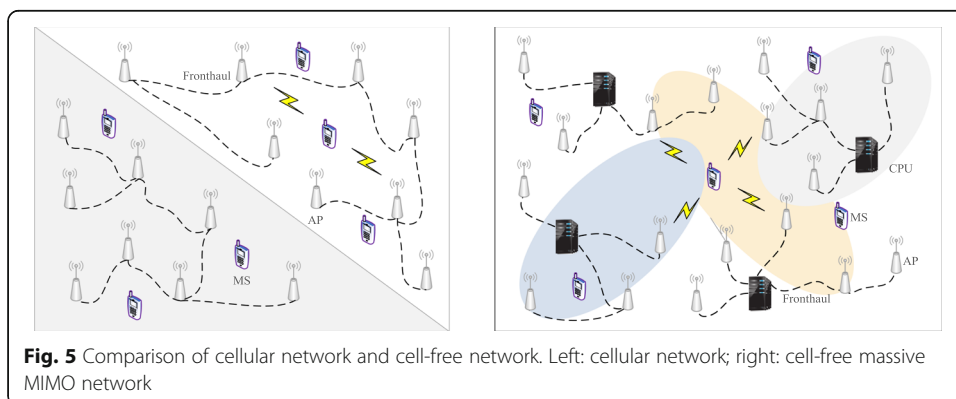
Table 2 Comparison among cellular mMIMO, network MIMO, and CF-mMIMO (metric weighting in percentage)

Configuration	Cellular	Network	Cell-free	Ref.
Interference management	30%	50%	70%	[2, 46]
EE	70%	30%	85%	[78, 103]
Hardware efficiency	30%	50%	70%	[48, 112]
Channel hardening	85%	30%	50%	[62, 103]
Uniform coverage	30%	50%	70%	[103]
Macro-diversity	30%	50%	70%	[103, 113]
Number of antennas	85%	70%	85%	[103, 114]
Favorable propagation	85%	30%	50%	[103, 115]
SE	70%	50%	85%	[116, 117]

selected to serve UEs within disjoint cells, thus achieving considerable throughput and coverage improvement. However, for the CF scenario, a plethora of geographically distributed single APs are chosen to serve a smaller number of UEs. The coverage area is not divided into disjoint cells leading to a CF network where signals from surrounding APs only influence each UE. The distributed AP antennas are connected via a fronthaul network to one or multiple central processing units (CPUs), facilitating effective coordination.

System model of cell-free massive MIMO

The CF-mMIMO network arbitrarily distributed over a wide coverage area operating on a one-time frequency resource is discussed in this framework. Let there be K UEs and M randomly located APs, each equipped with N_{ap} antennas, where $N_{ap} \geq 1$. It is often assumed that $M \gg K$. Besides, all APs are connected through an unlimited back-haul network to edge-cloud processors, called the CPU. Data-decoding is performed, ensuring that the UEs’ coherent joint transmission and reception in the coverable area are enabled. Remarkably, the pathloss between a user and any AP antenna is unique. The pathloss matrix possesses distinct diagonal elements, and as a result, performance analysis is generally challenging and considerably different from related prior works. TDD protocol with channel reciprocity and a single data stream transmitted per UE is assumed. The communication protocol is usually divided into several phases. These include UL training, UL payload data transmission, DL training, and DL payload data



transmission. For the overview of the system model of CF-mMIMO networks captured in this survey, a concise list of relevant mathematical notations used and their meanings are presented in Table 3.

First, by taking into consideration a DL CF massive MIMO system, let a set of BSs $\beta \triangleq \{1, \dots, B\}$, each equipped with M antennas serves a set of UEs $K \triangleq \{1, \dots, K\}$, each loaded with N antennas. Moreover, let $H_{b, k} \in \mathbb{C}^{M \times N}$ denote the UL channel matrix between BS $b \in \beta$ and UE $k \in K$, while $H_k \triangleq [H_{1,k}^T, \dots, H_{B,k}^T]^T \in \mathbb{C}^{BM \times N}$ represents the global UL channel matrix seen by UE k . More so, let $Y_{b, k} \in \mathbb{C}^{M \times 1}$ denote the BS-Specific precoding vector utilized by BS b for UE k , while $Y_k \triangleq [Y_{1,k}^T, \dots, Y_{B,k}^T]^T \in \mathbb{C}^{BM \times 1}$ represents the global precoding vector utilized UE k .

Thus, the received signal at UE k reads as (1)

$$p_k \triangleq \sum_{b \in \beta} \sum_{\bar{k} \in K} H_{b,k}^H y_{b,\bar{k}} g_{\bar{k}} + z_k \in \mathbb{C}^{N \times 1} \tag{1}$$

where $g_k \sim CN(0, 1)$ denotes the transmit data symbol for UE k , and $z_k \sim CN(0, \sigma_k^2 I_N)$ represents the average AWGN at UE k . When p_k is collected, UE k employs the combining vector $q_k \in \mathbb{C}^{N \times 1}$. The resulting signal-to-interference-plus-noise ratio (SINR) [118] is given by (2)

$$SINR_k \triangleq \frac{\left| \sum_{b \in \beta} q_k^H H_{b,k}^H y_{b,k} \right|^2}{\sum_{\bar{k} \in K \setminus \{k\}} \left| \sum_{b \in \beta} q_k^H H_{b,k}^H y_{b,\bar{k}} \right|^2 + \|q_k\|^2 \sigma_k^2} \tag{2}$$

In addition, the sum rate is expressed as $R \triangleq \sum_{k \in K} \log_2(1 + SINR_k)$. Next, the realistic pilot-aided channel state information (CSI) acquired at the BSs, and the UEs are considered.

Uplink pilot-aided channel estimation

Let the effective UL channel vector between UE k and BS b be denoted by $d_{b, k} \triangleq H_{b, k} q_k \in \mathbb{C}^{M \times 1}$. Likewise, let the pilot assigned to UE k be denoted by $l_k \in \mathbb{C}^{p \times 1}$, where $\|l_k\|^2 = \rho$. In this phase, each UE k jointly transmits its pilot precoded with its combining vector and is expressed as (3)

Table 3 Mathematical notations and definitions

Notations	Definitions
K, M, N_{ap}	Number of UEs, APs, and antennas per AP
$(\cdot)^T, (\cdot)^D, (\cdot)^*$	Transpose, conjugate transpose, and the complex conjugate of a matrix
$tr(R), \ R\ , R $	Trace, Euclidean norm, and the determinant of matrix R
\otimes	Kronecker product between two matrices
I_n	$n \times n$ identity matrix
\mathbb{E}	Expectation operator
k, l	Index of the UEs and index of the APs
τ_c, τ_s	The length of the channel coherence time, length of the UL training phase
Boldface lower case x	Column vectors
Boldface upper case X	Matrices
$w \sim \mathcal{N}(0, \sigma^2)$	Real-valued Gaussian random variable
$w \sim \mathcal{CN}(\mu, \sigma^2)$	Circularly symmetric complex Gaussian random variable with mean μ and variance σ^2

$$W_k^{UL} \triangleq q_k l_k^H \in \mathbb{C}^{N \times \rho} \tag{3}$$

Thus, for each BS b , X_b^{UL-1} is given by (4) and (5)

$$X_b^{UL-1} \triangleq \sum_{k \in K} H_{b,k} W_k^{UL-1} + Z_b^{UL-1} \tag{4}$$

$$= \sum_{k \in K} h_{b,k} l_k^H + Z_b^{UL-1} \in \mathbb{C}^{M \times \rho} \tag{5}$$

where $Z_b^{UL-1} \in \mathbb{C}^{M \times \rho}$ denotes the AWGN at BS b having elements distributed as $(0, \sigma_b^2)$. Likewise, the LS estimate of $d_{b,k}$ is given by (6) and (7)

$$\hat{d}_{b,k} \triangleq \frac{1}{\rho} X_b^{UL-1} l_k \tag{6}$$

$$= d_{b,k} + \frac{1}{\rho} \sum_{\bar{k} \in K \setminus \{k\}} d_{b,\bar{k}} l_{\bar{k}}^H l_k + \frac{1}{\rho} Z_b^{UL-1} l_k \tag{7}$$

Downlink pilot-aided channel estimation

Let the effective DL channel vector between all the BSs and UE k be denoted by $h_k \triangleq \sum_{b \in \mathcal{B}} H_{b,k}^H y_{b,k} \in \mathbb{C}^{N \times 1}$. In this phase, each BS jointly transmits a superposition of pilots after they have been precoded with the corresponding precoding vector and is expressed as (8)

$$W_k^{DL} \triangleq \sum_{k \in K} y_{b,k} P_k^H \in \mathbb{C}^{M \times \rho} \tag{8}$$

Thus, for each UE k , X_k^{DL} is given by (9)

$$X_k^{DL} \triangleq \sum_{b \in \mathcal{B}} \sum_{\bar{k} \in K} H_{b,k}^H y_{b,\bar{k}} P_{\bar{k}}^H + Z_k^{DL} \in \mathbb{C}^{N \times \rho} \tag{9}$$

where

$Z_k^{DL} \in \mathbb{C}^{N \times \rho}$ denotes the AWGN at UE k with elements distributed as $(0, \sigma_k^2)$. Likewise, the LS estimate of h_k is given by (10) and (11)

$$h_k \triangleq \frac{1}{\rho} X_k^{DL} P_k \tag{10}$$

$$= h_k + \frac{1}{\rho} \sum_{b \in \mathcal{B}} \sum_{\bar{k} \in K \setminus \{k\}} H_{b,k}^H y_{b,\bar{k}} P_{\bar{k}}^H P_k + \frac{1}{\rho} Z_k^{DL} P_k \tag{11}$$

There exist several pilot-based channel estimators, namely LS estimator, minimum mean-squared error (MMSE), element-wise minimum mean-squared error (EW-MMSE), phase-aware minimum mean-squared error (PA-MMSE), and linear MMSE. Table 4 presents a summary of pilot training-based channel estimators [119]. Next, the UL training phase, DL training phase, and outage probability of the communication protocol are considered.

Uplink training

In the uplink training phase, the UEs send UL training pilot sequences to allow channel estimation at the APs. The uplink training phase also applies to the user-centric (UC) massive MIMO architecture. Let τ_c represent the length of the channel coherence time in discrete-time samples and τ_s represent the length of the UL training phase, also in

Table 4 Summary of pilot training-based channel estimation schemes

Scheme	Estimate of d_{kl}	Mean and covariance of estimate	Mean and covariance of estimate error
LS	$\hat{d}_{kl}^{LS} = \frac{1}{\sqrt{P_{k,T_p}}} \mathbf{X}_{t_k,l}^{pilot}$	$\mathbb{E}\{\hat{d}_{kl}^{LS}\} = 0$ $\mathbf{C}\{\hat{d}_{kl}^{LS}\} = \sum_{i \in S_k} \frac{P_i}{P_k} \mathbf{R}_{kl} + \frac{\sigma_{w,l}^2}{P_{k,T_p}} \mathbf{I}_N$	$\mathbb{E}\{\hat{d}_{kl}^{LS}\} = 0$ $\mathbf{C}\{\hat{d}_{kl}^{LS}\} = \mathbf{C}\{\hat{d}_{kl}^{LS}\} - \mathbf{R}_{kl}$
MMSE	$\hat{d}_{kl}^{MMSE} = \sqrt{P_{k,T_p}} \mathbf{R}_{kl} \Psi_{t_k,l}^{-1} \mathbf{X}_{t_k,l}^{pilot}$	$\mathbb{E}\{\hat{d}_{kl}^{MMSE}\} = 0$ $\mathbf{C}\{\hat{d}_{kl}^{MMSE}\} = \tau_p P_k \mathbf{R}_{kl} \Psi_{t_k,l}^{-1} \mathbf{R}_{kl}$	$\mathbb{E}\{\hat{d}_{kl}^{MMSE}\} = 0$ $\mathbf{C}\{\hat{d}_{kl}^{MMSE}\} = \mathbf{R}_{kl} - \mathbf{C}\{\hat{d}_{kl}^{MMSE}\}$
EW-MMSE	$\hat{d}_{kl}^{EW-MMSE} = \frac{\sqrt{P_{k,T_p}} \mathbf{R}_{kl} \mathbf{R}_{kl}^{-1} \mathbf{R}_{kl} \Psi_{t_k,l}^{-1} \mathbf{X}_{t_k,l}^{pilot}}{\sum_{i \in S_k} P_i T_p (\mathbf{R}_{kl})_{mm} + \sigma_{w,l}^2}} \times [\mathbf{X}_{t_k,l}^{pilot}]_{-n}$	$\mathbb{E}\{\hat{d}_{kl}^{EW-MMSE}\} = 0$ $\mathbf{C}\{\hat{d}_{kl}^{EW-MMSE}\} = \sum_{i \in S_k} \frac{P_i T_p (\mathbf{R}_{kl})_{mm}^2}{\sum_{i \in S_k} P_i T_p (\mathbf{R}_{kl})_{mm} + \sigma_{w,l}^2}$	$\mathbb{E}\{\hat{d}_{kl}^{EW-MMSE}\} = 0$ $\mathbf{C}\{\hat{d}_{kl}^{EW-MMSE}\} = [\mathbf{R}_{kl}]_{mm} - \mathbf{C}\{\hat{d}_{kl}^{EW-MMSE}\}_{-n}$
PA-MMSE	$\hat{d}_{kl}^{PA-MMSE} = \bar{d}_{kl} e^{j\phi_{kl}} + \sqrt{P_k} \mathbf{R}_{kl} \times \Psi_{t_k,l}^{-1} (\mathbf{X}_{t_k,l}^{pilot} - \bar{\mathbf{z}}_{t_k,l})$	$\mathbb{E}\{\hat{d}_{kl}^{PA-MMSE} \phi_{kl}\} = \bar{d}_{kl} e^{j\phi_{kl}}$ $\mathbf{C}\{\hat{d}_{kl}^{PA-MMSE} \phi_{kl}\} = P_k T_p \mathbf{R}_{kl} \Psi_{t_k,l}^{-1} \mathbf{R}_{kl}$	$\mathbb{E}\{\hat{d}_{kl}^{PA-MMSE}\} = 0$ $\mathbf{C}\{\hat{d}_{kl}^{PA-MMSE}\} = \mathbf{R}_{kl} - P_k T_p \mathbf{R}_{kl} \Psi_{t_k,l}^{-1} \mathbf{R}_{kl}$
LMMSE	$\hat{d}_{kl}^{LMMSE} = \sqrt{P_k} \mathbf{R}_{kl}^E (\Psi_{t_k,l}^E)^{-1} \mathbf{X}_{t_k,l}^{pilot}$	$\mathbb{E}\{\hat{d}_{kl}^{LMMSE}\} = P_k T_p \mathbf{R}_{kl}^E (\Psi_{t_k,l}^E)^{-1} \mathbf{R}_{kl}^E$	$\mathbb{E}\{\hat{d}_{kl}^{LMMSE}\} = 0$ $\mathbf{C}\{\hat{d}_{kl}^{LMMSE}\} = \mathbf{R}_{kl}^E - \mathbf{C}\{\hat{d}_{kl}^{LMMSE}\}$

discrete-time samples. At all times, $\tau_s < \tau_c$. The matrix has on its rows the pilot sequences transmitted by the k th UE is denoted by $\varnothing_k \in \mathbb{C}^{s \times \tau_s}$. While the rows of \varnothing_k are assumed to be orthogonal, i.e., $\varnothing_k \varnothing_k^D = I_s$, assuming there is no orthogonality for the pilot sequences directed to other UEs. Of course, by employing orthogonal pilot tout court, a robust system to the effects of pilot contamination is achievable. However, the peak value of the product KS that can be taken in the channel coherence time would be primarily limited. Thus, we define the $N_{AP} \times \tau_s$ dimensional matrix X_m by (12)

$$X_m = \sum_{k=1}^K \sqrt{sk} F_{k,m} \varnothing_k + Y_m, \tag{12}$$

where $F_{k,m} = D_{k,m} L_k$, Y_m denotes the matrix of thermal noise samples. Next, we explore the structure of the LMMSE channel estimator briefly. Defining parameters, $x_m = \text{vec}(X_m)$, $y_m = \text{vec}(Y_m)$, $f_{k,m} = \text{vec}(F_{k,m})$, the vectorized model is given as (13)

$$x_m = \sum_{k=1}^K \sqrt{sk} R_k f_{k,m} + y_m \tag{13}$$

where $R_k = \varnothing_k^T \otimes I$. We process x_m by a matrix $Q_{k,m}^D$, i.e., $\hat{f}_{k,m} = Q_{k,m}^D x_m$. Thus, the MSE is obtained as (14)

$$\begin{aligned} \mathbb{E} \left[\left\| Q_{k,m}^D x_m - f_{k,m} \right\|^2 \right] &= \text{tr} \left(Q_{k,m}^D \mathbb{E} [x_m x_m^D] Q_{k,m} \right) \\ &\quad + \mathbb{E} \left[\left\| f_{k,m} \right\|^2 \right] - \mathbb{E} \left[2 \Re \left\{ \text{tr} \left(f_{k,m}^D Q_{k,m}^D x_m \right) \right\} \right] \\ &= \text{tr} \left(Q_{k,m}^D \left(\sum_{l=1}^K s k R_l R_l^D + \delta^2 I \right) Q_{k,m} \right) + \mathbb{E} \left[\left\| f_{k,m} \right\|^2 \right] - \sqrt{sk} \text{tr} \left(Q_{k,m}^D R_k + Q_{k,m}^T R_k^* \right) \end{aligned} \tag{14}$$

In this case, the gradient of the MSE concerning the complex matrix $Q_{k,m}^*$ is assumed to be equal to zero. Solving for $Q_{k,m}$, the LMMSE estimator is given by (15)

$$Q_{k,m}^{LMMSE} = \sqrt{sk} \left(\sum_{l=1}^K s l R_l R_l^D + \delta^2 I \right)^{-1} R_k \tag{15}$$

Downlink training

In this section, the scalable beamforming training scheme is adopted. Let $\tau_{v,l}$ denote the length of the DL training duration per coherence interval; it suffices that $\tau_{v,l} < \tau - \tau_{u,l}$. By exploiting the channel estimates $\{\hat{h}_{mk}^{\mathbb{E}}\}$, and beamforming it to all users, the m th AP precodes the pilot sequences $\phi_{k^{\mathbb{E}}} \in \mathbb{C}^{\tau_{v,l} \times 1}$, $k^{\mathbb{E}} = 1, \dots, K$. Thus, the $\tau_{v,l} \times 1$ pilot vector $w_{m,l}$ sent from the m th AP is obtained as (16)

$$w_{m,l} = \sqrt{\tau_{v,l} \sigma_{v,l}} \sum_{k^{\mathbb{E}}=1}^K \sqrt{\mathbb{E} [h_{mk^{\mathbb{E}}}^* h_{mk^{\mathbb{E}}}] } \phi_{k^{\mathbb{E}}}, \tag{16}$$

where $\sigma_{v,l}$ is the normalized transmit SNR per DL pilot symbol and $\{\phi_k\}$ assume mutual orthonormality i.e. $\phi_k^D \phi_{k'} = 0$, for $k' \neq k$, and $\|\phi_k\|^2 = 1$. This requires that $\tau_{v,l} \geq K$. The k th user receives correspondingly, $\tau_{v,l} \times 1$ pilot vector which is given by (17)

$$x_{vl,k} = \sqrt{\tau_{v,l}\sigma_{v,l}} \sum_{k^E=1}^K r_{kk^E} \phi_k^E + y_{vl,k}, \tag{17}$$

where $y_{vl,k}$ denotes a vector additive noise at the k th user. The effective channel gain r_{kk} , $k = 1, \dots, K$ is estimated via the processing of the received pilot first by the k th user as (18)

$$\check{x}_{vl,k} = \phi_k^D \mathbf{x}_{vl,k} = \sqrt{\tau_{v,l}\sigma_{v,l}} r_{kk} + \phi_k^D \mathbf{y}_{vl,k} = \sqrt{\tau_{v,l}\sigma_{v,l}} r_{kk} + \eta_{l,k}, \tag{18}$$

where $\eta_{l,k} \stackrel{\Delta}{=} \phi_k^D \mathbf{y}_{vl,k} \sim CN(0, 1)$. Given $\check{x}_{vl,k}$, linear MMSE estimation of r_{kk} is performed, which is obtained as (19)

$$\hat{r}_{kk} = \mathbb{E}\{r_{kk}\} + \frac{\sqrt{\tau_{v,l}\sigma_{v,l}} \text{Var}\{r_{kk}\}}{\tau_{v,l}\sigma_{v,l} \text{Var}\{r_{kk}\} + 1} (\check{x}_{vl,k} - \sqrt{\tau_{v,l}\sigma_{v,l}} \mathbb{E}\{r_{kk}\}) \tag{19}$$

Outage probability

Obtaining the exact expression for outage probability is quite challenging due to the computational complexity in determining the cumulative distribution function (CDF) of the SINR at the APs [120]. The only exception for massive MIMO systems applies to perfect CSI and identically distributed channels unsatisfied in practice [121, 122]. Therefore, an alternate approach, approximate outage probability, is selected to provide the outage probability of massive MIMO networks where all the APs are collocated. Hence, $\beta_{mk} = \beta_k$, $\gamma_{mk} = \gamma_k$, $\forall m, k$. The outage probability approximation of the k th user is obtained as (20) and (21)

$$P_{out}^K(T) \approx 1 - M \sum_{i=1}^{K-1} \frac{\gamma_i^{K-2}}{\prod_{\substack{j=1 \\ j \neq i}}^{K-1} (\gamma_i - \gamma_j)} \left[1 - \frac{e^{-c_2^i}}{c_1^i + 1} \right] + (M-1) \sum_{i=1}^{K-1} \frac{\gamma_i^{K-2}}{\prod_{\substack{j=1 \\ j \neq i}}^{K-1} (\gamma_i - \gamma_j)} \left[1 - e^{-(c_1^i + c_2^i)} \right] \tag{20}$$

for $T \leq \frac{\rho_u(M-1)\gamma_K}{(1+\rho_u(\beta_K-\gamma_K))}$ and

$$P_{out}^K(T) \approx 1 - M \sum_{i=1}^{K-1} \frac{\gamma_i^{K-2}}{\prod_{\substack{j=1 \\ j \neq i}}^{K-1} (\gamma_i - \gamma_j)} \left[e^{-k} - \frac{e^{-c_2^i} e^{-k(c_1^i+1)}}{c_1^i + 1} \right] + (M-1) \sum_{i=1}^{K-1} \frac{\gamma_i^{K-2}}{\prod_{\substack{j=1 \\ j \neq i}}^{K-1} (\gamma_i - \gamma_j)} \left[1 - e^{-(c_1^i + c_2^i)} \right] U(c_3 + c_4 + c_5) \tag{21}$$

for $T > \frac{\rho_u(M-1)\gamma_K}{(1+\rho_u(\beta_K-\gamma_K))}$,

where c_1^i, c_2^i, c_3, c_4 and c_5 are given by (22), (23), (24), (25), and (26).

$$c_1^i = \frac{\gamma_K}{T\gamma_i} \quad (22)$$

$$c_2^i = \frac{(M-1)\gamma_K}{T\gamma_i} - \frac{1 + \rho_u(\beta_K - \gamma_K)}{\rho_u\gamma_i} \quad (23)$$

$$c_3 = \frac{1}{T}\gamma_K^2 \quad (24)$$

$$\begin{aligned} c_4 &= \frac{2}{T}(M-1)\gamma_K^2 - \frac{1}{\rho_u}\gamma_K(1 + \rho_u(\beta_K - \gamma_K)) \\ &= \frac{1}{T}(M-1)\gamma_K^2 + \gamma_K\left(\frac{(M-1)\gamma_K}{T} - \frac{(1 + \rho_u(\beta_K - \gamma_K))}{\rho_u}\right) \end{aligned} \quad (25)$$

$$c_5 = (M-1)\gamma_K\left(\frac{(M-1)\gamma_K}{T} - \frac{(1 + \rho_u(\beta_K - \gamma_K))}{\rho_u}\right). \quad (26)$$

Areas of application of cell-free massive MIMO

The wireless research community has explored the outstanding features of the mutually beneficial combination between CF structure and massive MIMO technology to enable seamless transfer from theory to practical implementation. Of course, significant progress in signal processing, communication, and optimization algorithms developed has further deepened the range of applications of this technology. Table 5 presents a summary of CF massive MIMO application areas alongside their strengths and limitations. A concise account of the past findings and current research trends based on SWIPT, channel hardening, hardware efficiency, power control, NOMA, SE, and EE for the CF-MIMO are detailed in the following subsections.

SWIPT in cell-free massive MIMO

The ultra-high transmission rate of wireless networks has been identified as a significant challenge that decreases the lifetime of battery-powered devices. SWIPT is considered an innovative candidate for the energy-limited environment through energy reclamation. It offers an effective solution to enable a guaranteed energy level and minimize backhaul resources and energy consumption. Compared to traditional massive MIMO, CF massive MIMO presents a new paradigm to boost the performance of SWIPT. A summary of recent advances on SWIPT technology in CF massive MIMO is presented in Table 6.

Additionally, the energy harvest and DL achievable rate for an energy user under a linear scheme are presented. First, for the harvested energy, it is assumed that the harvesting circuitry operates with an efficiency represented as η . With reference to the \tilde{j} th user which depicts a typical energy user, the ambient harvested energy E_j^- during a time slot is obtained as (27)

Table 5 Areas of application of CF massive MIMO

Ref.	Areas of application	Description	Strengths	Limitations
[68, 69]	SWIPT	Promising energy harvesting technology for an energy-limited environment	Optimized achievable energy-rate trade-off and improved EE	Adverse channel effects, reduced throughput
[62, 64, 123]	Channel hardening	In the regime of a massive number of antennas, fading channels become almost deterministic. This effect is referred to as channel hardening	High SE and reliable performance	Spatial correlation at the APs, pilot contamination and presence of line-of-sight (LoS) propagation
[66, 67, 77, 84, 124]	Hardware efficiency	Communication networks are generally affected by non-idealities under practical operational conditions. This inevitably degrades the system's performance dramatically	Economical transceivers	Decrease in hardware qualities, adverse effect of HI at UE, and performance degradation owing to the processing power of APs
[53, 81, 125]	Power control	Intelligent distribution of transmitter power along various antennas to manage interference and guarantee maximized performance within the system	Improved efficiency of wireless systems and improved throughput to all users	Shadowing effects, multi-objective optimization problem, and the complexity of power allocation algorithm
[81, 126]	Learning-based CF massive MIMO	It encompasses an ML framework where deep layers enable learning from a large amount of data	Robustness against pilot contamination and improved resource allocation	Shadowing effects and increase in training time as the number of UEs grows large
[26, 127]	Interference management	Techniques employed to manage interference abounded in wireless networks	Suppression of inter-cell interference	Residual self-interference (RSI)
[128–130]	NOMA	An insightful technique in which multiple users are simultaneously served using the same time-frequency resource block	Massive connectivity and attractive SE gains	Imperfect SIC and pilot contamination
[80, 85]	SE	A vital performance metric considered in the design of wireless communication systems and expressed as the ratio of data rate to bandwidth	Improved area throughput	Spatial correlation
[37, 41, 78, 131, 132]	EE	An essential energy-saving technique geared toward reducing the total energy consumption in wireless systems	Significant reduction in total power consumption improved radiated EE	Power lows, the trade-off between EE and SE

$$E_j = \eta T_E \sum_{l=1}^N \frac{r_{jl}^{-2\alpha_{jl}} \left(\frac{\zeta}{\zeta} \right) P_{jl} P_P}{\mathbb{E} \left[\left| \mathbf{a}_j^D x_l \right|^2 \right]}, \tag{27}$$

In this case, the noise factor is neglected to owe to its low comparative strength instead of other terms. As a step further, the DL achievable rate for a typical energy user is derived. The average achievable rate R_j can be expressed as (28)

Table 6 SWIPT technology in cell-free massive MIMO

Ref.	Focus and coverage	Key findings	Limitations	Year
[68]	The work seeks to leverage the underlying practical potentials presented by UL training-based CF-mMIMO with imperfect CSI on the performance of SWIPT. Also, the work explores the attainable harvested energy and UL/DL rates in closed form.	<ul style="list-style-type: none"> ▪ The performance of the SWIPT technique is substantially improved by adopting the CF massive MIMO model. ▪ Exploiting the benefits of distributed transmission/reception and many spatially distributed single antenna APs, an optimal achievable energy-rate trade-off of SWIPT is realized. ▪ Concerning the number of energy users (fixed in this case), the achievable sum rate is moderately increased when the number of APs becomes large. 	<ul style="list-style-type: none"> ▪ The authors did not discuss the cases of spatial randomness and channel changes when links are blocked. 	2018
[69]	The study investigates the coexistence of SWIPT and CF massive MIMO. The work aims at bridging the gap in CF literature by optimizing the underlying issues presented by SWIPT. Stochastic geometry is exploited to model the APs using a homogeneous PPP, resulting in a spatially random network.	<ul style="list-style-type: none"> ▪ The proposed arrangement improves the energy-rate trade-off of SWIPT networks considerably. ▪ A careful balance in power allocated to energy users enhances the mean harvested energy significantly, however, at the cost of a reduced DL rate for non-energy users. 	<ul style="list-style-type: none"> ▪ The UL performance of energy users after the energy harvest is not accounted for. ▪ The results show an improved DL rate for energy users due to reduced pilot sequence resulting in fewer users being served. 	2020

$$R_j = \left(1 - \frac{2T_E}{T - T_p}\right) \mathbb{E} \left[\log(1 + \gamma_j) \right], \tag{28}$$

where γ_j denotes the SNR of the \tilde{j} -th user and is expressed as (29)

$$\gamma_j = \frac{\sum_{l=1}^N r_{\tilde{j}l}^{-2\alpha_{jl}} \left(\frac{\zeta}{|d_{\tilde{j}l}|} \right) P_{jl} P_p}{\zeta \mathbb{E} \left[\left| \mathbf{a}_j^D x_l \right| \right]}. \tag{29}$$

Now, $R_{\tilde{j}}$ can be modeled as (30)

$$R_{\tilde{j}} = \left(1 - \frac{2T_E}{T - T_p}\right) \mathbb{E} \left[\log \left(1 + \frac{E_{\tilde{j}}}{\zeta \sigma \eta T_E} \right) \right] \tag{30}$$

where $E_{\tilde{j}}$ is given by (27). Thus, $R_{\tilde{j}}$ is obtained as (31) after some modifications.

$$R_{\tilde{j}} = \left(1 - \frac{2T_E}{T - T_p}\right) \int_{t=0}^{\infty} \Pr \left[E_{\tilde{j}} > \zeta \sigma \eta T_E (e^t - 1) \right] dt. \tag{31}$$

Further, the distribution of $E_{\tilde{j}}$ is approximated with the Gamma distribution employing moment matching. The scale parameters which define the Gamma distributions are

obtained as $k_h = (\mathbb{E}[E_j^-])^2 / \text{VAR}[E_j^-]$ and $\theta_h = \text{VAR}[E_j^-] / \mathbb{E}[E_j^-]$. Consequently, (31) can be re-modeled as (32)

$$R_j = \left(1 - \frac{2T_E}{T - T_p}\right) \int_{t=0}^{\infty} \left(1 - F_{E_j}(\sigma^2 \eta T_E (e^t - 1))\right) dt$$

$$= \left(1 - \frac{2T_E}{T - T_p}\right) \int_{t=0}^{\infty} \frac{1}{\Gamma(k_h)} \Gamma\left(k_h, \frac{\sigma^2 \eta T_E (e^t - 1)}{\theta_h}\right) dt, \tag{32}$$

which can be simplified numerically.

Channel hardening and favorable propagation in cell-free massive MIMO

Two essential virtues that appear in the regime of hundreds or even thousands of antennas: channel hardening and favorable propagation, are defined and analyzed. By increasing BS antennas, the propagation is assumed to happen through a quasi-deterministic flat-fading equivalent channel. In light of the above, the fading channel behaves as though it was not a fading channel (almost deterministically) [50]. This phenomenon is referred to as channel hardening. Also, when the channel directions of two UEs become spatially orthogonal, the inter-user and intra-cell interference vanishes automatically using a relatively simple signal processing technique called maximum-ratio processing (MRP). This desirable property is termed favorable propagation. The channel hardening effect has been exploited by massive MIMO to decrease the problem of small-scale fading in wireless communication systems to guarantee desirable reliability and low latency. However, channel hardening conditions have also been observed and remain valid for CF massive MIMO systems, with reduced pathloss exponent and increased antenna density. Table 7 presents a summary of recent trends and advances on channel hardening in CF-mMIMO systems.

The mathematical representation of channel hardening and favorable propagation in CF massive MIMO is presented. Let d_{jk} reflects the propagation channel response between the UE k and AP m . The channel hardening effect is defined as (33)

$$\frac{\|d_{jk}\|^\zeta}{\mathbb{E}\left\{\|d_{jk}\|^\zeta\right\}} \rightarrow 1 \text{ as the number of antennas } N_{ap} \rightarrow \infty \tag{33}$$

As a result, the impact of the small-scale fading variations on the communication performance is minimized while the challenge of large-scale fading remains. The degree of channel hardening in CF-mMIMO is dependent mainly on the number of antennas per AP and the geographical AP distribution [12]. The favorable propagation is expressed as (34)

$$\frac{d_{jk}^D d_{j\check{k}\check{e}}}{\sqrt{\mathbb{E}\left\{\|d_{jk}\|^\zeta\right\} \mathbb{E}\left\{\|d_{j\check{k}\check{e}}\|^\zeta\right\}}} \rightarrow 0 \text{ when } N_{ap} \rightarrow \infty \tag{34}$$

Table 7 Channel hardening in cell-free massive MIMO

Ref.	Focus and coverage	Key findings	Limitations	Year
[62]	This survey dwells on incorporating channel hardening in CF-MIMO using stochastic geometry while evaluating potential constraints to its practical implementation. A homogenous PPP is explored to model the AP distribution. In addition, the effect of channel hardening on AP density is evaluated.	<ul style="list-style-type: none"> ▪ The study reveals that channel hardening in CF-mMIMO mainly depends on the number of antennas per AP and the pathloss exponent of the propagation environment. ▪ A synergy between smaller pathloss exponent and multiple antennas per AP provides a modest level of channel hardening. 	<ul style="list-style-type: none"> ▪ The capacity bounds obtained from cellular massive MIMO are not so tight in CF-mMIMO. ▪ Channel hardening comes at the cost of reduced macro-diversity, which is undesirable in practice. 	2017
[64]	The authors considered the channel hardening effect extensively in CF massive MIMO under practical operational conditions. Closed-form expressions are presented for the hardening coefficients, taking cognizance of pilot contamination, power loading, and MMSE channel estimation.	<ul style="list-style-type: none"> ▪ Channel hardening is substantially improved with the NCB precoder compared to the CB scheme. 	<ul style="list-style-type: none"> ▪ The effects of spatial correlation at the APs are not considered. ▪ The system is largely affected by pilot contamination, given a small coverage area. 	2020
[133]	An enhanced normalized CB (ECB) precoding is proposed to boost the channel hardening effect in CF massive MIMO. An exact closed-form expression for the achievable DL SE concerning the pilot contamination, channel estimation errors, lack of CSI at the user side, along with an optimal max-min fairness power allocation scheme, is presented.	<ul style="list-style-type: none"> ▪ The effective channel is nearly deterministic, thus, validating the effectiveness of the proposed ECB. ▪ The DL SE is significantly improved compared to the case with CB. 	<ul style="list-style-type: none"> ▪ The proposed scheme does not support interference suppression. ▪ Acquiring CSI for the users is quite challenging. 	2021

Hardware impairments and pilot transmission in cell-free massive MIMO systems

Using practical systems with perfect hardware components during production could result in enormous energy consumption and prohibitive hardware costs, which are not satisfied in practice. In short, the closer to ideal a hardware transceiver is, the more costly, bulkier, and energy-hungry it becomes. This bottleneck, a trade-off between the quality of hardware components and cost, is usually considered a breakthrough. Nonetheless, this technique inevitably introduces hardware and channel impairments, including amplifier non-linearities, phase noise, I/Q imbalance, and ADC distortions into the system. Analyzing CF massive MIMO under the effects of HI has gained significant research interest. Table 8 presents a summary of progress made in this regard. Additionally, mathematical models of the hardware impairment and pilot transmission are presented.

Hardware impairment model

In order to model the combined effect of hardware distortions, the transmitted/received signal is assumed to be distorted by an additive Gaussian noise [92]. The distorted signal is expressed as (35)

$$w_i = \sqrt{\xi} w + z_i, \quad (35)$$

Table 8 Cell-free massive MIMO systems with hardware impairments

Ref.	Focus and coverage	Key findings	Limitations	Year
[77]	The work considers the secure transmission issue in CF-mMIMO networks, considering the effects of HI and the presence of spoofing attacks. The work is analyzed using hardware quality scaling law, continuous approximation, convex approximation, and path-following algorithms.	<ul style="list-style-type: none"> The proposed power control scheme outperforms the conventional average power allocation. 	<ul style="list-style-type: none"> The performance of the system is significantly impacted by the active attacks and the decrease of hardware qualities. 	2019
[134]	The effect of HI on the UL transmission of a CF massive MIMO system constrained by limited capacity fronthaul links is investigated. Low-complexity fronthaul rate allocations are proposed to minimize transmission of the compressed version of CSI and data signals.	<ul style="list-style-type: none"> The system's sum spectral/energy efficiency is significantly improved with the estimate-multiply-compress-forward compared to the other two strategies applied. 	<ul style="list-style-type: none"> Large portions of the fronthaul capacity for signal transmission impact the achievable rate considerably. The performance gain is affected mainly by the processing power of the AP. 	2019
[84]	The authors examined the impact of RF impairments and ADCs imperfections on the performance of UL CF-mMIMO. The work aims at improving the accuracy of channel estimation while ensuring a maximized signal-to-interference-plus-noise ratio.	<ul style="list-style-type: none"> The hardware expenses can be minimized by reducing the quality of transceiver RF chains and the quantization bits of low-resolution ADCs. 	<ul style="list-style-type: none"> The benefits come at the cost of significant performance degradation. 	2020
[124]	The performance of distributed massive MIMO (CF and UC systems) and SC systems under practical deployment scenarios is investigated. More precisely, the impact of non-ideal hardware distortions and the Doppler shift effect is considered.	<ul style="list-style-type: none"> The study results revealed that distributed massive MIMO is more robust to hardware distortion and the Doppler shift effect compared to SC systems. Moreover, SC systems perform poorly under max-min power control. 	<ul style="list-style-type: none"> Distributed massive MIMO suffers significant performance loss when the number of served users per AP is reduced. Additionally, the network is preferable for majorly high-mobility conditions. 	2020
[135]	The authors quantitatively examined the effect of HI on the performance of CF-mMIMO. Four low-complexity receiver cooperation is adopted, and a comprehensive review of the fronthaul requirements of the different receiver cooperation is provided.	<ul style="list-style-type: none"> Results obtained show that the SE is significantly improved as the hardware qualities increases. More so, the reducing hardware quality diminishes with increasing APs. 	<ul style="list-style-type: none"> The negative effect of HI at UE is not elaborated. 	2020
[136]	This survey focuses on maximizing the hardware quality in CF massive MIMO. Specifically, the authors examined the optimal HI and ADC bit allocation problem based on the large-scale fading variations of the channel for maximal SE and EE. Regularized zero-forcing (RZF) combined with statistical channel inversion power control is employed in the system.	<ul style="list-style-type: none"> Compared to equal ADC bit allocation, the EE and sum SE is moderately increased by the optimal ADC bit allocation. 	<ul style="list-style-type: none"> Hardware quality is not fully optimized. 	2021

where w refers to the input signal to the non-ideal hardware. Moreover, $\xi_i \in [0, 1]$, $i = \{t, r\}$ reflects the hardware quality coefficient. The distortion noise is obtained as (36) and is independent of the input signal w .

$$z_i \sim CN(0, (1-\xi_i)\mathbb{E}\{|w|^2\}) \tag{36}$$

The term $\mathbb{E}\{|w|\} = \mathbb{E}\{|w_i|\}$ indicates the equivalence of the variance of both the input and output signals for the non-ideal hardware device. Besides, the hardware quality is obtained through $\xi_i \in [0, 1]$, where $\xi_i = 1$ and $\xi_i = 0$ denotes perfect and useless hardware, respectively.

Pilot transmission

In this context, it is assumed that τ -length orthogonal pilots represented as $\psi_k \in \mathbb{C}^{\tau \times 1}$ are assigned to UEs, where $\tau = K \leq T$, and $\psi_k^D \psi_{k'}^E = \delta(k-k')$ for $k, k' \in \{1, 2, \dots, K\}$. As a result, the pilot signal $\sqrt{\tau P_p} \psi_k$ is transmitted by UE_k, and the signal modeled as (37) is received by the m th AP

$$\mathbf{x}_{p,m} = \sqrt{\xi_r} \sum_{k=1}^K h_{mk} \left(\sqrt{\tau P_p \xi_t} \psi_k + z_{t,k} \right) + z_{r,m} + \mathbf{n}_m \tag{37}$$

where P_p refers to the pilot power, $z_{t,k}$ expressed as (38) accounts for the distortion caused by a non-ideal hardware device, $z_{r,m}$ expressed as (39) denotes the distortion caused by hardware impairment at the m th AP and \mathbf{n}_m represented as (40) indicates the additive noise [92, 137]

$$z_{t,k} \sim CN(0, P_p(1-\xi_t)\mathbf{I}_\tau), \tag{38}$$

$$z_{r,m} | \{h_{mk}\} \sim CN\left(0, P_p(1-\xi_r) \sum_{k=1}^K |h_{mk}|^2 \mathbf{I}_\tau\right), \tag{39}$$

$$\mathbf{n}_m \sim CN(0, N\mathbf{I}_\tau). \tag{40}$$

Power control in cell-free massive MIMO

Power control has appeared as a key feature and one of the most impacting algorithms in mobile networks. It entails an intelligent selection of transmitter power output to improve the overall performance of wireless systems. The power control techniques find handy applications in CF massive MIMO to limit the generated interference, minimize pilot contamination, maximize the power of the desired received signal, and provide a more uniform QoS to the UEs. Table 9 presents a survey of various areas of application of power control in CF-mMIMO systems. Furthermore, Table 10 shows a more concise account of power control/algorithms (alternative optimization, successive convex approximation (SCA), GP, bisection, SOCP, fractional, and ML-based techniques) used in solving specific utility optimization problems [119].

Additionally, an insight into different power control policies is highlighted. In particular, the equal transmits power policy, equal receive power policy, and inverse leakage policy are considered. In all policies, it is assumed that $G_{ik} = f_k^D V_i f_k$.

- (1) Equal Transmit Power Policy: In this policy, the same power is transmitted to each UE i , taking into consideration the power constraints and can be expressed as (41)

Table 9 Power control in cell-free massive MIMO

Ref.	Focus and coverage	Key findings	Limitations	Year
[53]	Power control techniques to minimize the pilot contamination effect in CF-mMIMO are investigated. The goal is to distribute pilot power to each network user while ensuring accurate channel estimation. The efficacy of the proposed pilot power control is investigated by comparison with the case of full-pilot power.	<ul style="list-style-type: none"> ▪ The pilot contamination effect is generally reduced. ▪ Notably, the 95% likely throughput in both UL and DL transmission is considerably improved. ▪ The case without pilot power control is sub-optimal at all times compared to the case with pilot power control. 	<ul style="list-style-type: none"> ▪ Pilot power control is a multi-objective optimization problem and providing an optimal solution that simultaneously optimizes each objective is quite challenging. 	2018
[81]	The authors present power allocation techniques in the UL of a CF-mMIMO network. The work aims at maximizing the sum rate and the minimum rate of CF massive MIMO systems using the ANN-based power control method.	<ul style="list-style-type: none"> ▪ The effect of pilot contamination on the learning capabilities of deep neural networks (DNN) is highly minimal, as near-optimal performance is obtained. 	<ul style="list-style-type: none"> ▪ The shadowing effect degrades the performance of the suggested ANN-based power control considerably. 	2019
[125]	The DL performance of a partially distributed CF massive MIMO network under the assumption of different power control policies is investigated. These policies are extended to cover the case when the power control is coordinated only within subsets of APs and not across the subsets.	<ul style="list-style-type: none"> ▪ The SCA policy is shown to outperform other power control policies in terms of the SE gains. ▪ Moreover, the gain in SE for SCA is higher for CB precoding compared to ZF precoding. 	<ul style="list-style-type: none"> ▪ Computational complexity and loss in sum SE are major bottlenecks to the optimal performance of the SCA policy. 	2019
[138]	In this correspondence, a DNN-based power allocation for CF massive MIMO is proposed. Particularly, DNNs are trained to perform both centralized and distributed power allocation with reduced computational complexity.	<ul style="list-style-type: none"> ▪ A properly trained framework is shown to improve power allocation significantly. 	<ul style="list-style-type: none"> ▪ The gap between the distributed and centralized methods is substantial and requires further improvement. 	2019
[129]	The UL data transmission of a NOMA-aided CF-mMIMO is investigated. An optimal backhaul combining scheme to enhance the worst SINR among users in the network is proposed. The work is further analyzed using a max-min QoS power control problem which is iteratively solved by a successive inner approximation technique.	<ul style="list-style-type: none"> ▪ A significant performance improvement is obtained with the proposed OBC compared to equal-gain combining and ZF combining. 	<ul style="list-style-type: none"> ▪ The SINR degrades dramatically as the number of antennas on each BS grows large. 	2020
[139]	A novel unsupervised learning-based to address the max-min rate problem in CF massive MIMO is proposed. A DNN is adopted and trained in an unsupervised manner to learn user power allocations. An online learning stage is further introduced to maximize the minimum user rate.	<ul style="list-style-type: none"> ▪ The proposed DNN achieves comparable performance to the optimization-based max-min power control. ▪ The online complexity is relatively low due to a fairly simpler network configuration. ▪ The performance-complexity trade-off is quite modest. 	<ul style="list-style-type: none"> ▪ Processing complexity is sacrificed for improved max-min performance. ▪ Complex setups with a large number of APs and users as obtainable in practical configurations were omitted. 	2021
[140]	The performance of a CF-mMIMO having single-antenna APs and single-antenna users in the presence of imperfect CSI is investigated. An iterative	<ul style="list-style-type: none"> ▪ The proposed RMMSE precoder outperformed other existing schemes regarding bit error rate, per-user rate, and sum rate. 	<ul style="list-style-type: none"> ▪ Although the computational cost is comparable to existing techniques, there is a need for low-cost low-complex optimization techniques. 	2021

Table 9 Power control in cell-free massive MIMO (Continued)

Ref.	Focus and coverage	Key findings	Limitations	Year
	robust minimum mean-squared error (RMMSE) precoder based on generalized loading and optimal power allocation techniques based on the maximization of the minimum SINR is proposed.			

$$p_i \sum_{j=1}^M |f_{ji}|^{\zeta} = C \tag{41}$$

where C denotes a constant chosen to satisfy the power constraints. The maximum value of C is obtained as (42)

$$C = \left[\max_{1 \leq m \leq M} \sum_{k=1}^K \frac{|f_{mk}|^{\zeta}}{\sum_{j=1}^M |f_{jk}|} \right]^{-1} \tag{42}$$

Thus, the total power p_i transmitted to any UE i , for $i = 1, \dots, K$, can be written as (43)

$$p_i = \frac{1}{\sum_{j=1}^M |f_{ji}|^{\zeta}} \left[\max_{1 \leq m \leq M} \sum_{k=1}^K \frac{|f_{mk}|^{\zeta}}{\sum_{j=1}^M |f_{jk}|} \right]^{-1} \tag{43}$$

(2) Equal Receive Power Policy: This policy ensures that the average received signal power that is conditioned on \hat{D} remains the same for all UE by selecting power scaling factors. Therefore, $p_i G_{kk} = C$, for $i = 1, \dots, K$. The constant C is also selected to satisfy the power constraints. After some mathematical analysis, p_i can be obtained as (44)

Table 10 Power control optimization techniques

Utility optimization problems	Alternative optimization	SCA	GP	Bisection	SOCP	Fractional	ML-based
Max-min fairness	[79, 141–145]	-	[79, 141, 144, 145]	[146]	[147]		[138, 148, 149]
Max EE	[52]	[150, 151]	[151]	-	[150]	[152–154]	-
Max sum SE	[155]	[49, 125, 156, 157]	-	-	[49, 157]		[81, 158, 159]

$$p_i = \frac{1}{G_{ii}} \left[\max_{1 \leq m \leq M} \sum_{k=1}^K \frac{|f_{mk}|}{G_{kk}} \right]^{-1} \tag{44}$$

(3) Inverse Leakage Policy: This policy allocates lower powers to UEs to minimize the interference in the system, resulting in higher leakage to other UEs. In this policy, it is assumed that p_i is inversely proportional to $\sum_{k=1, k \neq i}^K G_{ki}$. Solving for p_i yields (45)

$$p_i = \frac{1}{\sum_{k=1, k \neq i}^K G_{ki}} \left[\max_{1 \leq m \leq M} \sum_{k=1}^K \frac{|f_{mk}|}{\sum_{j=1, j \neq k}^K G_{jk}} \right]^{-1} \tag{45}$$

NOMA-aided cell-free massive MIMO

Currently, there is a growing interest in implementing NOMA in 5G and beyond 5G systems due to its attractive SE gains and potential to support low latency massive connectivity. NOMA technique, a paradigm shift from the OMA scheme, primarily seeks to allocate non-orthogonal resources to users to manage interference. Considering the enormous benefits of CF-mMIMO and NOMA, integrating these two techniques is envisioned to reap further gains. Recent research efforts on this hybrid combination are summarized in Table 11.

The channel model of a NOMA-aided CF massive MIMO system is presented. The DL channel between the k th user and the m th AP in the n th cluster, where $k \in \{1, \dots, K\}$, $m \in \{1, \dots, M\}$ and $n \in \{1, \dots, N\}$ can be expressed as (46)

$$h_{mnk} = \zeta_{mnk}^{1/2} \tilde{h}_{mnk}, \tag{46}$$

where ζ_{mnk} accounts for the large-scale fading, which changes at a prolonged rate [162]. Besides, the circularly symmetric Gaussian assigned with zero mean unit variance can be written as (47)

$$\tilde{h}_{mnk} \sim CN(0, 1) \tag{47}$$

Spectral efficiency of cell-free massive MIMO

The need to improve the SE by network service providers owing to an ever-increasing number of users and high rate expectations in B5G wireless networks cannot be over-emphasized. Interestingly, massive and dense antennae deployment has been at the forefront, and thanks to its ability to upgrade the BS hardware rather than the deployment of new BS sites. Compared to conventional massive MIMO systems, CF has a great potential of substantially improving the SE by employing additional antennas at

Table 11 NOMA-aided cell-free massive MIMO

Ref.	Focus and coverage	Key findings	Limitations	Year
[87]	This survey focuses on the capacity limit of a power-domain NOMA technique for CF massive MIMO systems. The authors emphasize that OMA would be hugely inadequate in satisfying the high demands of next-generation wireless standards, having almost reached its fundamental SE limits. To this end, the work aims at meeting the high demand for massive connectivity in future wireless systems.	<ul style="list-style-type: none"> ▪ The research revealed that CF massive MIMO-OMA outperforms the proposed model in terms of the achievable sum rate when the number of users is low, owing to intra-cluster pilot contamination and imperfect SIC. ▪ Nevertheless, NOMA can serve a large number of users than its counterpart by grouping users into clusters and at the same time outperform OMA considering the sum rate when the number of users within a cluster grows large. 	<ul style="list-style-type: none"> ▪ Guaranteeing high reliability with user-fairness is quite complex. 	2018
[29]	The authors present the performance of a NOMA-aided CF massive MIMO under stochastic AP and user locations. The goal is to maximize the achievable rate of CF systems. The imperfect SIC is explored to develop the achievable rates and the probability of successful SIC.	<ul style="list-style-type: none"> ▪ NOMA outperforms its OMA counterpart under a low path loss environment and networks with high AP density in terms of rate performance. 	<ul style="list-style-type: none"> ▪ The rate gain in NOMA diminishes as the density of AP becomes smaller. ▪ The overall rate of NOMA is generally reduced while providing reduced latency for higher path loss exponents. 	2019
[128]	The work considers the performance of a NOMA-aided CF massive MIMO with three linear precoders. The goal is to maximize the SE of the system. A closed-form expression for the achievable DL sum rate with MRT and fpZF is presented considering the effects of inter-cluster interference, intra-cluster pilot contamination, and imperfect SIC.	<ul style="list-style-type: none"> ▪ The proposed hybrid CF massive MIMO-NOMA permits more users to be supported at the same time-frequency resource than its OMA counterpart. 	<ul style="list-style-type: none"> ▪ Pilot contamination and imperfect SIC degrades the performance of NOMA considerably. 	2019
[160]	A NOMA-enabled CF massive MIMO with CB and multiple clustered users is investigated. A closed-form expression for the bandwidth efficiency (BE) assuming no DL training is presented. The work also formulates a max-min BE optimization problem, and a bisection search method is proposed to address the non-convexity of the max-min fairness problem.	<ul style="list-style-type: none"> ▪ The max-min BE is significantly enhanced with NOMA compared to OMA. 	<ul style="list-style-type: none"> ▪ Selecting the optimal mode from the set mode is mainly dependent on the length of the channel coherence time and the total number of users. 	2019
[161]	The achievable rate of a NOMA-aided CF massive MIMO underlaid below a primary massive MIMO is investigated. The goal is to address the physical challenges presented by MIMO-OMA. The work considers the effects of intra-cluster pilot contamination, inter-cluster interference, imperfect SIC, and statistical DL CSI at secondary users to develop the closed-form secondary DL sum rate.	<ul style="list-style-type: none"> ▪ The proposed underlay CF massive MIMO improves the sum rate considerably by exploiting the channel gain differences. 	<ul style="list-style-type: none"> ▪ The adverse effects of imperfect SIC and intra-cluster pilot contamination impact the system's performance severely. 	2019

Table 11 NOMA-aided cell-free massive MIMO (Continued)

Ref.	Focus and coverage	Key findings	Limitations	Year
[130]	A CF massive MIMO-NOMA employing underlay spectrum sharing is proposed. The goal is to enable massive connectivity in both primary and secondary networks. The work considers the adverse effects of primary/secondary pilot contamination, inter/intra-cluster interference, imperfect SIC, and partial CSI to develop the achievable rates of the secondary system.	<ul style="list-style-type: none"> The proposed system model enhances the number of concurrent connections significantly. Moreover, all users are served with an improved QoS compared to the equal power allocation scheme. 	<ul style="list-style-type: none"> The detrimental effects of imperfect SIC and error propagation degrade the achievable rate substantially. 	2020

users, power allocation, and the receiver filter coefficient design. Table 12 presents certain areas of application of CF massive MIMO in improving the SE.

Additionally, a closed-form expression for the UL SE of CF massive MIMO with the LS estimator is presented. In this context, spatially correlated Rayleigh fading channels are taken into consideration. The received signal $r_{u, k}$ at the CPU is expressed as (48)

$$r_{u,k} = \sum_{m=1}^M \hat{h}_{mk}^D \mathbf{x}_{u,m} = \sqrt{\rho} \sum_{k^\epsilon=1}^K \sum_{m=1}^M \sqrt{\mathbb{E}k^\epsilon} \hat{h}_{mk}^D h_{mk^\epsilon} v_{k^\epsilon} + \sum_{m=1}^M \hat{h}_{mk}^D \mathbf{y}_{u,m}. \tag{48}$$

where v_k depicts the desired signal detected by $r_{u, k}$. The received signal in (48) can be further expressed as (49)

$$r_{u,k} = DS_k \cdot v_k + BU_k \cdot v_k + \sum_{k^\epsilon \neq k}^K UI_{kk^\epsilon} \cdot v_{k^\epsilon} + NI_k, \tag{49}$$

where the desired signal (DS) is given by (50), the beamforming uncertainty gain (BU) is given by (51), the multiuser interference (UI) is given by (52), and the noise interference (NI) is given by (53).

$$DS_k \triangleq \sqrt{\rho \mathbb{E}k} \mathbb{E} \left\{ \sum_{m=1}^M \hat{h}_{mk}^D h_{mk} \right\} \tag{50}$$

$$BU_k \triangleq \sqrt{\rho \mathbb{E}k} \left(\sum_{m=1}^M \hat{h}_{mk}^D h_{mk} - \mathbb{E} \left\{ \sum_{m=1}^M \hat{h}_{mk}^D h_{mk} \right\} \right) \tag{51}$$

$$UI_{kk^\epsilon} \triangleq \sqrt{\rho} \sum_{m=1}^M \sqrt{\mathbb{E}k^\epsilon} \hat{h}_{mk}^D h_{mk^\epsilon} \tag{52}$$

$$NI_k \triangleq \sum_{m=1}^M \hat{h}_{mk}^D \mathbf{y}_{u,m} \tag{53}$$

The UL SINR of the k th user is given by (54)

Table 12 Spectral efficiency of cell-free massive MIMO

Ref.	Focus and coverage	Key findings	Limitations	Year
[55]	The work presents the effect of multi-antenna users on CF massive MIMO networks. The work aims at optimizing the multiplexing gain, as well as improving the SE. In order to achieve this, a simple CB scheme is considered. By using the max-min data power control and mutually orthogonal pilot sequence, the effect of the proposed model is analyzed.	<ul style="list-style-type: none"> ▪ In terms of per-user net throughput, the multiple antennas at both APs and users outperform a single antenna. ▪ Also, the array gain is improved while the inter-user interference is minimized. 	<ul style="list-style-type: none"> ▪ A decrease in the per-user net throughput value is imminent due to an increase in antennas per user. 	2018
[104]	A comprehensive survey of CF massive MIMO under different cooperation levels is presented. Specifically, four different levels of implementation, from fully centralized to fully distributed with arbitrary linear processing and spatially correlated fading, are examined. In addition, the achievable SE expression for the different CF implementations is presented.	<ul style="list-style-type: none"> ▪ The proposed scheme significantly outperforms cellular massive MIMO and SC systems, however, with MMSE processing. 	<ul style="list-style-type: none"> ▪ For centralized implementation with MMSE, the SE is generally minimized in the regime of fewer APs equipped with multiple antennas. ▪ Notably, the distributed implementation is marginalized and requires further improvement. 	2019
[80]	This survey characterized the UL performance of CF massive MIMO with multi-antennas at both APs and users. Motivated by the gaps in CF systems with multi-antenna users, the work aims at maximizing the UL SE using ZF combining at the APs and data power control at users.	<ul style="list-style-type: none"> ▪ The UL SE of CF systems with ZF combining is substantially improved. ▪ Integration of CF systems with maximum-ratio (MR) combining is sub-optimal compared to its ZF combining counterpart. ▪ Notably, additional antennas at users provide significant performance gain is minimal active users in the system. 	<ul style="list-style-type: none"> ▪ The results indicate that the interference increases when the number of active users grows large, and the SINR of each antenna generally decreases, which is undesirable in practice. 	2019
[85]	This work considers the impact of spatially correlated fading channels on the UL performance of CF architecture. The LS estimator is used, and a rigorous closed-form expression is designed to analyze the effects of the system's parameters-number of users. The number of APs and the fronthaul on the SE and EE is developed, considering the spatial correlation matrices and the number of APs antennas.	<ul style="list-style-type: none"> ▪ The low-complexity LS estimator optimizes the SE and EE significantly as opposed to collocated massive MIMO. ▪ A compromise between the number of APs and the number of users is essential to maximize the performance of SE and EE. ▪ In addition, the performance of SE and EE in correlated Rayleigh fading channels is sub-optimal compared to the uncorrelated Rayleigh fading channel. 	<ul style="list-style-type: none"> ▪ The system is significantly impacted by spatial correlation. 	2019
[131]	The authors considered limited-fronthaul CF massive MIMO system in the presence of quantization errors, imperfect channel acquisition, and pilot contamination. By exploiting the max algorithm and Bussgang decomposition, an optimal uniform quantization model is presented under the assumption of estimate and quantize, quantize and estimate, and decentralized scheme. Moreover, analytical	<ul style="list-style-type: none"> ▪ Only a few bits for quantization are sufficient for the limited-fronthaul CF-mMIMO to support the system's performance with perfect fronthaul. ▪ The power consumption and the SE have been shown to increase with the number of quantization bits. ▪ The exact number of bits quantifying the estimated channel at the APs and quantifying the received signal 	<ul style="list-style-type: none"> ▪ The performance of the decentralized scheme is considerably enhanced with the proposed AP assignment algorithm, however, only in the case of a large number of APs. 	2020

Table 12 Spectral efficiency of cell-free massive MIMO (Continued)

Ref.	Focus and coverage	Key findings	Limitations	Year
	expressions for the maximal SE and the EE of the system with three different linear receivers—MRC, ZF, and MMSE—are presented.	is enough to achieve optimal performance.		
[163]	The work considers improving the spectral/energy efficiency of wireless communication systems using intelligent multi-objective optimization techniques. Multi-objective genetic algorithm, multi-objective particle swarm optimization, and multi-objective differential evolution algorithms are proposed and applied at different circuit power levels.	<ul style="list-style-type: none"> The SE-EE trade-off is generally maximized with the proposed intelligent optimization scheme compared to some other schemes investigated. 	<ul style="list-style-type: none"> The SE-EE trade-off is not optimized with respect to the different number of UEs served in the network. 	2021
[164]	The authors quantitatively examined the achievable sum SE of a frequency-selective CF massive MIMO system considering the effect of imperfect CSI and phase noise (PN). Two low-complexity receivers, namely time-reversal maximum-ratio combining (TR-MRC) and time-reversal large-scale fading decoding (TR-LSFD), are employed at the CPU for data detection. Furthermore, the corresponding lower bound on the UL achievable SE of both receivers is presented.	<ul style="list-style-type: none"> Numerical results show that the TR-LSFD receiver outperforms the TR-MRC receiver in attaining higher SE. Moreover, the performance gain of the TR-LSFD receiver is mainly dependent on the number of APs and the propagation losses between APs and users. 	<ul style="list-style-type: none"> The impact of PN on the achievable sum SE and duration of data transmissions is quite severe. 	2021

$$SINR_k = \frac{\mathbb{E}\left\{ |DS_k^C| \right\}}{\mathbb{E}\left\{ |BU_k^C| \right\} + \sum_{k^{\epsilon} \neq k}^K \mathbb{E}\left\{ |LU_{kk^{\epsilon}}^C| \right\} + \mathbb{E}\left\{ |NI_k^C| \right\}} \tag{54}$$

Thus, the SE is obtained as (55)

$$SE_k^{cf} = \left(1 - \frac{\tau_p}{\tau_c} \right) \log_2 \left(1 + \frac{\rho \mathbb{E}k \left| \sum_{m=1}^M \beta_{mk} \mathbf{tr}(\mathbf{R}_{mk}) \right|}{\rho \sum_{k^{\epsilon}=1}^K \mathbb{E}k^{\epsilon} \sum_{m=1}^M \beta_{mk^{\epsilon}} \mathbf{tr}(\mathbf{R}_{mk^{\epsilon}}) + \frac{1}{\tau_p} \sum_{k^{\epsilon}=1}^K \mathbb{E}k^{\epsilon} \sum_{m=1}^M \beta_{mk^{\epsilon}} \mathbf{tr}(\mathbf{R}_{mk^{\epsilon}}) + \sum_{m=1}^M \beta_{mk} \mathbf{tr}(\mathbf{R}_{mk}) + \frac{MN}{\rho \tau_p}} \right) \tag{55}$$

Energy efficiency of cell-free massive MIMO

While state-of-the-art technologies are consistently developed to address data, QoS, and capacity demands, issues related to environmental concerns and high-power consumption are escalating rapidly. EE has become an essential criterion in designing future wireless networks, and its importance has been realized even more. The cellular configuration can deliver higher EE, and it is widely recognized as naturally energy-efficient. As a step further, the EE of CF-mMIMO has been characterized by

researchers worldwide, and several sophisticated optimization techniques and comprehensive power models have been developed accordingly. Table 13 presents a summary of research efforts and future research directions on the EE of CF-mMIMO.

Furthermore, the total EE model of a CF massive MIMO network is presented. From correspondence [168], the total power consumption can be written as (56)

$$P_{total} = P_A + P_C, \tag{56}$$

where P_A represents the power amplifier’s power consumption and P_C represents the circuit power consumption. The power consumption P_A and P_C is obtained as (57) and (58), respectively

$$P_A = \frac{1}{\zeta} \rho N_0 \sum_{k=1}^K v_k, \tag{57}$$

$$P_C = MP_f + KP_U + \sum_{k=1}^K P_{b,m}, \tag{58}$$

where ζ reflects the power amplifiers efficiency at each user, P_f denotes the fixed power consumption at each AP, P_U accounts for the power required to run circuit components at each user, and $P_{b,m}$ denotes the backhaul power consumption from the m th AP to the CPU and is expressed in the following [169, 170]

$$P_{b,m} = P_{BT} \frac{R_{b,m}}{C_{b,m}} \tag{59}$$

where P_{BT} accounts for the total power to operate the backhaul traffic at full capacity, R_b refers to the backhaul rate between the m th AP and the CPU, and C_b reflects the capacity of the backhaul link between the m th AP and the CPU. More precisely, the backhaul rate R_b can be expressed as (60)

$$R_{b,m} = \frac{2K \tau_f \sigma_m}{T_c}, \tag{60}$$

where σ_m represents the quantization bits of the m th AP. Thus, the total EE is obtained as (61)

$$E_e(v_k, \mathbf{U}_k, \sigma) = \frac{BS(v_k, \mathbf{U}_k, \sigma)}{P_{total}} \text{ (bit/Joule)} \tag{61}$$

Open research issues and lessons learned

The concept of CF massive MIMO has received considerable research efforts to understand its essential features and immense benefits. While significant progress has been made, many open questions, unresolved practical, and various deployment challenges persist, requiring substantial research efforts before realizing its promised gains. Table 14 presents an outline of some research directions in HI, signal detection, EE, channel estimation, pilot contamination, and security and privacy issues. As a step further, we highlight vital lessons learned for future research exploration in the area of CF massive MIMO.

Table 13 Energy efficiency of cell-free massive MIMO systems

Ref.	Focus and coverage	Key findings	Limitations	Year
[78]	The work aims at quantifying the improvements in EE of CF massive MIMO over cellular massive MIMO. The authors opine that service providers have ignored the EE for SE over time, which is presumed to be a prerequisite for practical energy-efficient technologies.	<ul style="list-style-type: none"> ▪ The SE and EE for cellular systems in an urban scenario with equal power and max-min power control strategies are comparable. ▪ However, CF systems with max-min power control significantly outperform those with equal power control (EPC) regarding the radiated EE. ▪ In the suburban and rural scenarios, CF-mMIMO with max-min power control improves the radiated EE considerably and optimizes the 95% likely per-user throughput alongside. 	<ul style="list-style-type: none"> ▪ The complexity and time delay in determining max-min power control for CF systems largely limits the EE. 	2018
[41]	An efficient energy management strategy for CF massive MIMO systems is examined. The authors posit that APs powered jointly by energy harvested from renewable sources and grid sources offer better performance improvement. To this end, the work aims at compensating for the intermittent and random nature of the harvested energy while ensuring optimized total grid power consumption.	<ul style="list-style-type: none"> ▪ Compared to traditional non-cooperative techniques, results obtained indicate a significant reduction in total grid power consumption. ▪ Specifically, as the SINR increases, the performance gap between the proposed scheme and the traditional systems without cooperation becomes noticeable. 	<ul style="list-style-type: none"> ▪ CF systems enabled with energy exchange capabilities generally suffer from power lows. 	2019
[88]	Presents the EE of limited backhaul links, which connects the APs to a CPU for coordination and data processing in CF massive MIMO. The authors opine that the backhaul links from the APs to the CPU are somewhat limited in capacity, presenting a major challenge. In order to address this issue, an MRC technique is proposed, where the only quantized weighted signal is forwarded to the CPU.	<ul style="list-style-type: none"> ▪ The proposed model is shown to satisfy the optimization constraints effectively. ▪ Also, the EE is considerably improved compared to equal power allocation. ▪ Moreover, an optimal number of quantization bits enhances the backhaul links' capacity and simultaneously maximizes the EE of the system. 	<ul style="list-style-type: none"> ▪ An optimal trade-off between the total number of APs and antennas per APs is required to maximize the EE. 	2019
[165]	EE maximization techniques for CF massive MIMO communication systems with fpZF precoding strategy are investigated. The work aims at mitigating inter-cell interference while enabling an optimized EE. Contrary to conventional precoding schemes, no instantaneous CSI exchange occurs among the APs.	<ul style="list-style-type: none"> ▪ The DL EE is considerably improved compared to the case with full power transmission. 	<ul style="list-style-type: none"> ▪ It is mainly sub-optimal in real-time applications. 	2019
[166]	This survey considers power optimization techniques to maximize the total EE in CF-mMIMO. The authors remark that energy consumption in communication systems has expanded rapidly owing to increasing growth in information.	<ul style="list-style-type: none"> ▪ The proposed algorithm converges quickly, thereby validating its effectiveness. ▪ The total EE is considerably improved compared to the EPC scheme. 	<ul style="list-style-type: none"> ▪ Although the proposed novel path-following algorithm provides low complexity and a modest performance gain, it is not fully optimized. 	2019

Table 13 Energy efficiency of cell-free massive MIMO systems (*Continued*)

Ref.	Focus and coverage	Key findings	Limitations	Year
	In order to boost the EE, a pilot-contaminated UL CF system assuming a ZF receiver is analyzed.			
[132]	Strategies to maximize the overall power consumed in CF systems without compromising the SE are investigated. The authors consider the possibility of turning off inactive APs after SE requirements have been fully satisfied, thereby optimizing EE.	<ul style="list-style-type: none"> ▪ Significant power reduction is achieved by turning off inactive APs after users' SE requirements have been fully satisfied. ▪ The developed sparsity-based method minimizes the total power consumption in CF massive MIMO network. 	<ul style="list-style-type: none"> ▪ The proposed scheme is primarily limited by high complexity. 	2020
[37]	The work presents a CF massive MIMO system enabled with energy exchange capabilities and powered by independent micro-grids. The work aims at offsetting power consumption costs while ensuring maximized EE. A minimization problem of total grid power consumption is developed with reference to users' QoS constraints and energy exchange constraints.	<ul style="list-style-type: none"> ▪ The EE is considerably improved compared to the case of traditional non-cooperative techniques 	<ul style="list-style-type: none"> ▪ A closer look indicates that there is a performance gap between the proposed algorithm and the optimal AP selection, and user scheduling is quite significant and requires further optimization. 	2020
[42]	This research considered integrating the new revolutionary technology called RIS in a CF system to maximize the network EE, considering the impact of limited backhaul capacity. An alternating descent algorithm based on the inner approximation (IA) framework is proposed to tackle the computationally intractable nonconvex optimization problem.	<ul style="list-style-type: none"> ▪ The alternating descent algorithm converges to a locally optimal solution. ▪ The authors proposed the RIS-CF network, which is shown to improve the EE greatly compared to the schemes considered. 	<ul style="list-style-type: none"> ▪ The trade-off between the total sum rate and power consumption is not fully optimized. 	2021
[167]	This survey considered the EE of an mMIMO-NOMA network with WPT. Novel joint transmits power, antenna selection WPT, time and subcarrier resource allocation schemes are proposed to solve the EE maximization problem. A distributed ADMM-based resource allocation algorithm is also adapted to provide an optimal solution to the problem.	<ul style="list-style-type: none"> ▪ Compared to alternative schemes, the EE is substantially improved with the proposed distributed ADMM-based algorithm. 	<ul style="list-style-type: none"> ▪ Channel estimation error greatly impacts the system's performance. ▪ Practical and implementable scenarios were omitted. 	2021

Lessons learned

In this section, a comprehensive summary of lessons learned from this survey is presented. The summary covers CF massive MIMO, mmWave, Terahertz, EE, NOMA, security and privacy, HI, and SWIPT, as outlined briefly.

Lesson one

The current wireless network infrastructure is faced with unprecedented demand for ultra-reliability and higher data rates. CF massive MIMO, where many APs are densely

Table 14 Open research issues in cell-free massive MIMO

Open research issues	Brief explanation
Hardware impairments	Most literature on CF-mMIMO has centered on perfect hardware components, which are unrealistic in practice due to high financial cost, bulkiness, and energy-hungry devices [171]. Achieving ideal hardware in both transceiver and receiver under practical implementation remains a general challenge. In order to alleviate this detrimental imperfection, an insight into the impact of RF impairments and ADCs imperfections on CF massive MIMO systems is presented in [84]. Results obtained show that the hardware expenses can be minimized by limiting the quality of transceiver RF chains and the quantization bits of low-resolution ADCs, however, at the cost of significant performance degradation. The effect of HI on the performance of CF-mMIMO has been considered extensively [134, 135]. The adverse impact of HI at UE is not well accounted for, though the SE is shown to be significantly boosted as the hardware qualities increase. Further research is required to investigate the detrimental influence of HI.
Channel estimation	Acquiring CSI is an important part of any telecommunication system for resource allocation and detecting user signals. Unfortunately, the complex architecture of the transceiver and the plethora of distributed antennas in CF massive MIMO has made channel estimation quite challenging [172]. DL, ML, and compressed sensing have recently been proposed to predict statistical channel characteristics during channel estimation [173–176]. Thus, obtaining an efficient estimation method is one of the crucial areas requiring further investigation.
Security and privacy	The security and privacy of user data are essential in deploying 5G and B5G wireless networks due to the need to support billions of connected devices and deliver reliable Gigabit connection speeds [177]. As a result, investigations toward finding new approaches to improve trust and security of future wireless networks are exciting for research. More precisely, combining quantum communication (frequencies higher than 300 GHz) with CF massive MIMO is an excellent area worthy of further investigation.
Signal detection	In massive MIMO systems, signal detection requires sophisticated processing due to the massive number of antennas, thus incurring a high computational complexity. High-quality research aimed at obtaining an optimal trade-off between computational complexity and its performance has been proposed [178]. To further downplay this challenge, ML, deep learning-based techniques, sphere decoder, and SIC techniques have been explored for signal detection [9, 179, 180]. The design of cutting-edge signal detection algorithms is an exciting area calling for further research.
Pilot contamination	Here, non-orthogonal pilot sequences need to be employed by the users due to the limited length of the coherence interval in the UL training phase. This, in turn, causes a so-called severe effect identified as pilot contamination which presents a significant bottleneck to the performance of CF massive MIMO [85, 101, 181, 182]. Specifically, the channel hardening effect is primarily affected by pilot contamination, particularly for a small coverage area [64]. The authors in [128] demonstrated that pilot contamination severely impacts the performance of CF-mMIMO-NOMA considerably. A new insightful pilot assignment scheme utilizing graph coloring is investigated in [183]. Indeed, the throughput is improved dramatically with the proposed graph coloring-based pilot assignment scheme. At the same time, a modest throughput complexity trade-off is obtained. To further optimize the performance of CF massive MIMO, developing optimal models that reduce the effect of pilot contamination is an interesting area worthy of further investigation.
Energy efficiency	EE has become a major concern for network operators owing to increased power consumption, carbon emissions, and global warming related to wireless communication technologies. Although CF massive MIMO is a natively greener technology than its cellular counterpart, power consumption in 5G networks is relatively higher than 4G networks [78, 184]. In order to address the crucial demanding green specifications, simplified deployment, and efficient energy-saving in next-generation wireless systems; there is a need for more advanced, low complexity, and low-cost optimization models and algorithms for greener CF massive MIMO systems.

deployed across the entire coverage area linked to a CPU, has been proposed to address this problem. However, there are still issues to contend with in network management, hardware design, and practical implementation of CF-mMIMO.

Lesson two

By a careful analysis of the current 5G wireless systems, employing the highly congested microwave frequency band spanning from about 300 MHz to 6 GHz alongside the use of large-scale antenna arrays may not be sufficient to satisfy the demands for increased throughput, ubiquitous QoS, and ubiquitous connectivity. The so-called mmWave frequency band, though a promising physical layer solution to the envisioned beyond 5G wireless communication network, is susceptible to high molecular absorption. This lends the terahertz band a natural candidate for 6G wireless networks. However, distance is a major problem in terahertz communication. However, the combined use of an ultra-dense wireless network, CF-mMIMO, and the less-congested terahertz

band is a crucial enabler to much larger bandwidths and a basic pillar to sustain the SE and EE. Terahertz-enabled CF-mMIMO will be a key enabler for next-generation wireless communication systems.

Lesson three

Compared to earlier generations of wireless communication networks, the total power consumption of 5G and beyond-5G systems have increased greatly. This is primarily due to the higher density of APs, larger bandwidths, and larger antenna numbers, resulting in increased environmental and economic concerns. Thus, EE has become a critical requirement in the design of emerging wireless networks. In order to address this issue, highly comprehensive power models, efficient energy management strategies, and more sophisticated optimization techniques are required. Specifically, these systems may be enabled with energy harvesting and energy exchange capabilities. The grid source will be incorporated to compensate for the random and intermittent nature of the harvested energy owing to uncontrollable environmental conditions. Also, the possibility of turning off inactive APs is another useful technique to improve the overall EE of CF massive MIMO systems.

Lesson four

An indispensable candidate technique for next-generation wireless standards is NOMA. The power domain-based concept represents a paradigm shift from OMA, which is fast approaching its fundamental SE limit. An interplay of the distinctive benefits of NOMA and CF massive MIMO is expected to substantially boost the system's performance with respect to bandwidth efficiency, spectral and energy efficiency, massive connectivity with low latency, and concurrent transmission from multiple users. Nonetheless, the additional hardware complexity due to error propagation and SIC processing is undesirable in practice. In order to tackle the trade-off between complexity and performance (sum rate), high-quality optimization techniques are required.

Lesson five

From the inception of wireless communication networks, security and privacy threats have been a real concern for network operators. With the deployment of 5G and the emerging beyond 5G systems to support billions of connected devices and drive high user mobility, threats to availability and integrity of networks, besides the growing concerns for user privacy, will become more visible. The security threat is envisaged to be greater than ever. There is a need for advanced cryptographic schemes to provide a robust security architecture in wireless networks to protect user privacy. More needs to be done in blockchain technology and quantum communication to tackle the confidentiality and privacy threats posed to future wireless networks.

Lesson six

Deployment of CF massive MIMO depends on multiple antenna elements, which increase the system complexity, energy consumption, and hardware design cost. By using low-cost components, the hardware imperfections increase, which is detrimental to the overall system's performance. These imperfections consisting of phase noise, I/Q

imbalance, amplifier non-linearities, and more are referred to as HIs. There is a need for an optimal trade-off between the quality of the transceiver hardware design and cost. Additionally, there is a need for suitable compensation algorithms to minimize the effects of HI.

Lesson seven

Compared to traditional energy storage methods, SWIPT is considered a potential solution to ease the transmission rate and minimize the energy consumed by battery-powered devices. However, the exponential growth in the number of connected devices coupled with the issues posed by mmWave communication in 5G-aided SWIPT networks presents an entirely new challenge. Therefore, there is a need to find proper allocation schemes to optimize the rate-energy trade-off between information retention and energy allocation.

Conclusions

Cell-free massive MIMO has been proposed as a novel architecture to address the ever-increasing demands for high SE, coverage probability, green output, and uniformly distributed throughput for all network users. In the ubiquitous 5G and the envisioned beyond 5G wireless communication systems, CF-mMIMO enables the deployment of dense APs over a wide network area to communicate with several UEs cooperatively. Motivated by the distinctive benefits of CF-mMIMO, this paper attempted to give a concise survey of the design, application scenarios, potentials, and deployment challenges of this disruptive technology. The system model of CF-mMIMO, covering the UL/DL pilot-aided channel estimation, UL/DL training, and channel hardening, is discussed elaborately. Additionally, the performance characteristics of CF-mMIMO using key design metrics like EE, channel hardening, SE, and more, are discussed extensively. Furthermore, the viable application areas of CF-mMIMO are outlined, and an up-to-date review of key findings and current research trends in CF-mMIMO is presented. Finally, open research issues and key take-away lessons are drawn from the survey to explore this exciting area of wireless communications systems deeply.

Abbreviations

5G: Fifth generation; 6G: Sixth generation; ADC: Analog-to-digital converter; ADMM: Alternating direction method of multipliers; AI: Artificial intelligence; ANN: Artificial neural networks; AP: Access point; B5G: Beyond 5G; BE: Bandwidth efficiency; BS: Base station; BU: Beamforming uncertainty gain; CB: Conjugate beamforming; CDF: Cumulative distribution function; CF: Cell-free; CS: Central station; CPU: Central processing unit; CSI: Channel state information; DCC: Dynamic cooperation cluster; DE: Deterministic equivalent; DL: Downlink; DNN: Deep neural network; DRX: Discontinuous reception; DS: Desired signal; ECB: Enhanced bormalized conjugate beamforming; EE: Energy efficiency; EMCF: Estimate-multiply-compress-forward; EPC: Equal power control; EW-MMSE: Element-wise minimum mean-squared error; FD: Full-duplex; FL: Federated learning; fpZF: Full-pilot zero-forcing; GP: Geometric programming; HD: Half-duplex; HI: Hardware impairment; IA: Inner approximation; IoT: Internet of Things; I/Q: In-phase/quadrature; JT-CoMP: Joint transmission coordinated multi-point; LMMSE: Linear minimum mean-squared error; LOS: Line-of-sight; LS: Least-square; LTE: Long-term evolution; MF: Matched filtering; MIMO: Multiple input multiple output; ML: Machine learning; mMIMO: Massive MIMO; MMSE: Minimum mean-squared error; MR: Maximum ratio; MRC: Maximum ratio combining; MRT: Maximum ratio transmission; MS: Mobile station; M2M: Machine-to-machine; NCB: Normalized conjugate beamforming; NI: Noise interference; NOMA: Non-orthogonal multiple-access; OBC: Optimal backhaul combining; OMA: Orthogonal multiple-access; PA-MMSE: Phase-aware minimum mean-squared error; PN: Phase noise; PPP: Poisson point process; QoS: Quality of service; RIS: Reconfigurable intelligent surface; RI: Residual self-interference; RF: Radio frequency; RMMSE: Robust minimum mean-squared error; RZF: Regularized zero-forcing; SC: Small-cell; SCA: Successive convex approximation; SE: Spectral efficiency; SIC: Successive interference cancelation; SINR: Signal-to-interference-plus-noise ratio; SLNR: Signal-to-leakage-and-noise ratio; SOCP: Second-order cone program; SNR: Signal-to-noise ratio; SWIPT: Simultaneous wireless information and power transfer; TDD: Time-division duplex; TR-LSFD: Time-reversal large-scale fading decoding; TR-MRC: Time-reversal maximum-ratio combining; TS: Tabu search; UE: User equipment; UI: Multiuser interference; UL: Uplink; WPT: Wireless power transfer; ZF: Zero-forcing

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References

1. Bhuvaneshwari P, Nithyanandan L (2018) Improving energy efficiency in backhaul of LTE-A network with base station cooperation. *Proc Comput Sci* 143. <https://doi.org/10.1016/j.procs.2018.10.378>
2. Saad W, Bennis M, Chen M (2019) A vision of 6G wireless systems: applications, trends, technologies, and open research problems. *IEEE Netw*. <https://doi.org/10.1109/MNET.001.1900287>
3. Ngo HQ, Ashikhmin A, Yang H, Larsson EG, Marzetta TL (2017) Cell-free massive MIMO versus small cells. *IEEE Transact Wireless Commu* 16(3):1834–1850. <https://doi.org/10.1109/TWC.2017.2655515>
4. Gangakhedkar S, Cao H, Ali AR, Ganesan K, Gharba M, Eichinger J (2018) Use cases, requirements and challenges of 5G communication for industrial automation. <https://doi.org/10.1109/ICCW.2018.8403588>
5. Gandotra P, Jha RK (2017) A survey on green communication and security challenges in 5G wireless communication networks. *J Network Comp Appl* 96. <https://doi.org/10.1016/j.jnca.2017.07.002>
6. Imoize AL, Adedeji O, Tandiya N, Shetty S (2021) 6G enabled smart infrastructure for sustainable society: opportunities, challenges, and research roadmap. *Sensors* 21(5):1709. <https://doi.org/10.3390/s21051709>
7. Bhat JR, AlQahtani SA (2021) 6G ecosystem: current status and future perspective. *IEEE Access* 10(6). <https://doi.org/10.1109/access.2021.3054833>
8. Rajatheva N et al (2020) White paper on broadband connectivity in 6G, pp 1–46
9. Chataut R, Akl R (2020) Massive MIMO systems for 5G and beyond networks—overview, recent trends, challenges, and future research direction. *Sensors (Switzerland)* 20(10). <https://doi.org/10.3390/s20102753>
10. Hoang TM, Ngo HQ, Duong TQ, Tuan HD, Marshall A (2018) Cell-free massive MIMO networks: optimal power control against active eavesdropping. *IEEE Trans Commun* 66(10):4724–4737. <https://doi.org/10.1109/TCOMM.2018.2837132>
11. Bjornson E, Sanguinetti L (2019) A new look at cell-free massive MIMO: making it practical with dynamic cooperation. <https://doi.org/10.1109/PIMRC.2019.8904101>
12. Demir ÖT, Björnson E, Sanguinetti L (2021) Foundations of user-centric cell-free massive MIMO. *Found Trends Signal Process* 14(3–4). <https://doi.org/10.1561/2000000109>
13. Akyildiz IF, Han C, Nie S (2018) Combating the distance problem in the millimeter wave and terahertz frequency bands. *IEEE Commun Mag* 56(6):102–108. <https://doi.org/10.1109/MCOM.2018.1700928>
14. Sun J, Chang H, Gao X, Wang CX, Huang J (2020) Multi-frequency multi-scenario millimeter wave MIMO channel measurements and modeling for B5G wireless communication systems. *IEEE J Sel Areas Commun* 38(9):2010–2025
15. MacCartney GR, Rappaport TS (2019) Millimeter-wave base station diversity for 5G coordinated multipoint (CoMP) applications. *IEEE Trans Wirel Commun* 18(7):3395–3410. <https://doi.org/10.1109/TWC.2019.2913414>
16. Akyildiz IF, Jornet JM, Han C (2014) Terahertz band: next frontier for wireless communications. *Phys Commun* 12:16–32. <https://doi.org/10.1016/j.phycom.2014.01.006>
17. Petrov V, Pyattaev A, Moltchanov D, Koucheryavy Y (2016) Terahertz band communications: applications, research challenges, and standardization activities. *Int Congr Ultra Mod Telecommun Control Syst Work* 2016:183–190. <https://doi.org/10.1109/ICUMT.2016.7765354>
18. Chaccour C, Soorki MN, Saad W, Bennis M, Popovski P, Debbah M (2021) Seven defining features of terahertz (THz) wireless systems: a fellowship of communication and sensing. 1(4) Available: <http://arxiv.org/abs/2102.07668>

19. Nawaz SJ, Sharma SK, Wyne S, Patwary MN, Asaduzzaman M (2019) Quantum machine learning for 6G communication networks: state-of-the-art and vision for the future. *IEEE Access* 7(c):46317–46350. <https://doi.org/10.1109/ACCESS.2019.2909490>
20. Cacciapuoti AS, Caleffi M, Tafuri F, Cataliotti FS, Gherardini S, Bianchi G (2020) Quantum internet: networking challenges in distributed quantum computing. *IEEE Netw* 34(1):137–143. <https://doi.org/10.1109/MNET.001.1900092>
21. Wu Q, Zhang R (2020) Towards smart and reconfigurable environment: intelligent reflecting surface aided wireless network. *IEEE Commun Mag* 58(1):106–112. <https://doi.org/10.1109/MCOM.001.1900107>
22. Wu Q, Zhang R (2019) Intelligent reflecting surface enhanced wireless network via joint active and passive beamforming. *IEEE Trans Wirel Commun* 18(11):5394–5409. <https://doi.org/10.1109/TWC.2019.2936025>
23. Huang C, Zappone A, Alexandropoulos GC, Debbah M, Yuen C (2019) Reconfigurable intelligent surfaces for energy efficiency in wireless communication. *IEEE Trans Wirel Commun* 18(8):4157–4170. <https://doi.org/10.1109/twc.2019.2922609>
24. Tang W, Chen MZ, Chen X, Dai JY, Han Y, di Renzo M, Zeng Y, Jin S, Cheng Q, Cui TJ (2021) Wireless communications with reconfigurable intelligent surface: path loss modeling and experimental measurement. *IEEE Trans Wirel Commun* 20(1):421–439. <https://doi.org/10.1109/TWC.2020.3024887>
25. Ngo HQ, Ashikhmin A, Yang H, Larsson EG, Marzetta TL (2015) Cell-free massive MIMO: uniformly great service for everyone. <https://doi.org/10.1109/SPAWC.2015.7227028>
26. Interdonato G, Björnson E, Quoc Ngo H, Frenger P, Larsson EG (2019) Ubiquitous cell-free massive MIMO communications. *EURASIP J Wirel Commun Netw* 1(1):2019. <https://doi.org/10.1186/s13638-019-1507-0>
27. Buzzi S, D'andrea C, Zappone A, D'elia C (2020) User-centric 5G cellular networks: resource allocation and comparison with the cell-free massive MIMO approach. *IEEE Trans Wirel Commun*. <https://doi.org/10.1109/TWC.2019.2952117>
28. Ngo HQ, Tran LN, Duong TQ, Matthaiou M, Larsson EG (2017) Energy efficiency optimization for cell-free massive MIMO. <https://doi.org/10.1109/SPAWC.2017.8227722>
29. Zhu WP, Ajib W, Amarasuriya G, Kusaladharna S (2019) Achievable rate analysis of NOMA in cell-free massive MIMO: a stochastic geometry approach. <https://doi.org/10.1109/ICC.2019.8761506>
30. Lu L, Li GY, Swindlehurst AL, Ashikhmin A, Zhang R (2014) An overview of massive MIMO: benefits and challenges. *IEEE J Selected Topics Signal Process* 8(5):742–758. <https://doi.org/10.1109/JSTSP.2014.2317671>
31. Björnson E, Zakhour R, Gesbert D, Ottersten B (2010) Cooperative multicell precoding: rate region characterization and distributed strategies with instantaneous and statistical CSI. *IEEE Trans Signal Process*. <https://doi.org/10.1109/TSP.2010.2049996>
32. Nayebi E, Ashikhmin A, Marzetta TL, Yang H, Rao BD (2017) Precoding and power optimization in cell-free massive MIMO systems. *IEEE Trans Wirel Commun*. <https://doi.org/10.1109/TWC.2017.2698449>
33. Nayebi E, Ashikhmin A, Marzetta TL, Yang H (2016) Cell-free massive MIMO systems. <https://doi.org/10.1109/ACSSC.2015.7421222>
34. Boughaci D (2021) Solving optimization problems in the fifth generation of cellular networks by using meta-heuristics approaches. *Proc Comput Sci* 182. <https://doi.org/10.1016/j.procs.2021.02.008>
35. Hamdi R, Driouch E, Ajib W (2017) Energy management in hybrid energy large-scale MIMO systems. *IEEE Trans Veh Technol* 66(11). <https://doi.org/10.1109/TVT.2017.2757401>
36. Alamu O, Gbenga-Ilori A, Adelabu M, Imoize A, Ladipo O (2020) Energy efficiency techniques in ultra-dense wireless heterogeneous networks: an overview and outlook. *Eng Sci Technol an Int J* 23(6):1308–1326. <https://doi.org/10.1016/j.jestch.2020.05.001>
37. Hamdi R, Qaraqe M (2020) Power allocation and cooperation in cell-free massive MIMO systems with energy exchange capabilities. <https://doi.org/10.1109/VTC2020-Spring48590.2020.9129410>
38. Piovesan N, Fernandez Gambin A, Miozzo M, Rossi M, Dini P (2018) Energy sustainable paradigms and methods for future mobile networks: a survey. *Comput Commun* 119. <https://doi.org/10.1016/j.comcom.2018.01.005>
39. Mahapatra R, Nijssure Y, Kaddoum G, Ul Hassan N, Yuen C (2016) Energy efficiency tradeoff mechanism towards wireless green communication: a survey. *IEEE Commun Surv Tutor* 18(1):686–705. <https://doi.org/10.1109/COMST.2015.2490540>
40. Zuo J, Zhang J, Yuen C, Jiang W, Luo W (2016) Energy efficient downlink transmission schemes for multi-cell massive distributed antenna systems. *IEEE Vehicular Technol Conf* 2016. <https://doi.org/10.1109/VTCSpring.2016.7504221>
41. Hamdi R, Qaraqe M (2019) Energy cooperation in renewable-powered cell-free massive MIMO systems. <https://doi.org/10.1109/APCC47188.2019.9026523>
42. Le QN, Nguyen VD, Dobre OA, Zhao R (2021) Energy efficiency maximization in RIS-aided cell-free network with limited backhaul. *IEEE Commun Lett*. <https://doi.org/10.1109/LCOMM.2021.3062275>
43. Li S, Duo B, Yuan X, Liang Y-C, Di Renzo M (2020) Reconfigurable intelligent surface assisted UAV communication: joint trajectory design and passive beamforming. *IEEE Wirel Commun Lett* 2337(c):1–720. <https://doi.org/10.1109/lwc.2020.2966705>
44. Amarasuriya G, Larsson EG, Poor HV (2016) Wireless information and power transfer in multiway massive MIMO relay networks. *IEEE Trans Wirel Commun* 15(6). <https://doi.org/10.1109/TWC.2016.2530067>
45. Varshney LR (2008) Transporting information and energy simultaneously. <https://doi.org/10.1109/ISIT.2008.4595260>
46. Ding Z et al (2015) Application of smart antenna technologies in simultaneous wireless information and power transfer. *IEEE Commun. Mag* 53(4). <https://doi.org/10.1109/MCOM.2015.7081080>
47. Xia X, Zhang D, Xu K, Ma W, Xu Y (2015) Hardware impairments aware transceiver for full-duplex massive MIMO relaying. *IEEE Trans Signal Process*. 63(24). <https://doi.org/10.1109/TSP.2015.2469635>
48. Zhang J, Wei Y, Björnson E, Han Y, Jin S (2018) Performance analysis and power control of cell-free massive MIMO systems with hardware impairments. *IEEE Access*. <https://doi.org/10.1109/ACCESS.2018.2872715>
49. Zhang Y, Cao H, Zhou M, Li L, Yang L (2020) Power optimization in cell-free massive MIMO with non-ideal hardware transceiver. *Chin J Electron* 29(1). <https://doi.org/10.1049/cje.2019.12.005>
50. Zhang J, Dai L, He Z, Jin S, Li X (2017) Performance analysis of mixed-ADC massive MIMO systems over rician fading channels. *IEEE J Sel Areas Commun* 35(6). <https://doi.org/10.1109/JSAC.2017.2687278>
51. Zhang J, Dai L, Sun S, Wang Z (2016) On the spectral efficiency of massive MIMO systems with low-resolution ADCs. *IEEE Commun Lett* 20(5). <https://doi.org/10.1109/LCOMM.2016.2535132>

52. Alonzo M, Buzzi S, Zappone A, D'Elia C (2019) Energy-efficient power control in cell-free and user-centric massive MIMO at millimeter wave. <https://doi.org/10.1109/TGCN.2019.2908228>
53. Mai TC, Ngo HQ, Egan M, Duong TQ (2018) Pilot power control for cell-free massive MIMO. *IEEE Trans Veh Technol*. <https://doi.org/10.1109/TVT.2018.2867606>
54. Chen Z, Bjornson E (2018) Channel hardening and favorable propagation in cell-free massive MIMO with stochastic geometry. *IEEE Trans Commun*. <https://doi.org/10.1109/TCOMM.2018.2846272>
55. Mai TC, Quoc Ngo H, Duong TQ (2019) Cell-free massive MIMO systems with multi-antenna users. <https://doi.org/10.1109/GlobalSIP.2018.8646330>
56. Gkonis PK, Trakadas PT, Kaklamani DI (2020) A comprehensive study on simulation techniques for 5G networks: state of the art results, analysis, and future challenges. *Electronics (Switzerland)* 9(3). <https://doi.org/10.3390/electronics9030468>
57. Memon ML, Maheshwari MK, Saxena N, Roy A, Shin DR (2019) Artificial intelligence-based discontinuous reception for energy saving in 5G networks. *Electron*. 8(7). <https://doi.org/10.3390/electronics8070778>
58. Alkhateeb A, Alex S, Varkkey P, Li Y, Qu Q, Tujkovic D (2018) Deep learning coordinated beamforming for highly-mobile millimeter wave systems. *IEEE Access* 6. <https://doi.org/10.1109/ACCESS.2018.2850226>
59. Lee W, Kim M, Cho DH (2018) Deep power control: transmit power control scheme based on convolutional neural network. *IEEE Commun Lett* 22(6). <https://doi.org/10.1109/LCOMM.2018.2825444>
60. Luo C, Ji J, Wang Q, Yu L, Li P (2018) Online power control for 5G wireless communications: a deep q-network approach. *IEEE Int Conf Commun* 2018. <https://doi.org/10.1109/ICC.2018.8422442>
61. Zhou P, Fang X, Wang X, Long Y, He R, Han X (2019) Deep learning-based beam management and interference coordination in dense mmWave networks. *IEEE Trans Veh Technol* 68(1). <https://doi.org/10.1109/TVT.2018.2882635>
62. Chen Z, Bjoernson E (2018) Can We Rely on Channel Hardening in Cell-Free Massive MIMO? <https://doi.org/10.1109/GLOCOMW.2017.8269162>
63. Ojo S, Imoize A, Alienyi D (2021) Radial basis function neural network path loss prediction model for LTE networks in multitransmitter signal propagation environments. *Int J Commun Syst* 34(e4680):1–26. <https://doi.org/10.1002/dac.4680>
64. Polegre AA, Riera-Palou F, Femenias G, Armada AG (2020) New insights on channel hardening in cell-free massive MIMO networks. <https://doi.org/10.1109/ICWorkshops49005.2020.9145215>
65. Tu LT, Di Renzo M (2017) Analysis of millimeter wave cellular networks with simultaneous wireless information and power transfer. <https://doi.org/10.1109/SIGTELCOM.2017.7849792>
66. Liao Y, Zhang J, Zhang Y, Chen M, Li Q, Han T (2016) Performance analysis of K-tier cellular networks with time-switching energy harvesting. <https://doi.org/10.1109/PIMRC.2016.7794611>
67. Di Renzo M, Lu W (2017) System-level analysis and optimization of cellular networks with simultaneous wireless information and power transfer: stochastic geometry modeling. *IEEE Trans Veh Technol*. <https://doi.org/10.1109/TVT.2016.2574811>
68. Shrestha R, Amarasuriya G (2018) SWIPT in cell-free massive MIMO. <https://doi.org/10.1109/GLOCOM.2018.8648129>
69. Kusaladharmas S, Zhu WP, Ajib W, Amarasuriya G (2020) Performance of SWIPT in cell-free massive MIMO: a stochastic geometry based perspective. <https://doi.org/10.1109/CCNC46108.2020.9045726>
70. Liu A, Lau VKN (2017) Joint BS-user association, power allocation, and user-side interference cancellation in cell-free heterogeneous networks. *IEEE Trans Signal Process*. <https://doi.org/10.1109/TSP.2016.2620962>
71. Interdonato G, Frenger P, Larsson EG (2019) Scalability aspects of cell-free massive MIMO. <https://doi.org/10.1109/ICC.2019.8761828>
72. Li T, Sahu AK, Talwalkar A, Smith V (2020) Federated learning: challenges, methods, and future directions. *IEEE Signal Process Mag*. <https://doi.org/10.1109/MSP.2020.2975749>
73. Brendan McMahan H, Moore E, Ramage D, Hampson S, Agüera y Arcas B (2017) Communication-efficient learning of deep networks from decentralized data
74. Tran NH, Bao W, Zomaya A, Nguyen MNH, Hong CS (2019) Federated learning over wireless networks: optimization model design and analysis. <https://doi.org/10.1109/INFOCOM.2019.8737464>
75. Wang S, Tuor T, Salonidis T, Leung KK, Makaya C, He T, Chan K (2019) Adaptive federated learning in resource constrained edge computing systems. *IEEE J Sel Areas Commun* 37(6):1205–1221. <https://doi.org/10.1109/JSAC.2019.904348>
76. Yang K, Jiang T, Shi Y, Ding Z (2020) Federated learning via over-the-air computation. *IEEE Trans Wirel Commun*. <https://doi.org/10.1109/TWC.2019.2961673>
77. Zhang X, Guo D, An K, Zhang B (2020) Secure communications over cell-free massive MIMO networks with hardware impairments. *IEEE Syst J*. <https://doi.org/10.1109/JSYST.2019.2919584>
78. Yang H, Marzetta TL (2018) Energy efficiency of massive MIMO: cell-free vs. cellular. <https://doi.org/10.1109/VTCSpring.2018.8417645>
79. Bashar M, Cumanan K, Burr AG, Ngo HQ, Debbah M, Xiao P (2019) Max-min rate of cell-free massive MIMO uplink with optimal uniform quantization. *IEEE Trans Commun* 67(10). <https://doi.org/10.1109/TCOMM.2019.2926706>
80. Mai TC, Ngo HQ, Duong TQ (2019) Uplink spectral efficiency of cell-free massive MIMO with multi-antenna users. <https://doi.org/10.1109/SIGTELCOM.2019.8696221>
81. D'Andrea C, Zappone A, Buzzi S, Debbah M (2019) Uplink power control in cell-free massive MIMO via deep learning. <https://doi.org/10.1109/CAMSAP45676.2019.9022520>
82. Ajani TS, Imoize AL, Atayero AA (2020) An overview of machine learning within embedded and mobile devices – optimizations and applications, pp 1–44
83. Ngo HQ, Tran LN, Duong TQ, Matthaiou M, Larsson EG (2018) On the total energy efficiency of cell-free massive MIMO. <https://doi.org/10.1109/TGCN.2017.2770215>
84. Zhang Y, Zhou M, Cheng Y, Yang L, Zhu H (2020) RF impairments and low-resolution ADCs for nonideal uplink cell-free massive MIMO systems. *IEEE Syst J*. <https://doi.org/10.1109/JSYST.2020.2990709>
85. Fan W, Zhang J, Bjornson E, Chen S, Zhong Z (2019) Performance analysis of cell-free massive MIMO over spatially correlated fading channels. <https://doi.org/10.1109/ICC.2019.8762051>
86. Interdonato G, Ngo HQ, Larsson EG, Frenger P (2016) On the performance of cell-free massive MIMO with short-term power constraints. <https://doi.org/10.1109/CAMAD.2016.7790362>

87. Li Y, Aruma Baduge GA (2018) NOMA-aided cell-free massive MIMO systems. *IEEE Wirel Commun Lett*. <https://doi.org/10.1109/LWC.2018.2841375>
88. Bashar M, Cumanan K, Burr AG, Ngo HQ, Larsson EG, Xiao P (2019) On the energy efficiency of limited-backhaul cell-free massive MIMO. <https://doi.org/10.1109/ICC.2019.8761134>
89. Imoize AL, Ibhaze AE, Atayero AA, Kavitha KVN (2021) Standard propagation channel models for MIMO communication systems. *Wirel Commun Mob Comput* 2021(8838792):36. <https://doi.org/10.1155/2021/8838792>
90. Ogbebor JO, Imoize AL, Atayero AA-A (2020) Energy efficient design techniques in next-generation wireless communication networks: emerging trends and future directions. *Wirel Commun Mob Comput* 2020(7235362):19. <https://doi.org/10.1155/2020/7235362>
91. Marzetta TL, Larsson EG, Yang H, Ngo HQ (2016) *Fundamentals of massive MIMO*. Cambridge: Cambridge University Press. <https://doi.org/10.1017/CBO9781316799895>
92. Björnson E, Hoydis J, Sanguinetti L (2017) Massive MIMO networks: spectral, energy, and hardware efficiency. *Foundations Trends in Signal Process* 11(3–4) Now Publishers Inc:154–655. <https://doi.org/10.1561/2000000093>
93. Larsson EG, Edfors O, Tufvesson F, Marzetta TL (2014) Massive MIMO for next generation wireless systems. *IEEE Commun Mag* 52(2):186–195. <https://doi.org/10.1109/MCOM.2014.6736761>
94. Marzetta TL (2010) Noncooperative cellular wireless with unlimited numbers of base station antennas. *IEEE Trans Wirel Commun*. <https://doi.org/10.1109/TWC.2010.092810.091092>
95. Ngo HQ, Larsson EG, Marzetta TL (2013) Energy and spectral efficiency of very large multiuser MIMO systems. *IEEE Trans Commun* 61(4):1436–1449. <https://doi.org/10.1109/TCOMM.2013.020413.110848>
96. Rusek F, Persson D, Buon Kiong Lau, Larsson EG, Marzetta TL, Tufvesson F (2013) Scaling up MIMO : opportunities and challenges with very large arrays. *IEEE Signal Process Mag* 30(1):40–60. <https://doi.org/10.1109/MSP.2011.2178495>
97. Truong KT, Heath RW (2013) The viability of distributed antennas for massive MIMO systems. https://doi.org/10.1109/A_CSSC.2013.6810508
98. Venkatesan S, Lozano A, Valenzuela R (2007) Network MIMO: overcoming intercell interference in indoor wireless systems. <https://doi.org/10.1109/ACSSC.2007.4487170>
99. Gesbert D, Hanly S, Huang H, Shamai Shitz S, Simeone O, Yu W (2010) Multi-cell MIMO cooperative networks: a new look at interference. *IEEE J Sel Areas Commun*. <https://doi.org/10.1109/JSAC.2010.101202>
100. Zhang J, Dai L, Li X, Liu Y, Hanzo L (2018) On low-resolution ADCs in practical 5G millimeter-wave massive MIMO systems. *IEEE Commun Mag* 56(7). <https://doi.org/10.1109/MCOM.2018.1600731>
101. Björnson E, Larsson EG, Debbah M (2016) Massive MIMO for maximal spectral efficiency: how many users and pilots should be allocated? <https://doi.org/10.1109/TWC.2015.2488634>
102. Yang H, Marzetta TL (2013) Total energy efficiency of cellular large scale antenna system multiple access mobile networks. <https://doi.org/10.1109/OnlineGreenCom.2013.6731024>
103. Zhang J, Chen S, Lin Y, Zheng J, Ai B, Hanzo L (2019) Cell-free massive MIMO: a new next-generation paradigm. *IEEE Access*. <https://doi.org/10.1109/access.2019.2930208>
104. Björnson E, Sanguinetti L (2020) Making cell-free massive MIMO competitive with MMSE processing and centralized implementation. *IEEE Trans Wirel Commun*. <https://doi.org/10.1109/TWC.2019.2941478>
105. Dai L, Wang B, Ding Z, Wang Z, Chen S, Hanzo L (2018) A survey of non-orthogonal multiple access for 5G. *IEEE Commun Surv Tutor* 20(3):2294–2323. <https://doi.org/10.1109/COMST.2018.2835558>
106. Yang K, Yang N, Ye N, Jia M, Gao Z, Fan R (2019) Non-orthogonal multiple access: achieving sustainable future radio access. *IEEE Commun Mag*. <https://doi.org/10.1109/MCOM.2018.1800179>
107. An J, Yang K, Wu J, Ye N, Guo S, Liao Z (2017) Achieving sustainable ultra-dense heterogeneous networks for 5G. *IEEE Commun Mag* 55(12). <https://doi.org/10.1109/MCOM.2017.1700410>
108. Zhang Z, Sun H, Hu RQ, Qian Y (2016) Stochastic geometry based performance study on 5G non-orthogonal multiple access scheme. <https://doi.org/10.1109/GLOCOM.2016.7842300>
109. Saito Y, Kishiyama Y, Benjebbour A, Nakamura T, Li A, Higuchi K (2013) Non-orthogonal multiple access (NOMA) for cellular future radio access. <https://doi.org/10.1109/VTCSpring.2013.6692652>
110. Sun Q, Han S, Chin-Lin I, Pan Z (2015) On the ergodic capacity of MIMO NOMA systems. *IEEE Wirel Commun Lett* 4(4). <https://doi.org/10.1109/LWC.2015.2426709>
111. Burr A, Bashar M, Maryopi D (2018) Ultra-dense radio access networks for smart cities: cloud-RAN, fog-RAN and ‘cell-free’ massive MIMO. arXiv
112. Gustavsson U et al (2014) On the impact of hardware impairments on massive MIMO. <https://doi.org/10.1109/GLOCOMW.2014.7063447>
113. Bacha MN, Evans JS, Hanly SV (2006) On the capacity of MIMO cellular networks with macrodiversity. <https://doi.org/10.1109/ausctw.2006.1625264>
114. Xiang Z, Tao M, Wang X (2014) Massive MIMO multicasting in noncooperative cellular networks. *IEEE J Sel Areas Commun*. <https://doi.org/10.1109/JSAC.2014.2328144>
115. Ngo HQ, Larsson EG, Marzetta TL (2014) Aspects of favorable propagation in massive MIMO. <https://doi.org/10.5281/zenodo.43970>
116. Liu P, Luo K, Chen D, Jiang T (2020) Spectral efficiency analysis of cell-free massive MIMO systems with zero-forcing detector. *IEEE Trans Wirel Commun*. <https://doi.org/10.1109/TWC.2019.2948841>
117. Huh H, Caire G, Papadopoulos HC, Ramprasad SA (2012) Achieving ‘massive MIMO’ spectral efficiency with a not-so-large number of antennas. *IEEE Trans Wirel Commun*. <https://doi.org/10.1109/TWC.2012.070912.111383>
118. Imoize AL, Orolu K, Atayero AA-A (2020) Analysis of key performance indicators of a 4G LTE network based on experimental data obtained from a densely populated smart city. *Data Br* 29(105304):1–17. <https://doi.org/10.1016/j.dib.2020.105304>
119. Shuaifei Chen BA, Zhang J, Zhang J, Björnson E (2021) A survey on user-centric cell-free massive MIMO systems
120. Kumar S, Chandrasekaran G, Kalyani S (2015) Analysis of outage probability and capacity for κ - μ / η - μ faded channel. *IEEE Commun Lett* 19(2). <https://doi.org/10.1109/LCOMM.2014.2371051>
121. Beiranvand J, Meghdadi H (2018) Analytical performance evaluation of MRC receivers in massive MIMO systems. *IEEE Access* 6. <https://doi.org/10.1109/ACCESS.2018.2866795>

122. Atapattu S, Dharmawansa P, Tellambura C, Evans J (2017) Exact outage analysis of multiple-user downlink with MIMO matched-filter precoding. *IEEE Commun Lett* 21(12). <https://doi.org/10.1109/LCOMM.2017.2749302>
123. Interdonato G, Ngo HQ, Larsson EG, Frenger P (2016) How much do downlink pilots improve cell-free massive MIMO? <https://doi.org/10.1109/GLOCOM.2016.7841875>
124. Elhoushy S, Hamouda W (2020) Performance of distributed massive MIMO and small-cell systems under hardware and channel impairments. *IEEE Trans Veh Technol*. <https://doi.org/10.1109/TVT.2020.2998405>
125. Francis J, Baracca P, Wesemann S, Fettweis G (2019) Downlink power control in cell-free massive MIMO with partially distributed access points. <https://doi.org/10.1109/VTCFall.2019.8891216>
126. Vu TT, Ngo DT, Tran NH, Ngo HQ, Dao MN, Middleton RH (2020) Cell-free massive MIMO for wireless federated learning. *IEEE Trans Wirel Commun*. <https://doi.org/10.1109/TWC.2020.3002988>
127. Vu TT, Ngo DT, Ngo HQ, Le-Ngoc T (2019) Full-duplex cell-free massive MIMO. <https://doi.org/10.1109/ICC.2019.8761711>
128. Rezaei F, Tellambura C, Tadaion AA, Heidarpour AR (2020) Rate analysis of cell-free massive MIMO-NOMA with three linear precoders. *IEEE Trans Commun*. <https://doi.org/10.1109/TCOMM.2020.2978189>
129. Nguyen TK, Nguyen HH, Tuan HD (2020) Max-min QoS power control in generalized cell-free massive MIMO-NOMA with optimal backhaul combining. *IEEE Trans Veh Technol*. <https://doi.org/10.1109/TVT.2020.3006054>
130. Galappaththige DL, Amarasuriya G (2020) NOMA-aided cell-free massive MIMO with underlay spectrum-sharing. <https://doi.org/10.1109/ICC40277.2020.9149105>
131. Bashar M et al (2020) Uplink spectral and energy efficiency of cell-free massive MIMO with optimal uniform quantization. *IEEE Trans Commun*. <https://doi.org/10.1109/tcomm.2020.3028305>
132. Van Chien T, Bjornson E, Larsson EG (2020) Optimal design of energy-efficient cell-free massive MIMO: joint power allocation and load balancing. <https://doi.org/10.1109/ICASSP40776.2020.9054083>
133. Interdonato G, Ngo HQ, Larsson EG (2021) Enhanced normalized conjugate beamforming for cell-free massive MIMO. *IEEE Trans Commun*. <https://doi.org/10.1109/TCOMM.2021.3055522>
134. Masoumi H, Emadi MJ (2020) Performance analysis of cell-free massive MIMO system with limited fronthaul capacity and hardware impairments. *IEEE Trans Wirel Commun*. <https://doi.org/10.1109/TWC.2019.2950316>
135. Zheng J, Zhang J, Zhang L, Zhang X, Ai B (2020) Efficient receiver design for uplink cell-free massive MIMO with hardware impairments. *IEEE Trans Veh Technol*. <https://doi.org/10.1109/TVT.2020.2975354>
136. Verenzuela D, Bjornson E, Matthaiou M (2021) Optimal per-antenna ADC bit allocation in correlated and cell-free massive MIMO. *IEEE Trans Commun*. <https://doi.org/10.1109/TCOMM.2021.3067699>
137. Zhang J, Wei Y, Bjornson E, Han Y, Li X (2017) Spectral and energy efficiency of cell-free massive MIMO systems with hardware impairments. In: 2017 9th International Conference on Wireless Communications and Signal Processing, WCSP 2017 - Proceedings, 2017. <https://doi.org/10.1109/WCSP.2017.8171057>
138. Chakraborty S, Bjornson E, Sanguinetti L (2019) Centralized and distributed power allocation for max-min fairness in cell-free massive MIMO. <https://doi.org/10.1109/IEEECONF44664.2019.9048903>
139. Nuwanthika Rajapaksha ML, Shashika Manosha KB, Rajatheva N (2021) Deep learning-based power control for cell-free massive MIMO networks. *Cent Wirel Commun Univ Oulu Finl*
140. Palhares VMT, Flores A, De Lamare RC (2021) Robust MMSE precoding and power allocation for cell-free massive MIMO systems. *IEEE Trans Veh Technol*. <https://doi.org/10.1109/tvt.2021.3072828>
141. Bashar M, Cumanan K, Burr AG, Ngo HQ, Poor HV (2018) Mixed quality of service in cell-free massive MIMO. *IEEE Commun Lett* 22(7). <https://doi.org/10.1109/LCOMM.2018.2825428>
142. Buzzi S, Zappone A (2018) Downlink power control in user-centric and cell-free massive MIMO wireless networks. In: IEEE International Symposium on Personal, Indoor and Mobile Radio Communications, PIMRC, vol 2017. <https://doi.org/10.1109/PIMRC.2017.8292293>
143. Demir ÖT, Björnson E (2021) Joint power control and LSF for wireless-powered cell-free massive MIMO. *IEEE Trans Wirel Commun* 20(3). <https://doi.org/10.1109/TWC.2020.3036281>
144. Bashar M, Cumanan K, Burr AG, Debbah M, Ngo HQ (2018) Enhanced max-min SINR for uplink cell-free massive MIMO systems. *arXiv*. p. 1-6. <https://doi.org/10.1109/ICC.2018.8422577>
145. Bashar M, Cumanan K, Burr AG, Debbah M, Ngo HQ (2019) On the uplink max-min SINR of cell-free massive MIMO systems. *IEEE Trans Wirel Commun* 18(4). <https://doi.org/10.1109/TWC.2019.2892463>
146. Zhang Y, Cao H, Yang L (2019) Max-min power optimization in multigroup multicast cell-free massive MIMO. *IEEE Wirel Commun Networking Conf* 2019. <https://doi.org/10.1109/WCNC.2019.8885776>
147. Zhou A, Wu J, Larsson EG, Fan P (2020) Max-min optimal beamforming for cell-free massive MIMO. *IEEE Commun Lett* 24(10). <https://doi.org/10.1109/LCOMM.2020.3000067>
148. Nikbakht R, Jonsson A, Lozano A (2019) Unsupervised-learning power control for cell-free wireless systems. In: IEEE International Symposium on Personal, Indoor and Mobile Radio Communications, PIMRC, 2019. <https://doi.org/10.1109/PIMRC.2019.8904394>
149. Zhao Y, Niemegeers IG, De Groot SH (2020) Power allocation in cell-free massive MIMO: a deep learning method. *IEEE Access* 8. <https://doi.org/10.1109/ACCESS.2020.2992629>
150. Nguyen LD, Duong TQ, Ngo HQ, Tourki K (2017) Energy efficiency in cell-free massive MIMO with zero-forcing precoding design. *IEEE Commun Lett* 21(8). <https://doi.org/10.1109/LCOMM.2017.2694431>
151. Bashar M, Cumanan K, Burr AG, Ngo HQ, Larsson EG, Xiao P (2019) Energy efficiency of the cell-free massive MIMO uplink with optimal uniform quantization. *IEEE Trans Green Commun Netw* 3(4). <https://doi.org/10.1109/TGCN.2019.2932071>
152. Nikbakht R, Lozano A (2019) Uplink fractional power control for cell-free wireless networks. *IEEE Int Conf Commun* 2019. <https://doi.org/10.1109/ICC.2019.8761096>
153. Papazafeiropoulos AK, Bjornson E, Kourtessis P, Chatzinotas S, Senior JM (2020) Scalable cell-free massive MIMO systems with hardware impairments. <https://doi.org/10.1109/PIMRC48278.2020.9217151>
154. Chen S, Zhang J, Bjornson E, Zhang J, Ai B (2021) Structured massive access for scalable cell-free massive MIMO systems. *IEEE J Sel Areas Commun* 39(4). <https://doi.org/10.1109/JSAC.2020.3018836>
155. Tripathi SC, Trivedi A, Rajoria S (2018) Power optimization of cell free massive MIMO with zero-forcing beamforming technique. <https://doi.org/10.1109/INFOCOMTECH.2018.8722368>

156. Nguyen TH, Nguyen TK, Han HD, Nguyen VD (2018) Optimal power control and load balancing for uplink cell-free multi-user massive MIMO. *IEEE Access* 6. <https://doi.org/10.1109/ACCESS.2018.2797874>
157. Zhang Y, Cao H, Guo Y, Yang L (2018) SCA power optimization in cell-free massive MIMO with short-term power constraints. <https://doi.org/10.1109/WCSP.2018.8555614>
158. Bashar M et al (2020) Exploiting deep learning in limited-fronthaul cell-free massive MIMO uplink. *IEEE J Sel Areas Commun* 38(8). <https://doi.org/10.1109/JSAC.2020.3000812>
159. Liang F, Shen C, Yu W, Wu F (2020) Towards optimal power control via ensembling deep neural networks. *IEEE Trans Commun* 68(3). <https://doi.org/10.1109/TCOMM.2019.2957482>
160. Bashar M, Cumanan K, Burr AG, Ngo HQ, Hanzo L, Xiao P (2019) NOMA/OMA mode selection-based cell-free massive MIMO. <https://doi.org/10.1109/ICC.2019.8761072>
161. Rezaei F, Heidarpour AR, Tellambura C, Tadaion A (2020) Underlaid spectrum sharing for cell-free massive MIMO-NOMA. *IEEE Commun Lett*. <https://doi.org/10.1109/LCOMM.2020.2966195>
162. Ashikhmin A, Li L, Marzetta TL (2018) Interference reduction in multi-cell massive MIMO systems with large-scale fading precoding. *IEEE Trans Inf Theory* 64(9). <https://doi.org/10.1109/TIT.2018.2853733>
163. GÜL BK, TAŞPINAR N (2021) Application of intelligent optimization techniques to spectral and energy efficiencies in massive MIMO systems at different circuit power levels. *Mühendislik Bilim ve Araştırmaları Derg* 3(1):102–111. <https://doi.org/10.46387/bjesr.893643>
164. Jin SN, Yue DW, Nguyen HH (2021) Spectral efficiency of a frequency-selective cell-free massive MIMO system with phase noise. *IEEE Wirel Commun Lett* 10(3). <https://doi.org/10.1109/LWC.2020.3035364>
165. Wang X, Zhou M, Qiao X, Zhang Y, Ruan X, Yang L (2019) Energy efficiency of downlink cell-free massive MIMO system with full-pilot zero-forcing. <https://doi.org/10.1109/ICC47050.2019.9064337>
166. Zhang Y, Cao H, Zhou M, Yang L (2019) Power optimization for energy efficiency in cell-free massive MIMO with ZF receiver. <https://doi.org/10.23919/ICACT.2019.8702035>
167. Wang Z, Lin Z, Lv T, Ni W (2021) Energy-efficient resource allocation in massive MIMO-NOMA networks with wireless power transfer: a distributed ADMM approach. *IEEE Internet Things J*. <https://doi.org/10.1109/JIOT.2021.3068721>
168. Björnson E, Sanguinetti L, Hoydis J, Debbah M (2015) Optimal design of energy-efficient multi-user MIMO systems: is massive MIMO the answer? 14(*IEEE Trans. Wirel. Commun.*, 6). <https://doi.org/10.1109/TWC.2015.2400437>
169. Falconetti L, Yassin E (2014) Towards energy efficiency with uplink cooperation in heterogeneous networks. <https://doi.org/10.1109/WCNC.2014.6952477>
170. Fehske AJ, Marsch P, Fettweis GP (2010) Bit per joule efficiency of cooperating base stations in cellular networks. <https://doi.org/10.1109/GLCOMM.2010.5700169>
171. Björnson E, Hoydis J, Kountouris M, Debbah M (2014) Massive MIMO systems with non-ideal hardware: energy efficiency, estimation, and capacity limits. *IEEE Trans Inf Theory* 60(11):7112–7139. <https://doi.org/10.1109/TIT.2014.2354403>
172. Hassan K, Masarra M, Zwingelstein M, Dayoub I (2020) Channel estimation techniques for millimeter-wave communication systems: achievements and challenges. *IEEE Open J Commun Soc* 1. <https://doi.org/10.1109/ojcoms.2020.3015394>
173. Ke M, Gao Z, Wu Y, Gao X, Schober R (2020) Compressive sensing-based adaptive active user detection and channel estimation: massive access meets massive MIMO. *IEEE Trans Signal Process* 68. <https://doi.org/10.1109/TSP.2020.2967175>
174. Mei K, Liu J, Zhang X, Wei J (2019) Machine learning based channel estimation: a computational approach for universal channel conditions
175. Chun CJ, Kang JM, Kim IM (2019) Deep learning-based channel estimation for massive MIMO systems. *IEEE Wirel Commun Lett* 8(4). <https://doi.org/10.1109/LWC.2019.2912378>
176. Waseem A, Naveed A, Ali S, Arshad M, Anis H, Qureshi IM (2019) Compressive sensing based channel estimation for massive mimo communication systems. *Wirel Commun Mob Comput* 2019:15. <https://doi.org/10.1155/2019/6374764>
177. Wang M, Zhu T, Zhang T, Zhang J, Yu S, Zhou W (2020) Security and privacy in 6G networks: new areas and new challenges. *Digit Commun Networks* 6(3). <https://doi.org/10.1016/j.dcan.2020.07.003>
178. Albroom MA, Juntti M, Shahabuddin S (2019) Massive MIMO detection techniques: a survey. *IEEE Commun Surv Tutor* 21(4):3109–3132. <https://doi.org/10.1109/COMST.2019.2935810>
179. Jeon YS, Lee N, Hong SN, Heath RW (2018) One-bit sphere decoding for uplink massive MIMO systems with one-bit ADCs. *IEEE Trans Wirel Commun* 17(7). <https://doi.org/10.1109/TWC.2018.2827028>
180. Elghariani A, Zoltowski M (2015) Successive interference cancellation for large-scale MIMO OFDM. *IEEE Int Conf Electro Inform Techn* 2015. <https://doi.org/10.1109/EIT.2015.7293412>
181. Akbar N, Yan S, Yang N, Yuan J (2018) Location-aware pilot allocation in multicell multiuser massive MIMO networks. *IEEE Trans Veh Technol*. <https://doi.org/10.1109/TVT.2018.2831224>
182. Liu H, Zhang J, Zhang X, Kurniawan A, Juhana T, Ai B (2020) Tabu-search-based pilot assignment for cell-free massive MIMO systems. *IEEE Trans Veh Technol*. <https://doi.org/10.1109/TVT.2019.2956217>
183. Liu H, Zhang J, Jin S, Ai B (2020) Graph coloring based pilot assignment for cell-free massive MIMO systems. *IEEE Trans Veh Technol*. <https://doi.org/10.1109/TVT.2020.3000496>
184. You X et al (2021) Towards 6G wireless communication networks: vision, enabling technologies, and new paradigm shifts. *Sci China Inform Sci* 64(1). <https://doi.org/10.1007/s11432-020-2955-6>

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