Massive MIMO

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***Abstract*—Massive MIMO has been regarded as a promising technique for 5G wireless communication networks. It equips the base station (BS) with a large number of antennas to serve a set of user equipment (UEs) simultaneously. Due to channel hardening, the uncorrelated noise and the small-scale fading can be eliminated. As a result, the transmitted signal can be focused into very focused areas, which brings orders of magnitude improvements in both spectral efficiency and energy efficiency with simple (linear) processing. In this chapter, we present a comprehensive overview of the state-of-the-art research on massive MIMO. We begin with an information theoretic analysis to illustrate the advantages of massive MIMO. Then we introduce both the physical layer and networking issues of massive MIMO. The integration of other 5G technologies with massive MIMO is also reviewed. Finally we conclude this chapter with a discussion of challenges and future research topics.**

***Index Terms*—Massive MIMO, networking, physical layer.**

I. Introduction

With the explosive data traffic growth in wireless communication networks, the Multiple-Input Multiple-Output (MIMO) technology has received tremendous interest due to its great potential in improving data throughput and link range under the same bandwidth and power usage constraints. Compared with conventional single antenna technologies, MIMO improves the spectral efficiency by leveraging the diversity and multiplexing gain [1]. Nowadays, it has been used as one of the key technologies in the Fourth Generation (4G) wireless communication systems. To further scale-up these gains, the concept of massive MIMO, where the base station is equipped with hundreds of antennas to serve dozens of user equipments (UEs) has been proposed [2]. It breaks the scalability barrier by not attempting to achieve the Shannon capacity limit, but rather, by increasing the size of the system. Both theoretical and experiment results demonstrate that massive MIMO is capable of improving the spectrum efficiency significantly while reducing the transmit power. Therefore, it is an important candidate for the next-generation (5G) wireless communication systems.

Massive MIMO can provide significant spectrum efficiency gains due to the multiplexing gain. Meanwhile, it can also improve the energy efficiency (EE) of the system. This is because the use of a large number of antennas helps to form an extremely narrow beam toward the UE's location. As a result, the transmit power of each single antenna user in a massive MIMO system can be scaled down to the number of BS antennas when perfect channel state information (CSI) is available, or to the square root of the BS antennas with imperfect CSI [3].. Moreover, when the number of antennas at the BS is increased to infinity, the effect of uncorrelated noise and small-scale fading can be eliminated. As a result, even simple linear signal processing techniques, such as *matched-filter* (MF) and zero-forcing (ZF) precoding/detection, can achieve a promising result.

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In this chapter, we provide a comprehensive survey of massive MIMO. We first demonstrate the potential of deploying a large number of antennas at the BS from the point of information theory in Section II. In Section III, we focus on massive MIMO related physical layer issues, including channel estimation, signal detection, precoding, and pilot contamination. Some non-ideal factors that limit the performance of massive MIMO, such as imperfect CSI and non-ideal hardware, are also examined. In Section IV, massive MIMO networking issues such as interference coordination, user association and scheduling, and backhaul connections are introduced. Section V presents an overview of the integration of massive MIMO with other 5G technologies, e.g., mmWave, non-orthogonal multiple access (NOMA), and RF-energy harvesting. Section VI identifies the future research trends and challenges. Finally, Section VII concludes this chapter.

II. From Regular MIMO to Massive MIMO

In this section, we review the advantages of massive MIMO from the perspective of information theory. We show that both point-to-point massive MIMO and multiuser (MU) massive MIMO have the potential to achieve its maximum channel capacity [4]. In addition, simple linear signal processing algorithms become optimal [5].

A. Point-to-point MIMO

Fig. 1 shows a point-to-point MIMO system where the transmitter and receiver are equipped with N_t and N_r antennas, respectively. The received signal, $\mathbf{y} \in \mathbb{C}^{N_r \times 1}$, can be expressed as

$$\mathbf{y} = \sqrt{\rho}\mathbf{H}\mathbf{x} + \mathbf{n}, \tag{1}$$

where ρ is the transmit power, $\mathbf{x} \in \mathbb{C}^{N_t \times 1}$ is the transmitted signal with normalized power, i.e., $\mathbb{E}\{||\mathbf{x}||^2\} = 1$, $\mathbf{n} \in \mathbb{C}^{N_r \times 1}$ is the noise and interference, and $\mathbf{H} \in \mathbb{C}^{N_r \times N_t}$ is a narrow-band time-invariant channel matrix. For a frequency-selective wide-band channel, the orthogonal-frequency division multiplexing (OFDM) technology helps to convert it into multiple parallel narrow-band subchannels. When the transmitted signals are Gaussian distributed, the achievable rate can be expressed as

$$C = \log_2 \det \left(\mathbf{I} + \frac{\rho}{N_t}\mathbf{H}\mathbf{H}^H \right). \tag{2}$$

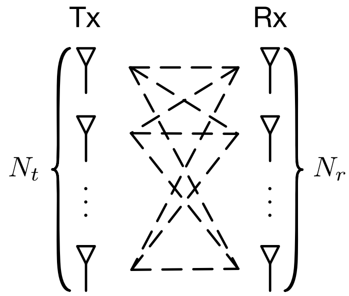

Fig. 1: point to point MIMO system

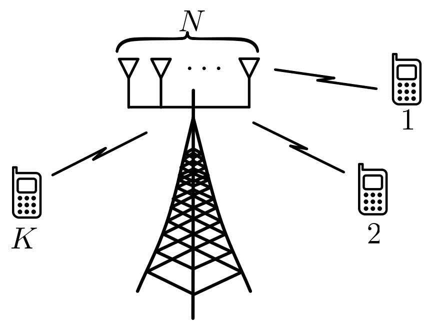

Fig. 2: MU-MIMO system

From (2), it can be seen that the achievable rate depends on the distributions of the singular values of $\mathbf{HH}^H$. Assume the channel matrix is normalized, i.e., $\text{tr}(\mathbf{HH}^H) = N_r N_t$, with the random matrix theory and Jensen's inequality, [4] shows that the achievable rate is bounded by the following bounds

$$\log_2(1+\rho N_r) \le C \le \min(N_r, N_t)\log_2\left(1 + \frac{\rho\max(N_r, N_t)}{N_t}\right). \tag{3}$$

When the singular values of $\mathbf{HH}^H$ are all equal, the highest achievable rate can be attained. When the singular values of $\mathbf{HH}^H$ only contains one non-zero value, the lowest achievable rate is attained. The best performance can be approached by a rich scattering environment, e.g., Rayleigh fading while the worse performance corresponds to a line-of-sight (LOS) transmission.

Without loss of generality, now suppose the number of transmit antennas greatly exceeds the number of receive antennas, i.e., $N_t \gg N_r$ and $N_t \to \infty$. In this case, the row vectors of the channel matrix $\mathbf{H}$ become asymptotically orthogonal, i.e., $\mathbf{HH}^N \approx N_t \mathbf{I}_{N_r}$. The achievable rate becomes

$$C \approx N_r \log_2(1+\rho), \tag{4}$$

which is exactly the upper bound in (3). Similar analysis can be done when the number of receive antennas greatly exceeds that of the transmit antennas. Hence massive point-to-point MIMO has the potential to achieve the best theoretical performance.

B. Multiuser MIMO

Multiuser MIMO (MU-MIMO) refers to a system where multiple users are served by a BS with massive antennas simultaneously using the same time-frequency resources. Fig. 2 shows an MU-MIMO system, where a BS with N antennas serves K single antenna users. The channel coefficient between the kth user to the nth antenna of the BS is denoted by $h_{k,n}$. Suppose each channel coefficient is composed of two parts, the small-scale fading part and the large-scale fading part. The large-scale fading caused by path loss are the same for different antennas at the same BS, while the small-scale fading part is different for different antennas as well as UEs. Then $h_{k,n}$ can be expressed as

$$h_{k,n} = g_{k,n}\sqrt{d_k}, \tag{5}$$

where $g_{k,n}$ and d_k represent the small-scale and large-scale fading, respectively. Then the channel matrix from all K users to the BS can be expressed as

$$\mathbf{H} = \begin{pmatrix} h_{1,1} & \cdots & h_{K,1} \\ \vdots & \ddots & \vdots \\ h_{1,N} & \cdots & h_{K,N} \end{pmatrix} = \mathbf{GD}^{\frac{1}{2}} \tag{6}$$

where

$$\mathbf{G} = \begin{pmatrix} g_{1,1} & \cdots & g_{K,1} \\ \vdots & \ddots & \vdots \\ g_{1,N} & \cdots & g_{K,N} \end{pmatrix}, \mathbf{D} = \begin{pmatrix} d_1 & & \\ & \ddots & \\ & & d_K \end{pmatrix}. \tag{7}$$

Assume the small-scale fading coefficient for different users are identically distributed and independent, then $\mathbf{G}^H\mathbf{G} \approx N\mathbf{I}_K$. As a result, the column channel vectors of the channel matrix $\mathbf{H}$ will become asymptotically orthogonal when the number of BS antennas is increased. That is

$$\mathbf{HH}^H = \mathbf{D}^{\frac{1}{2}}\mathbf{G}^H\mathbf{G}\mathbf{D}^{\frac{1}{2}} \approx N\mathbf{D}^{\frac{1}{2}}\mathbf{I}_K\mathbf{D}^{\frac{1}{2}} = N\mathbf{D}. \tag{8}$$

In massive MIMO where the number of BS antennas greatly exceeds the number of single antenna UEs, the channel vector between the BS and UEs become nearly orthogonal as shown in (8). This is called the *favorable propagation*, which is one of the key properties of massive MIMO. In this case, the system channel capacity can be expressed as

$$\begin{aligned} C &= \log_2\det\left(\mathbf{I} + \rho\mathbf{H}^H\mathbf{H}\right) & (9)\\ &\approx \log_2\det\left(\mathbf{I} + \rho N\mathbf{D}\right) & (10)\\ &= \sum_{k=1}^{K}\log_2(1 + N\rho d_k), & (11) \end{aligned}$$

where the noise power is assumed to be 1.

Now consider the uplink transmission, the received signal at the BS can be expressed as

$$\mathbf{y} = \sqrt{\rho}\mathbf{Hx} + \mathbf{n}, \tag{12}$$

where $\mathbf{x} \in \mathbb{C}^{K\times 1}$ is the signal vector from all users with $\mathbb{E}[x_k^2] = 1$ and $\mathbf{n} \in \mathbb{C}^{N\times 1}$ is the Gaussian noise vector with zero mean and identity covariance matrix. Suppose at the BS, we adopt a matched-filter (MF) receiver as

$$\begin{aligned} \mathbf{H}^H\mathbf{y} &= \mathbf{H}^H(\sqrt{\rho}\mathbf{Hx} + \mathbf{n}) \\ &= \sqrt{\rho}N\mathbf{Dx} + \mathbf{H}^H\mathbf{n}. \end{aligned} \tag{13}$$

From (13), it can be seen that the MF receiver can mitigate interference between different users, since $\mathbf{D}$ is a diagonal matrix. Hence the MIMO channel can be viewed as several parallel SISO channels. Consequently, the channel capacity in (11) can be achieved. For downlink transmission, similar analysis can also be done to show that simple signal processing techniques are optimal and can achieve channel capacity in massive MU-MIMO systems.

III. Physical Layer Technology

A. Single-cell Performance

1) Channel Estimation: Massive MIMO can work in two modes: the time-division duplexing (TDD) mode and the frequency-division duplexing (FDD) mode. The success of multi-user precoding and signal detection relies on the availability of precise CSI.

For TDD massive MIMO, in the uplink channel estimation stage, the BS can obtain an estimate of the uplink channel based on the pilots that it received from the users. The required time or frequency resource is proportional to the number of transmit antennas and is irrelevant to the number of BS antennas. In the downlink stage, channel reciprocity can be applied to obtain an estimate of the downlink CSI. Hence, it is relatively easy to do channel estimation in TDD massive MIMO. For FDD massive MIMO, in the uplink channel estimation stage, similar to TTD massive MIMO channel estimation, the required time or frequency resource is irrelevant to the number of BS antennas. However, in the downlink CSI estimation, since the uplink and downlink channel uses different frequencies, the CSIs corresponding to the uplink and downlink are different. As a result, channel reciprocity cannot be leveraged. The BS has to send pilots to all users and then all users send their estimated CSI back to the BS. The required time or frequency resource is proportional to the number of BS antennas, which becomes infeasible as the number of BS antennas goes to infinity.

Common channel estimation methods include some simple linear estimation techniques, such as zero-forcing (ZF) and minimum mean square error (MMSE) estimators. They achieve a promising result with low complexity. Furthermore, some works leverage the theory of compressed sensing [6]–[8], subspace methods [9]–[11], Bayesian estimation theory [12], [13] and so on. These methods differ in their complexity, performance metric, applied channel fading types, and the number of users.

2) Signal Detection: MIMO signal detection refers to the process to detect/decode the transmitted symbols from the received signals. It was proven to be an NP-hard problem [14], hence all algorithms that are conceived for achieving the optimal solution have an exponentially increasing complexity. As a result, the optimal maximum-likelihood (ML) criterion based MIMO detection or maximum a posterior (MAP) criterion based MIMO detection becomes excessive as the number of BS antennas goes to infinity. To solve this problem, a lot of low-complexity, yet sub-optimal MIMO detection algorithms have been proposed.

Reference [15] presents a comprehensive literature review of MIMO detection methods proposed in the past 15 years. The algorithms surveyed can be classified into two types, linear methods and non-linear methods. Linear methods include conventional ZF, MMSE, MF methods. Nonlinear methods include interference cancellation methods [16], tree-search methods [17], lattice-reduction aided methods [18], probabilistic data association (PDA) methods [19], semidefinite programming relaxation methods [20], and so on.

Recently, more advance MIMO detection methods, such as bayesian based message passing methods [21], [22] as well as convex optimization based methods [23], have been proposed. All these algorithms aim to strike a balance between performance and complexity.

3) Precoding: Just as multiuser detection ensures reliable uplink transmission, precoding at the BS guarantees reliable downlink transmission. The linear and non-linear methods that is used in uplink detection can similarly be adapted to the downlink precoding. Reference [24] presents an overview of linear massive MIMO precoding methods as well as their performance. Apart from linear precoding, many works design different types of precoding for different scenarios and present their performance analysis, e.g., hybrid precoding [25], [26], constant-evelop precoding [27], optimization based precoding [28], quantized precoding [29], and two-stage precoding [30].

B. Multi-cell Performance

1) Pilot Contamination: Consider an MU-MIMO system with L cells, where each cell has one BS with N antennas and K single antenna users as shown in Fig. 3. Without loss of generality, we consider the uplink transmission in a TDD-based massive MIMO system, where the BS receives pilot sequences from different users for uplink channel estimation. Ideally, the pilot sequences used by different users should be orthogonal so that the estimated channel vectors of different users are not correlated. However, the number of orthogonal pilot sequences is limited by the channel coherent time, which in turn limits the number of served users. As a result, pilot reuse has to be employed in different cells and the pilot sequences used by different users become correlated. The performance of the system will be limited by the interference imposed by pilot reuse. This phenomenon is know as *pilot contamination* and it is widely recognized as one of the most important factors that limit the performance of multi-cell massive MIMO systems.

Suppose each cell uses the same set of orthogonal pilot sequences and identical pilot sequences are assigned to users in neighboring cells. During uplink transmission, the BS will receive interference from undesired users. For example, in Fig. 3, the BS in cell 2 will not only receive the desired pilot sequences from UE k in cell 2, but also receive interference from users in neighboring cells. As a result, the BS in cell 2 will receive strong directional interference. The estimated channel vector in each cell will be a linear combination of channel vectors of users that adopt the same pilot sequences [5].

The performance under pilot contamination in massive MIMO is analyzed in many works, e.g., see [2], [31], [32]. Reference [2] shows that with increase of the number of BS,

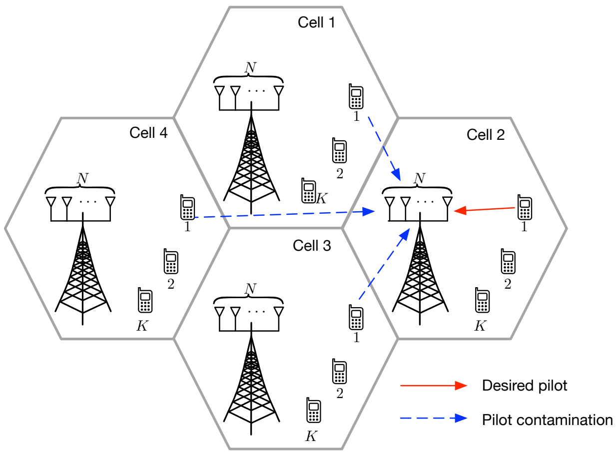

Fig. 3: An illustration of uplink pilot contamination

the fast-fading effect and intra-cell interference will disappear while the inter-cell interference caused by pilot contamination will remain. Reference [31] shows that the signal-to-interference-plus-noise (SINR) will saturate due to the inaccurate channel estimation caused by pilot contamination. Without pilot contamination, the SINR will increase linearly with the number of of antennas at the BS. Reference [32] again uses random matrix theory to show that the uplink channel estimates are prone to pilot contamination and the system performance is limited by pilot contamination. A comprehensive survey on massive MIMO pilot contamination can be found in [33].

2) Mitigating Pilot Contamination: Approaches that can mitigate pilot contamination can be classified into two categories, namely, pilot-based scheme and subspace-based scheme. In *pilot-based approaches*, the BS does not receive pilots in a non-overlapping fashion. Reference [34] proposes a time-shifted pilot transmission scheme to reduce the pilot contamination in multi-cell massive MIMO. The idea is to shift the location of the pilot sequences so that the pilot sequences for different cells do not overlap in time. Along with proper power control, this scheme can achieve a promising performance in eliminating pilot contamination. However, due to the multi-layer nature of emergence heterogeneous network, it is not easy to synchronize pilots across different cells. Pilots may always overlap in the network. Reference [35] combines both uplink and downlink training and designs a sophisticated contamination elimination scheme for multi-cell TDD and OFDM based massive MIMO systems. The BS can eliminate the pilot contamination completely by exploiting the estimated frequency-domain channel transfer function in the downlink training stage. A drawback is the training overhead will increase with the number of interfering cells.

In *subspace-based approaches*, second order statistics from the desired users and the interfering users are exploited. Reference [36] first observes that the covariance matrices of the desired users and the interference users span distinct subspaces. The exploitation of the second order statistics can lead to a complete removal of pilot contamination when the number of BS antennas goes to infinity. Based on this observation, a coordinated pilot sequence assignment strategy is proposed to offer a powerful way to discriminating across interfering users. Reference [37] performs singular value decomposition on the received signal matrix to separate the interference subspace from the desired signal space. Then a power-controlled hand-off strategy is used to mitigate pilot contamination.

In addition to the second order statistics, to further enhance the performance of pilot contamination, many works begin to use more information to enhance the performance of pilot contamination elimination, for example, the information of large-scale fading channels [38], [39] and location information [40]. Recently, Reference [41] points out that pilot contamination is no longer a limiting factor for massive MIMO system if proper precoding and combing methods are used. However, the resulting channel estimation error from pilot contamination will still degrade the system performance.

C. Non-ideal Factors

In practice, there may be many issues that cause massive MIMO performance degradation, e.g., hardware impairments and imperfect CSI [42].

1) Non-ideal Hardware: Reference [43] analyzes the capacity and estimation accuracy of massive MIMO with non-ideal hardware. The hardware impairments, including amplifier nonlinearity, I/Q imbalance, and phase noise, are modeled as additive distortion noise. Analysis shows that the hardware impairments limit the performance of massive MIMO in both single-cell and multi-cell scenarios. Despite that, massive MIMO still shows robustness to hardware impairments due to its huge degrees of freedom (DoF). For example, reference [44] shows that massive MIMO systems still achieve a high spectral efficiency under Rician fading channel with transceiver hardware impairments.

2) Imperfect CSI: Imperfect CSI can be caused by both channel estimation error and channel aging. In TDD channel estimation, due to pilot reuse in multi-cell scenarios, the estimated CSI is contaminated by interference [45]. As a result, various pilot contamination mitigation techniques have been proposed to help obtain a more accurate CSI. Besides CSI estimation errors, due to time variation of the propagation channel and delay, the CSI changes between when it is estimated at the BS and when it is used for detection and precoding, which is referred as channel aging [46]. For example, in high speed vehicles such as bullet trains, the channel various fastly. As a result, the achievable sum-rate would degrade significantly. In order to mitigate the effects of channel aging, reference [46] proposes an optimal causal linear finite impulse response (FIR) wiener predictor. The idea is to use the current and past observations to predict future CSI so that the impact of channel aging can be reduced.

IV. Networking Technology

Although physical layer massive MIMO technology provides foundations for efficient and reliable communications in practical systems, the upper layer technology also plays a vital role in harvesting an attainable performance of massive MIMO systems.

A. Interference Coordination

Interference coordination is a fundamental problem from the beginning of mobile communication. Since the 2G wireless systems, frequency reuse has been adopted to achieve a higher spectral efficiency. In future generation wireless communication systems, a more sophisticate scheme to coordinate the interference to further improve the spectral efficiency is always needed.

1) Homogeneous Networks: Homogeneous massive MIMO network is a single tier system where all the BS are working with the same access methods and type of transmissions. Fig. 3 is a typical homogeneous massive MIMO network. The BS either cooperates or non-cooperates with each other to serve a number of homogeneous UEs.

A single-cell massive MU-MIMO is the simplest homogeneous network. The main interference comes from intra-cell interference caused by neighboring UEs that work in the same time-frequency slot in the same cell. Physical layer technologies such as MU-MIMO precoding can be used to mitigate such interference. In the upper layers, appropriate user selection and scheduling schemes that decide which user should be selected for transmission at a particular time/frequency slot also contributes to alleviation of interference. For multi-cell massive MU-MIMO, the interference coordination problem becomes even more complex due to the inter-cell interference brought about by adjacent cells. In general, novel interference coordination algorithms should jointly consider user selection/scheduling, precoding/beam-forming, and resource (power/channel/frequency) allocation.

Reference [47] first addresses the importance of resource allocation and user scheduling in a multi-cell massive MIMO system. The main idea is to partition the UEs into equivalent classes and intelligently allocate the time-frequency resources. Based on this observation, reference [48] further considers the number of UEs that should be scheduled per cell to maximize the system spectral efficiency. The derived results shed insights on efficient system-level analysis with power control, pilot reuse, and user locations. Reference [30] proposes a two-stage precoder design to coordinate interference as well as reduce the downlink training and feedback overhead in FDD massive MIMO systems. The first stage works by grouping users with the same second order downlink statistics into groups and inter-group interference is suppressed. The second stage uses instantaneous effective channel realizations to mitigate the intra-group inferences. This way, the dimension of the effective channel is significantly reduced without sacrificing the sum capacity of the system. Following [30], several works that use different user grouping methods, such as k-means clustering [49], hierarchical clustering, and k-medoids clustering [50], have been proposed. In [51], the BS deployment density, pilot reuse factor, and the number of UEs to be served are jointly optimized to maximize the system energy efficiency (EE).

2) Heterogeneous Networks: With the demand for higher data rates, a promising solution is to reduce the size of the cell. By reducing the covering area of the cell (i.e., to form small cells [52]), the transmit power can be reduced and spectral efficiency can be increased due to a higher frequency reuse. At the same time, the original macro cell provides services to the UEs that are not covered by the small cell and to receivers that are of high mobility, e.g., in trains. A heterogeneous network (HetNet) is a combination of macro cell, pico cell, and femto cell [53]. It provides an increased spectral efficiency and a flexible covering area.

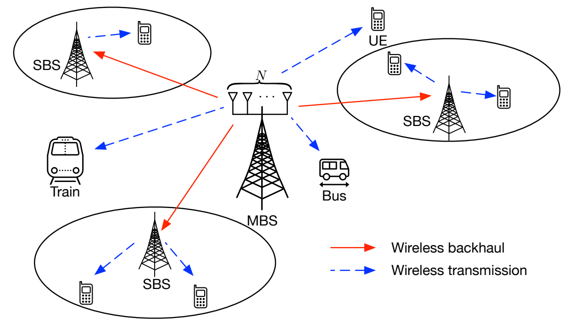

Fig. 4: An illustration of massive MIMO HetNet.

Fig. 4 shows an example of massive MIMO HetNet, where the macro BS (MBS) equipped with large antenna arrays work with small cell BSs (SBS) collectively to serve UEs. Different from homogeneous massive MIMO, heterogenous massive MIMO is a multi-tier system. The UEs can belong to any BS in any tier. This brings about a user association problem [52], [53]. Moreover, if the SBS are operated at the same time-frequency slots as the MBS, there would be severe inter-tier interference. This together with the existing intra-cell and inter-cell interference makes interference coordination in massive MIMO HetNet even more challenging.

The user association problem was often formulated as an optimization problem with different goals, such as maximize the system capacity [54] , minimize the power consumption [55], maximize the network utility [56], and maximize energy efficiency [57]. Either centralized or distributed algorithms can be used to provide low-complexity solutions. To address the interference cancellation problem, in addition to the techniques used in homogenous massive MIMO networks, new techniques that leverage the transmission property of massive MIMO have been proposed. For example, reference [58] exploits the directional property of massive MIMO channel to limit the MBS's transmission energy only in certain directions and create space for SBS lying in other directions. The interference between MBS and SBS can be significantly mitigated and the system achieved a significant gain. Reference [59] observes that the CSI acquirement of interfering links is difficult with dense small cell deployment and proposed a nested array approach to filter the desired and interference signals in the analog domain. The corresponding user association and interference cancellation problem is jointly formulated as an integer programming problem, which can be solved by distributed algorithms. Generally, user association, resource allocation, and interference management should be jointly considered. Based on the different targets to be optimized, optimization algorithms can be designed to achieve a tradeoff between complexity and system performance.

B. Backhaul Design

Most works assume wired backhaul connections between SBS and MBS to support a high and reliable data transmission. However, in practice, wired connection may not be cost-effective and sometimes may be infeasible. It is also inconvenient to upgrade when the topology of the network changes. As a result, wireless backhaul transmission becomes a promising candidate [60], [61]. However, the use of wireless backhaul also gives rise to additional source of interference, which will impact the cell associations and interference coordination methods.

In fact, massive MIMO-enabled wireless backhaul can be quite reliable and flexible. As shown in Fig. 4, the MBS is equipped with a large-scale antenna array and a wired high-capacity backhaul connection. The single antenna SBS, on the other hand, communicates with the MBS via in-band wireless backhaul. The MBS sees the wireless backhaul transmission as a special UE. Due to the spatial DoFs in massive MIMO, both intra-cell interference and inter-cell interference can be mitigated [4] with existing interference cancellation methods. MBS can provide high data rates to multiple wireless backhauls with simple linear processing methods.

Reference [62] formulates the joint cell association and wireless backhaul bandwidth allocation problem as mixed-integer nonlinear programming problem. A proposed two-level hierarchical decomposition-based method is shown to be efficient to address the problem to maximum the sum rates. Reference [63] investigates the problem of frame design, resource allocation, and user association in a massive MIMO HetNet with wireless backhaul transmission. This problem is formulated as an integer programming, which is solved by both centralized and distributed algorithms. Reference [64] uses stochastic geometry to model the massive MIMO-enabled wireless backhaul HetNet and a closed-form expression for coverage probability is derived. Reference [65] surveys the evolution of small cells and its impact on the baseband processing of the radio access network. The impact of the backhauling mechanism on the radio resource management have been discussed in the context of cell association, bandwidth allocation, and inter-cell coordination in a massive MIMO HetNet.

To support a higher rate, wireless backhaul is often associated with millimeter-wave (mm-wave) transmission because mmWave can be leveraged to provide potential Gigahertz transmission bandwidth and strong signal directivity and reliability [66], [67].

V. Integration with Other 5G Technologies

A. mmWave-Massive MIMO

Different from most existing wireless systems that operate at carrier frequencies below 6GHz, the mmWave makes use of spectrum from 24GHz to 300 GHz and provides huge available bandwidth [68]. Mm-wave wireless communications provide extremely high data rates for applications such as vehicular networks, wireless backhaul transmissions, and short-range communications. Meanwhile, massive MIMO provides huge gains from the massive antenna arrays used. When mmWave massive MIMO is deployed in HetNet, the benefits of the three key 5G core technologies can be harvested to a very large extend, realizing the anticipated 1000-fold capacity increase promised by 5G networks [69], [70].

In the physical layer, mmWave massive MIMO channel is specular and have low rank. They are generally incapable of exploiting all the DoFs promised by the large antenna array. Hence the achievable gain is limited. These features have to be incorporated into the process of channel modeling and measurement, channel estimation, precoding schemes, and detection algorithms [71].

1) Channel Modeling: Reference [72] addresses the importance of spatial and temporal fading correlation in MIMO communications. Since analytical models such as Rayleigh fading scattering is too rich for mmWave channels, reference [73] presents measured results and observes that the received signal power and the parameters such as angle-of-arrival of accurately model the spatial and temporal correlations of mmWave channels. Reference [74] presents a 3D statistic channel modeling method for mmWave MIMO channels, while [75] carries out mmWave massive MIMO channel measurements and the measurements are verified by the theoretical channel models.

2) Channel Estimation: MmWave massive MIMO channels exhibit sparsity and low-rank properties, hence channel estimation methods can be classified according to whether *compressed sensing* (CS) is used or not. The CS theory shows that if a signal preserves some sparsity in a certain domain, then it can be recovered with very few sample measurements. Different CS methods are leveraged to obtain the CSI in mmWave massive MIMO channel, e.g., orthogonal matching pursuit (OMP) [76], message passing [77], and sparse Bayesian learning [12]. The key idea is to efficiently use the sparsity of mmWave channel in the angle-domain. Non-CS based methods exploits the the structural characteristics of mmWave beam-space channel. For example, reference [78] proposes a support-detection scheme, where the total beam-space channel estimation problem is decomposed into a series of sub-problems. Each sub-problem can be solved by classical algorithms, such as least square (LS). As a result, the complexity of this algorithm is pretty low. Reference [79] proposes a channel estimation method based on the direction of arrival (DoA) estimation. The proposed method achieves better performance than conventional linear minimum mean squared error (LMMSE) estimation in terms of ergodic throughput.

3) Hybrid-precoding: The design of precoding is extremely important to cancel the interference from different UEs. For MIMO in conventional cellular frequency bands, precoding is realized in the digital domain. When the conventional digital precoding is applied to the mmWave massive MIMO, the associated energy consumption and hardware cost would be considerably high due to the large number of RF chains and the wide band at the mmWave frequency. To solve this problem, reference [80] proposes a hybrid analog and digital precoding scheme. As shown in Fig. 5, the conventional digital precoder is divided into a small-sized digital precoder with very few RF chains and a large-size analog precoder with a lot of cheaper analog phase shifters. This hybrid structure can enjoy a much higher energy efficiency without a significant performance

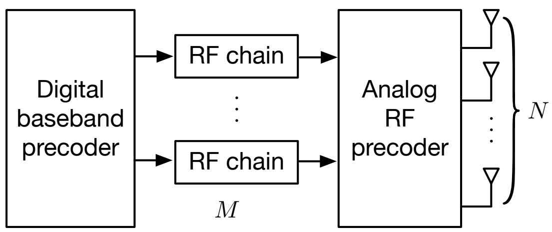

Fig. 5: The mmWave massive MIMO system with a hybrid precoding structure.

degradation [26].

In the context of mmWave massive MIMO hybrid precoding, a quantity of researchers have devoted to develop low-complexity precoding algorithms with enhanced performance. Reference [81] exploits the mmWave channel's sparsity to formulate the hybrid precoding problem as a sparse reconstruction problem. The proposed basis pursuit algorithm can accurately approximate optimal unconstrained precoder. Different from [81] that assumes the availability of full CSI, reference [82] assumes the availability of only a limited feedback channel between the BS and UEs.

The developed codebook design based hybrid precoding enjoys a low complexity and outperform the analog-only solutions. However, it suffers from a performance loss and it is not clear how large the performance gap from optimal is. In view of this, reference [83] proposes a successive interference cancelation (SIC)-based hybrid precoding structure. The total achievable rate optimization problem was decomposed into a series simple sub-rate optimization problems, each of which can be solved efficiently. Simulations show that the SIC-based algorithm is near-optimal and a higher energy efficiency than the spatially sparse precoding. Also, the joint optimization of analog and digital precoding can be formulated as a constrained matrix factorization problem. Some works propose efficient algorithms to solve this problem, e.g., the alternating minimization (AltMin) algorithm [84] and the Broyden-Fletcher-Goldfarb-Shanno-based algorithm [85]. More recently, a deep learning based mmWave massive MIMO hybrid coding approach is proposed to achieve an enhanced spectrum efficiency with reduced complexity [86].

4) Low Resolution ADC: MmWave massive MIMO is a key candidate for 5G cellular. In practice, more antennas means more extra radio-frontends (RF) chains. High energy consumption and hardware cost caused by numerous RF chains can be overwhelming. A possible solution is to use low-resolution analog-to-digital converters (ADCs). As shown in Fig. 6, each receive antenna is connected with two low-resolution ADCs, one for the in-phase element and the other for the quadrature-phase element. The low noise amplifier (LNA), automatic gain control (AGC), and variable gain amplifier (VGA) are used so that the signal is within a certain range before the baseband signal processing unit. Those low-resolution ADCs decrease both the power consumption and hardware cost and also relax the baseband hardware requirements. However, this also imposes great challenge on signal processing techniques due to the non-linear distortion caused by coarse quantization [87].

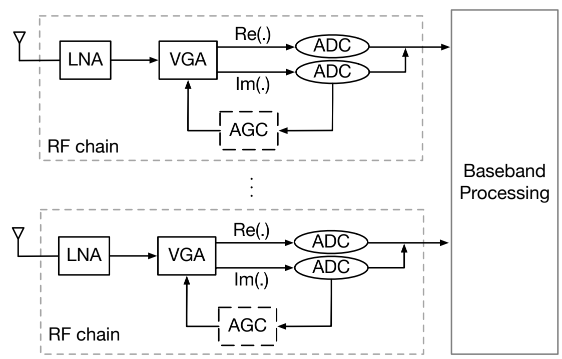

Fig. 6: MmWave massive MIMO receiver architecture with low-resolution ADCs.

To this end, reference [88] shows that the knowledge of CSI is essential to realize the performance gain of mmWave massive MIMO with low resolution ADCs. However, there would be a severe degradation due to the non-linearity of low resolution ADCs. As a result, various works develop efficient algorithms to improve the channel estimation quality. For example, reference [89] exploits the sparsity nature of mmWave MIMO channels in the angular domain and develops an efficient algorithm based on generalized approximate message passing (GAMP). A superior performance can be achieved. Reference [90] converts the channel estimation problem into a convex optimization problem, which can be solved by off-the-shelf methods. This work provides a complete low power solution for uplink massive MIMO channel estimation. Another research line is signal detection algorithms. Reference [91] shows that the classical maximum ratio combining (MRC) and ZF detector suffer from substantial performance degradations in high SNR regimes. As a result, message passing detectors and convex optimization based detectors are developed in [22] and [90], respectively.

B. Massive MIMO with Non-orthogonal Multiple Access

Different from conventional orthogonal multiple access, non-orthogonal multiple access (NOMA) can accommodate much more users via non-orthogonal resource allocation via either power-domain multiplexing or code-domain multiplexing [92], [93]. When NOMA is combined with MIMO, the capacity can be further improved [94]. For single-cluster MIMO-NOMA, the users use SIC to suppress intra cluster interference. For multi-cluster MIMO-NOMA, as shown in Fig. 7 the users need to be first partitioned into different clusters. The full potential of MIMO-NOMA is realized by a joint design of user clustering, beam-forming, SIC, and power control [95].

The application of NOMA in (mmWave) massive MIMO is highly anticipated. However, due to the features of massive antennas, sparse correlated channels, and possible hybrid (analog/digital) precoding structures, the existing MIMO-NOMA structure needs to be adjusted. Recently, NOMA has been, for the first time, integrated with mmWave massive MIMO in [96], where a dynamic power control scheme is used

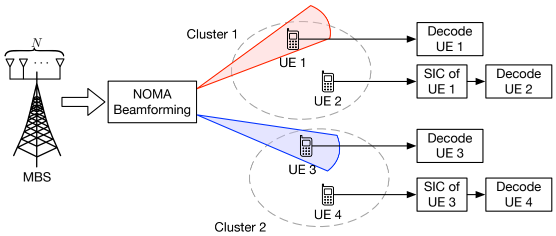

Fig. 7: A multi-user MIMO-NOMA system with 2 clusters and 4 users.

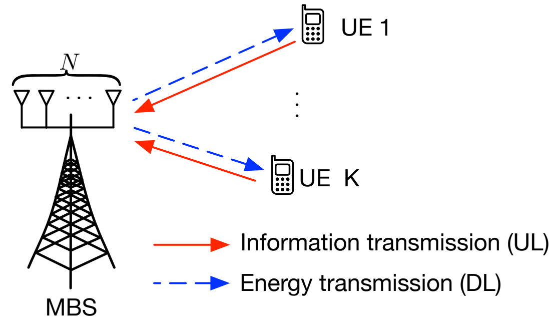

Fig. 8: A wireless power communication network (WPCN).

to maximize the system energy efficiency. Besides beamforming design and power control, when NOMA technology is deployed in HetNets, joint user scheduling and resource allocation should be considered [97]. This is a challenging and important research direction for future work.

C. RF Energy Harvesting with Massive MIMO

Wireless energy transfer has been viewed as a promising technique to address energy and lifetime bottlenecks for power-limited UEs. By forming the radiative electromagnetic (EM) wave emitted from the transmitter into a narrow beam and delivering the energy to the wireless UEs, the UEs can receive both energy and information simultaneously [98]. Simultaneous wireless information and power transfer (SWIPT) offers great flexibility to UEs with concurrent data and energy supplies and cuts the last mile limiting the *true wireless* communications [98], [99].

In wireless powered communication network (WPCN), the access point (AP) equipped with multiple antennas first deliver energy to multiple single-antenna UEs via downlink transmissions, then the UEs use the harvested energy to perform uplink transmissions, as shown in Fig. 8. However, due to the channel propagation loss, the efficiency of energy harvesting is not high. Massive MIMO, on the other hand, provides sharp energy beams towards UEs and hence improves the energy efficiency. Reference [100] considers a massive MIMO system powered by wireless energy harvesting and studies the throughput maximization problem. In [101], the overall power transfer efficiency and energy efficiency of the massive MIMO system with wireless energy transfer is studied. The overall system performance is analyzed and it is demonstrated that the energy efficiency benefits from operating the system in the large antenna regime. Reference [102] considers two working modes for the receiver to harvest energy from the received signal, i.e., the power splitting mode and the time switching mode. Results show that the power splitting mode outperforms the time splitting mode in terms of system EE and the minimum transmission rate.

VI. Research Trends

A. Integration with Machine Learning

Machine learning has achieved great success in many fields, such as computer version, natural language processing, and robot control. Intelligent mobile networking which integrates machine learning with wireless networks is becoming more and more popular [103]–[105]. Reference [106] introduces the potential of applying machine learning to the next-generation wireless networks including massive MIMO systems. The work reveals that machine learning in 5G is an exciting research area. Reference [107] shows that there are great opportunities and challenges when artificial intelligence (AI) is incorporated into the 5G network. Generally, machine learning can be categorized as supervised learning, unsupervised learning, and reinforcement learning, as shown in Fig. 9. In this section, we will introduce how these methods are applied to the field of massive MIMO communication systems.

1) Supervised Learning: Supervised learning infers the mapping function from labeled training data. In massive MIMO where the associated antenna number can be several hundreds, physical layer issues such as detection and channel estimation generally lead to a high-dimensional and high complexity search problem. Machine learning, especially supervised learning, can address these problems with effective learning models, such as support vector machine (SVM) and deep neural networks (DNN). For example, reference [86] proposes a deep-learning based mmWave massive MIMO hybrid precoding scheme, where a DNN is used to learn the optimal mapping through training. The obtained precoder is capable to achieve enhanced spectrum efficiency with much lower complexity. Reference [108] presents a DNN as a general framework for MIMO detection. The developed DNN based detector can learn a mapping from the received symbols and channel matrix to the input symbols. Compared with other detectors, DNN based detector is computationally inexpensive and has near-optimal accuracy without the knowledge of signal-to-noise (SNR) level. Reference [109] uses a DNN to learn the wireless channel statistics. The proposed deep learning based scheme is able to achieve a better performance in terms of DOA estimation and channel estimation.

Besides physical layer signal processing, some recent works also use supervised learning in upper layers. For example, reference [110] leverages a convolutional neural network (CNN) to learn the sparse structure of massive MIMO channel for positioning purposes. A high positioning accuracy can be achieved as long as the training dataset size is large. Reference [111] leverages the universal approximation property

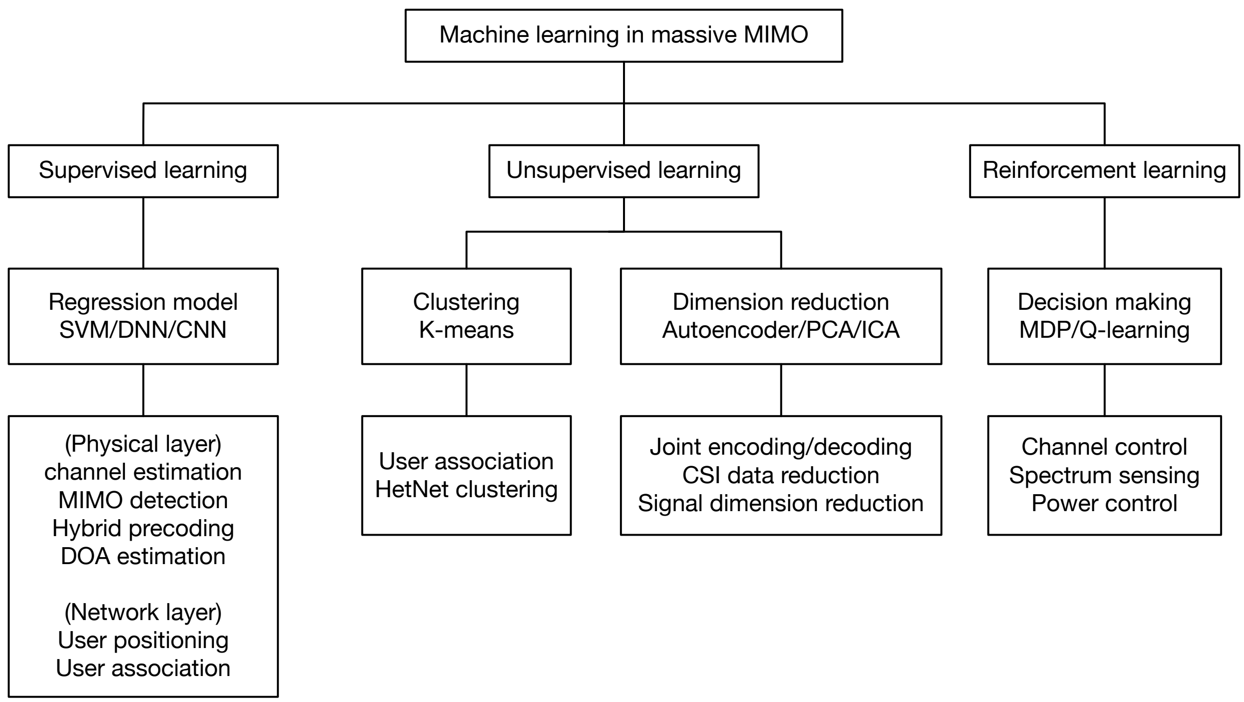

Fig. 9: The integration of machine learning with massive MIMO.

to learn the optimal user association strategy with a DNN. It guarantees the same performance of traditional optimization methods with a huge complexity reduction.

2) Unsupervised Learning: Unsupervised learning aims to find the hidden pattern and structure from unlabeled data. It can be utilized for cell clustering in massive MIMO HetNets, user grouping, load balancing. and signal dimension reduction. For example, reference [112] applies deep unsupervised learning with a loss function to jointly optimize the encoding, decoding, and signal processing modules. This work helps to illustrate the power of autoencoder in learning the encoding/decoding process for complex channels. Reference [113] uses an autoencoder to learn a representation for the dimension reduction of FDD massive MIMO CSI data. The proposed methods performed well at low compression ratios with reduced complexity. Reference [50] uses various clustering algorithms in unsupervised learning to group users that have similar covariance matrices. This way, the CSI overhead in FDD massive MIMO can be greatly reduced. Reference [114] uses the principal component analysis (PCA) to reduce the dimension of the received signal and uses the independent component analysis (ICA) to estimate channels.

3) Reinforcement Learning: Reinforcement learning solves the decision-making process in a dynamic iterative manner. It can be used to infer the UE's decision making under unknown wireless networks, for example, channel access control and power control problems in massive MIMO HetNets. Reference [115] considers a MIMO-NOMA system and formulates the anti-jamming transmission as a game. A Q-learning based transmission power control strategy that adaptively adjusts the UE's transmission power according to the observed state of the radio environment and the jamming power is then proposed. Reference [116] proposes a dynamic transmission power control scheme to improve the mmWave massive MIMO non-line-of-sight (NLOS) transmission performance. Particularly, this work applies a CNN to estimate the Q-function offline and uses a deep Q-learning to get the optimal power control online. As a result, the NLOS transmission performance can be enhanced.

B. *Extremely Large Aperture Arrays*

As the spectral efficiency of massive MIMO grows monotonically with the number of BS antennas, we can expect deploy hundreds or thousands of antennas to serve a few users. Instead of gathering these antennas together, we can distribute the antennas over a large area, e.g., the surface of each window in a tall building. This is called extremely large aperture arrays (ELAA). Different from conventional massive MIMO that uses channel hardening to average small-scale fading, ELAA relies on the great spatial resolution to make different users have nearly orthogonal channels. In ELAA, the spatial resolution of the antenna array is not determined by the number of BS antennas, but instead by the array's aperture. The ELAA terminology describes a family of recent research topics, e.g., cell-free massive MIMO [117]–[119], network MIMO [120], distributed massive MIMO [121], and large intelligent surface [122].

ELAA aims to provide orders-of-magnitude higher throughput than massive MIMO with compact antenna arrays. For example, a special ELAA system, a cell-free massive MIMO system is illustrated in Fig. 10. In cell-free massive MIMO, a large number of distributed access points (APs) serve a much smaller number of UEs simultaneously. There are no cell or cell boundaries. All the APs exchange information through a

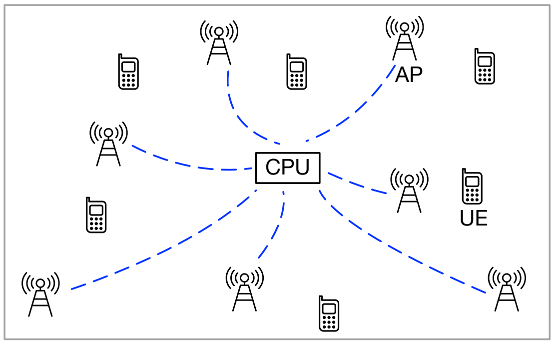

Fig. 10: The concept of cell-free massive MIMO.

central processing unit (CPU). Since cell-free massive MIMO combines the concepts of distributed MIMO and massive MIMO, it can reap the benefits of both technologies. Reference [117] shows that cell-free massive MIMO system can significantly outperform small-cell massive MIMO in terms of throughput.

C. FDD Massive MIMO

In TDD massive MIMO, the UE sends pilot symbols to the BS with large antenna arrays, allowing the BS to estimate the uplink channels. With channel reciprocity, the downlink channel can be predicted and the costly CSI feedback can be avoided. However, in frequency-division duplex (FDD) massive MIMO, DL and UL channel uses different frequencies and channel reciprocity no longer applies. In FDD massive MIMO, the downlink CSI can only be estimated by the UE and fed back to the BS. The downlink training and feedback overhead scales linearly with the number of BS antennas, resulting a huge signaling overhead. Considering that many wireless network providers nowadays have FDD licenses and FDD massive MIMO promises compatibility to current frequency assignment strategies for mobile communication, it is important to develop efficient pilot reduction algorithms for FDD massive MIMO systems.

Existing works aim to solve this problem with compressed sensing (CS) techniques and vector quantization approaches. For example, reference [123] uses quantization codebooks to reduce the CSI feedback. However, it also complicates the codebook design (which lead to heavier feedback overhead) especially when the number of antennas is large. Reference [124] exploits the signal sparsity in spatial and frequency domain resulted from spatially-correlated antenna arrays to compress the CSI feedback. Reference [7] designs a distributed compressive CSI estimation scheme, in which the compressed measurement is observed at the UEs locally and the CSI recovery is performed at the BS jointly. The problem of the CS-based algorithm is that it is still unclear whether the general assumption on channel sparsity holds in practice. Recently, more and more works apply deep-learning to FDD massive MIMO systems. For example, reference [125] uses a neural network at the BS to infer the DL CSI centered at a specific frequency by only observing the UL CSI on an adjacent frequency band around. This way, the feedback CSI overhead can be completely removed. We still have to mention that the machine learning based methods need to be tested in practice to validate their practical gains.

VII. Conclusions

This paper provided a survey on massive MIMO systems, including physical layer techniques, networking techniques, integration with other 5G technologies, and future research directions. By equipping the BS with hundreds of antennas, the system can improve its spectral and energy efficiency dramatically. However, to fully harvest the high potential of massive MIMO, significant research are needed on a number of issues, such as intelligent massive MIMO, ELAA system, and FDD massive MIMO.

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