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Massive MIMO: Survey and Future Research Topics

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Abstract: Massive multiple-input multiple-output technology has been considered a breakthrough in wireless communication systems. It consists of equipping a base station with a large number of antennas to serve many active users in the same time-frequency block. Among its underlying advantages is the possibility to focus transmitted signal energy into very short-range areas, which will provide huge improvements in terms of system capacity. However, while this new concept renders many interesting benefits, it brings up new challenges that have called the attention of both industry and academia: channel state information acquisition, channel feedback, instantaneous reciprocity, statistical reciprocity, architectures, and hardware impairments, just to mention a few. This paper presents an overview of the basic concepts of massive multiple-input multiple-output, with a focus on the challenges and opportunities, based on contemporary research.

Keywords: channel estimation, feedback, frequency-division multiplexing, massive multiple-input multiple-output, reciprocity, small cells, sparsity, time-division duplexing, 5G

1. Introduction

Over the last few years, massive multiple-input multiple-output (MIMO) has shown up as an emerging technology for wireless communication systems. Featuring up to thousands of transmit/receive antennas, the possibility of creating extremely narrow beams for many users is gaining the attention of industry and academia. Researchers are focusing their efforts on the promised benefits of this technology to create the next generation of communication systems. The underlying idea is to scale up the number of antennas at the base station (BS) by at least two orders of magnitude. The author in [1] shows that the end effects of indefinitely increasing the number of antennas are small fading effects and additive noise. In a multiuser MIMO scenario, Massive MIMO opens the possibility to steer many spatial streams to dozens of pieces of User Equipment (UE) in the same cell, at the same frequency, and at the same time.

Mobile networks are currently facing rapid traffic growth from both smartphones and tablets. Sequential improvements of service quality set the new challenge of increasing wireless network capacity about a thousand times within the next decade [2,3], but no current wireless access technique can provide a significant improvement in capacity. A possible solution to cope with such a capacity demand is through network densification by adding small cells (picocells and femtocells) that operate at high frequencies (e.g. 60GHz) within the macro cell area [4,5]. Small cells (SCs) that utilize the same band spectrum can increase the capacity of a mobile network from 10 to 100 times, depending on the number of small cells and frequency reuse method [6,7]. In recent literature, possible architectures for 5G networks have been discussed. In [8], the energy efficiency of Massive MIMO and SC has been studied. The authors proved that Massive MIMO has better energy efficiency when the number of small cells is low, while SC offers better performance when the number of small cells is high. However, a globally optimal trade-off between Massive MIMO and small cell efficiency is hard to achieve due to dynamic network behavior. A viable solution could be found by converging Massive MIMO, small cells, and device-to-device (D2D) communications into a single cloud-controlled heterogeneous network (HetNet), as shown in Fig. 1 [9].

Massive MIMO will play a key technological role to create new spectral and energy-efficient networks [9]. According to industry and academia, this technology has great potential to meet the requirements of a next-generation wireless system. On the other hand, there are still a lot of questions to be answered regarding the practical aspects and scenarios of Massive MIMO. For instance, we can ask about the development of low-cost antennas, the compensation of hardware impairments, channel characterization, and pilot contamination, just to mention a few [10].

In this survey, we follow up the discussions on massive MIMO systems proposed in [10-13] by adding new topics that have gained attention recently in the research community, such as hybrid beamforming, analog-digital converters (ADC)s with low resolution, signal detection complexity in massive arrays and deeper discussions on the time-division duplexing (TDD) and frequency-division Duplexing (FDD) paradigm.

The topics of this survey are divided as follows. In Section II, we discuss TDD and FDD paradigms. In Section III, problems and signal processing challenges are discussed. Section IV describes existing channel models. In Section V, attention is drawn to the applicability of Massive MIMO in heterogeneous networks. We conclude the paper in Section VI.

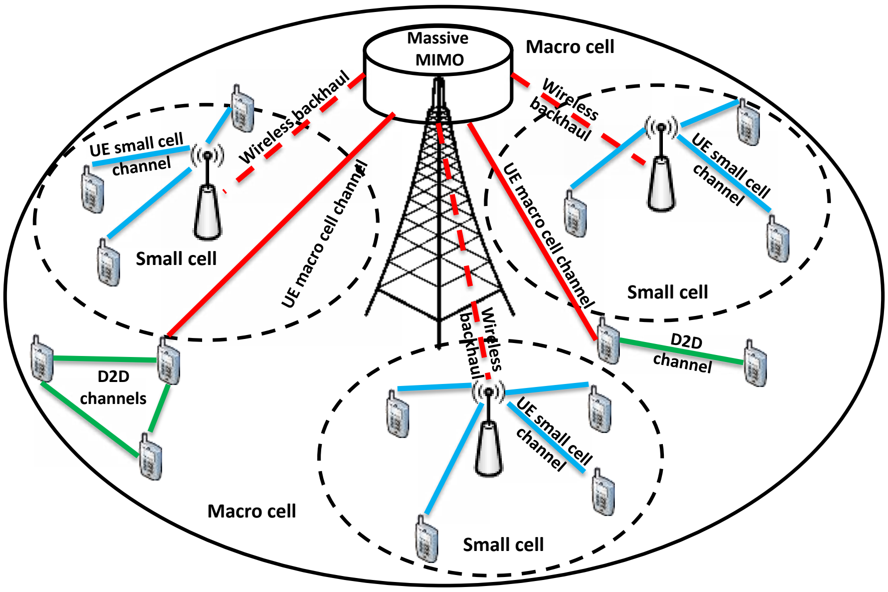

Figure 1. *Architecture of a heterogeneous mobile network.*

2. TDD vs. FDD Paradigms

The current literature indicates that a clear duplexing scheme has not yet been used in Massive MIMO systems. While most current wireless standards operate under the FDD scheme, several studies have mentioned the use of TDD as a candidate scheme. In this section, we discuss the aspects and bottlenecks in TDD and FDD in the context of a Massive MIMO system.

2.1. Issues in Multiuser/Massive MIMO TDD systems

1) Pilot Contamination

Ideally, orthogonal pilot sequences are assigned to each UE in a multiuser MIMO system for channel estimation. However, the number of orthogonal sequences is limited by the ratio between channel coherence time and delay spread [11]. In high-mobility and large-delay-spread scenarios, like when using mm-waves, the total number of available sequences can be easily achieved before all UEs are assigned a pilot sequence. Therefore, the re-use of pilot sequences among cells is required. Consequently, the outcome of a linear combination of UE channels sharing the same pilot sequence in different cells gives an estimate on channel state information (CSI) associated with a specific UE. This problem is termed "pilot contamination" and is illustrated in Fig. 2.

Pilot contamination places an ultimate theoretical limit on the performance of a multiuser Massive MIMO system which consists of non-cooperative BSs with an unlimited number of antenna elements [1, 11]. As a consequence of this problem, downlink beam forming introduces a significant amount of interference into the system. Some papers propose different solutions to mitigate the problem [14], [15] or even completely suppress it [16]. In [14], the author proposes a mean minimum square error (MMSE) estimator, which is shown to be more robust than least-square (LS) estimator used in [1]. In [15], the author exploits second-order statistics of each user channel and proposes a method to estimate semi-blind channels. It is shown that if the number of antennas grows large, the channel matrix can be estimated from the eigenvectors of the covariance matrix up to a multiplicative scalar ambiguity that can be solved using a short training sequence. In [16], the author proposes a joint pilot coordination scheme and a Bayesian channel estimation method using the covariance matrix of the interference cell. Therein, the efficiency of this approach for large-scale antenna systems is shown analytically, leading to a complete removal of the pilot contamination effect. Blind channel estimation techniques seem to be a growing trend, and some authors have proposed new methods to mitigate pilot contamination [17].

Another possibility to combat pilot contamination is to make use of a smarter allocation of the pilot tones. In [11], a possible approach is investigated using a less aggressive re-use factor for the channel estimation period, but not for the data transmission one. Such a strategy could, in principle, reduce the interference among UEs sharing the same pilots. Pre-coding has also been considered to deal with pilot contamination [18]. Basically, this approach uses slow fading coefficients to nullify the directed interference that results from pilot contamination [19].

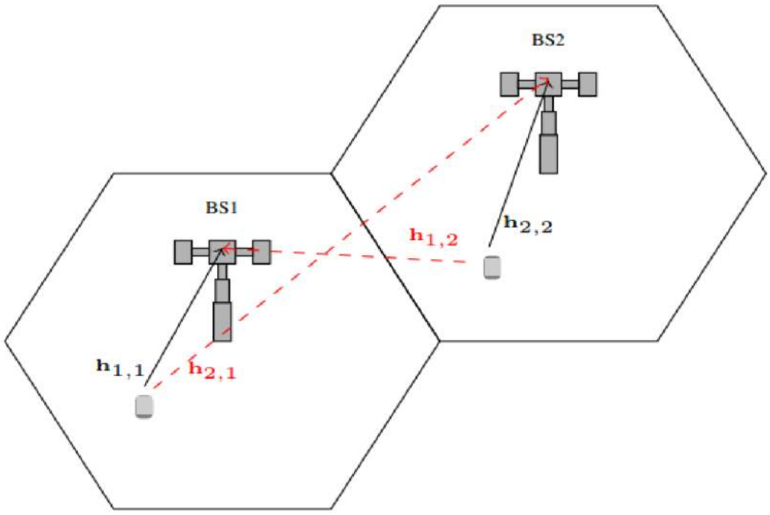

Figure 2. *The pilot contamination is represented in red dashed lines.*

2) Time Reciprocity

TDD operations fundamentally depend on channel reciprocity. This means that the UL channel matrix within the channel coherence time is a transposed version of the DL channel matrix. Therefore, in an ideal case, the UE sends out the pilots and the BS estimates the UL channel. Then, the BS is able to steer narrow beams towards the UEs with a transposed version of the estimated UL channel matrix. The overall process has to be performed within the duration of the channel coherence time, which may not hold in scenarios with moderate or high mobility. This is still true even though, in reality, each UE has RF mixers, filters, and A/D converters that make up the equivalent channel model and can potentially break the assumptions on uplink/downlink channel reciprocity [20].

It is important to highlight to the reader that this issue is not uniquely related to Massive MIMO cases, but it has also been studied over the past few years in the context of traditional MIMO systems [20]. However, with Massive MIMO systems, a lack of understanding about hardware impairments and a lack of proper modeling persist, and it is still not clear whether they will maintain time reciprocity or how to mitigate any associated negative effects to keep transmissions reliable. For example, mutual coupling among the BS antennas may not be neglected and may limit Massive MIMO performance.

Calibration in Massive MIMO has also been an object of intense investigation, as referenced in [21] and [22]. The former shows a test-bed for Massive MIMO and addresses the calibration problem in order to deal with the pre-coder design. The authors propose to first estimate the UL channel and then the relative CSI of the DL using the relative calibration concept. The latter investigates the same problem, but in a cognitive Massive MIMO scenario. Unlike in [23], the analysis includes coupling among the antennas, and uses channel feedback to handle the CSI acquisition problem.

2.2. Issues in Multiuser Massive MIMO FDD systems

In the multiuser Massive MIMO literature, most papers have considered TDD systems. Most choose this to specifically avoid making estimation of DL channel, since the amount of DL resources needed by the estimator is proportional to the (huge) number of BS antennas. Furthermore, even if a satisfactory estimate of channels is made, the CSI associated with the large-scale channel matrix could potentially exhaust the time-frequency resources of the feedback channel. These two ideas are summarized in Fig. 3.

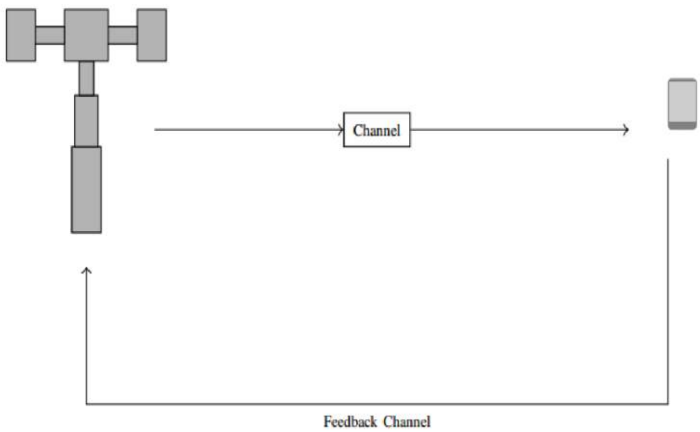

Figure 3. The FDD system is composed of two channels: uplink and downlink. The UE estimates the channel by using the training sequence sent in the downlink channel, then reports channel estimation in the feedback channel.

1) Pilot Overhead in Channel Estimation

The benefits of using conventional DL channel estimation techniques in traditional MIMO systems that assume small or moderate antenna array are well known. However, the amount of time-frequency resources used by the pilot sequence grows with the number of transmission antennas. In the absence of a specific strategy to reduce pilot sequence length and keep a reliable CSI acquisition, the gains in terms of spectral efficiency claimed for Massive MIMO might disappear. To tackle the DL channel estimation problem, effective pilot transmission methodologies that enable accurate CSI estimation with minimal signaling overhead play a crucial role in the success of Massive MIMO.

Although traditional MIMO channel estimation techniques require the length of the pilot sequence to be on the same order as the number of BS antennas, optimality is related to the channel covariance matrix [23]. Specifically, by considering the link between BS and UE, the training for each antenna element should be orthogonal. The optimal length is the same as the number of antennas at the transmitter in i.i.d./Rayleigh channels. However, under spatial correlated channels, and from the assumption that the BS knows the channel correlation matrix perfectly, the authors in [23] and [24] affirm that the optimal training sequence length is the same as the number of dominant eigenvalues. For Massive MIMO, since it is likely true that the number of eigenvalues is smaller than the number of antennas, the length of the sequence can potentially be reduced.

Additionally, future Massive MIMO systems will likely operate in the mm-wave range. In this "futuristic" system scenario, the channel matrix will likely be highly structured and rank deficient. The algebraic structure can be exploited to reduce the length of the pilot sequence. Paper [25] exploits the spatial structure of the channel, and the estimation is performed based not only on second order channel statistics but also the time correlation between two sequential block frames. The optimization of the training sequence length is determined by assigning the rank of the spatial correlation matrix.

Another possibility to reduce the training sequence is to exploit channel sparsity using compressed sensing (CS) tools. Developed in [26], CS has a large body of literature with very well-known algorithms that can be applied to solve wireless communication problems. The authors of [27] resort to a sparse modeling of the MIMO wireless channel and show that, for correlated channels, CS is an efficient strategy to save DL time-frequency resources and transmission power. In the Massive MIMO case, a sparse modeling of the Massive MIMO channel is used in [28] and [29] for CSI acquisition.

2) Feedback Channel

Another challenge to make Massive MIMO systems a reality is related to channel feedback. Recall that the channel estimation in an FDD-based multiuser Massive MIMO system is performed by the UE, which is responsible for reporting CSI to the BS. However, due to the huge number of channel coefficients, the amount of information that goes through channel feedback can easily take a great part of the available bandwidth. This problem also impacts the pre-coder design at the BS.

Channel feedback has gained much attention in the Massive MIMO research community. The overhead of the channel feedback increases exponentially as the number of antenna increases. Because of this, non-coherent trellis-coded quantization has been proposed by authors in [30] and it shows that computational complexity grows linearly with the number of antennas. Such channel feedback method leads to a similar performance as the random vector quantization method which is optimal when the number of antennas is large and the feedback channel has unlimited capacity [30].

CS can also be a potential solution to reduce the amount of channel feedback. As commented before, if sparsity-aware channel estimation techniques are used, only a few non-zero entries of the sparse-transformed channel coefficients would be fed back to the BS. Another possibility is the use of CS to identify the most representative "channel directions" (transmission angles), which can be fed back to the BS using a few bits [28], [29].

3) Channel Reciprocity in an FDD System

The reciprocity property is also capitalized in the FDD scheme, although it comes in another form. If the frequency offset between uplink and downlink frequency carriers is larger than the coherence bandwidth, the channels have independent fading effects, and reciprocity does not hold. One way to tackle the problem is to parameterize the channel in consonance with a direction-based model [28]. The underlying motivation of the directional modelling approach is that the channel is a superposition of multiple paths in which azimuth and elevation angles are shared by both uplink and downlink channels. Consequently, the downlink and uplink channels can be estimated by means of common angular information [31]. The angular information can be obtained either from uplink or downlink measurements. The first approach requires that the UE sends out a training sequence and the BS uses a simple direction-finding method to obtain the angles. The second one goes on the opposite sense, i.e. the UE performs the angular estimation and then sends the information through a feedback channel as shown in [31].

Power spectrum estimation can also be an alternative to deal with the reciprocity problem in FDD system. Instead of obtaining discrete rays, a possible approach is the estimation of the spatial power spectrum. Regardless of the specific method used, it is worth mentioning that in 5G systems, especially those operating at the mm-wave range, angular information will play an important role, much greater than in the current standards. Its importance is not exclusively restricted to the reduction of the pilot and channel feedback overhead, but it goes beyond by providing, for instance, an alternative way to address the problem of frequency offsets between uplink and downlink carriers.

2.3. Issues in M-MU-MIMO FDD systems

To summarize, the benefits of Massive MIMO relies on the CSI acquisition at the BS. The TDD scheme shifts this task to BSs by keeping the UEs away from the burden of estimation processing. On the other hand, FDD goes the other way round, where the UE receives the training sequence and obtains the CSI. Although TDD is very attractive in the sense that UEs signal processing can be kept at low cost, most existing cellular networks are based on the FDD scheme. It is important to understand the limit of both schemes, and that both tracks are considered to be important for investigation to yield a better understanding of the Massive MIMO benefits in practice.

The big problem of academia and industry is the foreseen fifth generation wireless system for 2020, for which there are still a lot of questions to be answered with respect to the implementation of the Massive MIMO technology. FDD may have a slight advantage, since most of the current standards are built on this duplex scheme.

3. Signal Processing in Massive MIMO

In this section, we discuss the basic aspects of signal processing applied to pre-coding schemes in Massive MIMO. They can drastically increase system capacity by properly shaping the signal and adding all the wavefronts up towards a specific location. Interference between UEs is another track that can be further improved in comparison with "traditional" MIMO systems. The Zero-Forcing (ZF) pre-coding efficiently suppresses such multiuser interference. However, when compared to a Matched Filter (MF), this may come at the cost of high computational complexity. Additionally, we also address hybrid beamforming for Massive MIMO, low-resolution ADCs, and signal detection complexity.

3.1. Pre-coding: Matched Filter (MF) and Zero-Forcing (ZF)

In the DL channel, the BS transmits data through each antenna creating a $N_t \times 1$ vector $\mathbf{x}_d$, in which $\mathbb{E}\left\{\|\mathbf{x}_d\|^2\right\} = 1$. If a suitable pre-coding scheme is applied at the BS, the K UEs can receive their own information while minimizing interference from other UEs. Consider a single cell with a BS equipped with N_t antennas and K UEs, the received signal in the DL channel is

$$\mathbf{y}_d = \sqrt{\rho_d}\mathbf{G}\mathbf{x}_d + \mathbf{n}_d, \tag{1}$$

where $\mathbf{n}_d$ is a $K \times 1$ noise vector, which entries follow a Gaussian distribution with zero mean and unity variance, ρ_d is the transmit power, $\mathbf{G}$ is the $N_t \times K$ channel matrix. We consider

$$\mathbf{G} = \mathbf{D}^{1/2}\mathbf{H}, \tag{2}$$

where $\mathbf{D}$ is a $K \times K$ matrix, the diagonal of which contains the large-scale fading coefficients, and $\mathbf{H}$ is a $K \times N_t$ matrix, the entries are i.i.d. and account for small-scale fading. We normalize the large-scale fading coefficients such that the small-scale fading ones typically have unity magnitudes. Note that the large-scale fading component takes into account path loss and shadow fading.

Zero-Forcing (ZF) Pre-coding: Fundamentally, the ZF applies the pseudo-inverse of $\mathbf{G}$ [11], $\mathbf{G}^{\dagger}$, as a pre-coder. From Eq. (1), we can formally define the ZF pre-coder as

$$\mathbf{x}_d = \frac{1}{\sqrt{\alpha}}\mathbf{G}^{\dagger}\mathbf{s}_d, \tag{3}$$

where $\mathbf{s}_d$ is an $N_t \times 1$ vector denoting the information source for each user, $\alpha = \mathrm{Tr}(\mathbf{G}\mathbf{G}^{H})^{-1}/K$ which normalizes the power of $\mathbf{x}_d$ to 1, and the operator $(\ )^{H}$ denotes the conjugate transpose of a matrix . The signal received at the k-th user with a ZF pre-coding is given by

$$y_{k,d} = \sqrt{\frac{\rho_d}{K\gamma}} s_{k,d} + n_{k,d}. \tag{4}$$

If the number K of UEs and the number N_t of antennas grow large at the same rate, we have [33]

$$\mathrm{SNR}_{ZF} = \frac{\rho_d}{K\gamma} = \frac{\rho_d}{\mathrm{Tr}(\mathbf{G}\mathbf{G}^{H})^{-1}}, \tag{5}$$

implying

$$\mathrm{Tr}(\mathbf{G}\mathbf{G}^{H})^{-1} \to \frac{1}{\beta - 1}, \tag{6}$$

where $\beta = N_t / K$. Therefore, Eq. (5) reduces to

$$\mathrm{SNR}_{ZF} = (\beta - 1)\rho_d. \tag{7}$$

Matched Filter (MF) Pre-coding: Basically, MF pre-coding applies the Hermitian of the channel matrix $\mathbf{G}^{H}$, yielding [1], [11]

$$\mathbf{x}_d = \frac{1}{\sqrt{\alpha}}\mathbf{G}^{H}\mathbf{s}_d. \tag{8}$$

As N_t grows, $\left(\mathbf{GG}^{H}\right)/N_t$ converges to an identity matrix. With a few manipulations shown in [11], it is possible to obtain the asymptotic expression for the SNR as follows

$$\mathrm{SNR}_{\mathrm{MF}} = \frac{\rho_d \beta}{\rho_d + 1} \tag{9}$$

since, as ρ_d increases, $\mathrm{SNR}_{\mathrm{MF}} \rightarrow \beta$, while $\mathrm{SNR}_{\mathrm{ZF}} \rightarrow \infty$. Furthermore, the spectral efficiency increases as the number of antenna increases for a fixed number of UEs.

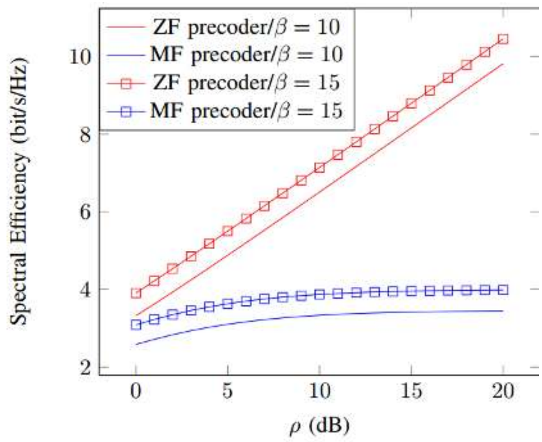

Figure 4. *Comparison between the theoretical SNR_{ZF} and SNR_{MF} .*

Assuming reciprocity between UL and DL channels, the receive combining and the transmit pre-coding have a very strong relationship; this is called uplink-downlink duality [32, 33]. The consequence of such a duality is that the optimum transmit precoding is also the optimum receive combining. The theorem shows that the signal-to-interference-plus-noise ratio (SINR)s achieved in DL and UL are the same. However, it is worth noting that power allocation varies for different UEs.

3.2. Hybrid Beamforming and Architecture

In a "traditional" MIMO system, the number of RF chains in a BS is determined by the number of antennas. However, when shifting to Massive MIMO systems, one should avoid using one RF chain and analog-digital converter ADC at each antenna output, due to the huge complexity and costs involved. In order to overcome this issue, recent studies [34]–[36] propose a two-stage pre-coding scheme known as hybrid beamforming to achieve a large spatial degree of freedom (DoF) in Massive MIMO systems by using a limited number M x N_t of RF chains. Fig. 5 shows a hybrid beamforming architecture. Basically, each RF pre-coder produces a constant-modulus and phase-variable output signal, which phases depend on the CSI information. The number of RF chains corresponds to the maximum number of streams supported by the spatial multiplexing scheme, which is less than the number of receive antennas [34]. Moreover, this structure provides a great simplification on the requirements of the pilot sequence length, since the BS needs to estimate only a low-dimensional equivalent of the CSI.

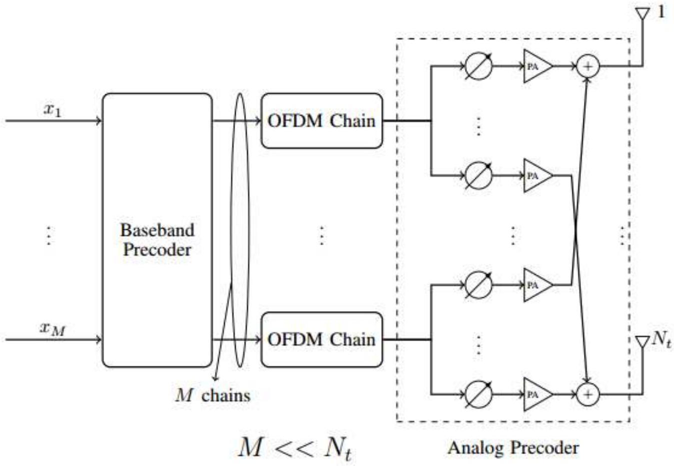

Figure 5. *Block diagram that represents the two stage RF/baseband pre-coding structure.*

The work [36] proposes a low-complexity hybrid pre-coding scheme to approach the performance of the traditional baseband ZF pre-coding. The proposed hybrid pre-coding scheme based on ZF essentially applies a phase-only control at the RF domain, and performs low-dimensional baseband ZF pre-coding based on the equivalent CSI seen in the baseband domain. The work [32] designs RF chains and a baseband pre-coder jointly in order to maximize the data rate. In [34], this design is done separately, i.e., a fixed analog pre-coder is first designed from the channel directions, while the baseband pre-coder is designed from the singular value decomposition (SVD) of the equivalent channel seen in the baseband domain.

3.3. Low-Resolution Analog-Digital Converter

In traditional MIMO, the (ADC)s have high-resolution in order to guarantee the signal waveform. However, as the number of antennas scales up the power consumption due to such ADCs becomes prohibitive [37, 38]. This problem has received great attention recently because it addresses not only the BS but also the UE. An envisaged scenario for the next generation considers systems operating at high frequencies (around 60 GHz), where it is possible to house hundreds of antennas in the BS and perhaps a dozen in the UE [38]. The reduction of the ADC resolution provides an efficient way to keep power consumption and system costs within manageable limits [37].

In [39] the authors propose to model the aggregate effect of hardware impairments as an additive Gaussian noise that is independent from the signal. Although this approach have been shown accurate for some set of hardware impairments, according to [37] it does not describe accurately the coarse quantization. The quantization errors are deterministic and depend on the transmitted signal.

In order to meet the hardware requirements, the use of one-bit ADC has gained much attention recently. The work [40] investigates the performance of a massive MIMO uplink system employing one-bit ADC, using a receiver performing maximum-ratio combiner, and a pilot sequence followed by LS channel estimation. The mathematical formulation obtained in [40] considers only the detection of QPSK symbols. In [41], the authors investigate the performance of one-bit ADC under the assumption that perfect CSI is not available in the BS and for higher-order modulations schemes. In this case, the channel estimation in the uplink becomes challenging due to the nonlinearities inserted by the one-bit ADC. From an information theory perspective, the work [38] shows the capacity for the MIMO and MISO channels using one-bit ADC, and compare with the case of no quantization.

Although one-bit ADC improves energy efficiency, it results in a rate loss, especially in the high SNR regime [42,43]. Furthermore, such type of ADC requires very long training sequences to obtain accurate channel estimation [42], which effectively increases the overhead. To tackle this limitation, the work [43] proposes a mixed architecture with one-bit ADCs and high-resolution ADCs. According to the results presented therein, the approach has the potential to reduce the power consumption and hardware cost while still partially preserving the performance gains of the architecture with full high-resolution ADCs.

Regarding detection algorithms under one-bit quantization, new algorithms must be developed so that they take into the quantized measurements and fulfill multiuser detection. In [44], the authors propose a near maximum-likelihood detector and channel estimator considering one-bit ADCs. They show that the proposed method can outperform the zero-forcing detector in different scenarios. However, the channel estimator proposed therein requires very long sequences, which greatly increases the system overhead. Another approach is to develop detectors based on distributed signal processing [45-47]. In [45], the authors provide a detector based on message passing that takes into account low-resolution ADCs. Exploiting the structured sparsity of a frequency selective channel and the prior probability distribution of the transmitted data, the detector outperforms linear detectors and achieves much lower bit error rates with reduced complexity. In [47], a distributed multiuser detection taking into account a mixed-ADC architecture is proposed. Using a Bayesian inference framework, the authors proposed a distributed detection strategy that relies on the generalized approximate messaging passing framework to implement the receiver algorithm. It is shown that the proposed method reduces the computational burden and provides near-optimal performances using the mixed-ADC architecture.

3.4. Signal Detection in Massive MIMO

The detectors used in traditional MIMO for spatially multiplexed signals may become infeasible in Massive MIMO. Techniques such as maximum likelihood detection and sphere decoder, whose complexities increase exponentially with the number of streams, are prohibitive at large-scale antenna systems. Hence, signal detection/decoding turns out to be a challenging task in large-array systems, due to the huge increase on the number of antennas and spatial multiplexing layers by orders of magnitude [48, 49]. In order to reduce computational complexity without losing reliability, some studies have proposed near-optimal receivers by considering graph-based solutions using belief propagation (BP) algorithms [48, 49.

In [48], the authors investigate the capability of the BP algorithm to detect spatially multiplexed signals. It has been revealed that BP combined with parallel interference cancellation (PIC) outperforms the minimum mean square error (MMSE) detector in terms of bit error rate (BER). Furthermore, such a method is obtained from a graph model which gives the possibility of implementing it in a distributed fashion using message passing. In [49], the authors use others variants of BP, namely: layered BP (LBP) and BP with forced convergence (BP-FC). In the original BP, the algorithm updates simultaneously the messages after processing all nodes, which is referred to as flooding scheduling. The LBP schedules the messages in a sequential fashion instead of simultaneously, and this approach provides enhanced convergence [49]. The BP-FC is based on the fact that some nodes converge faster than others. Therefore, it is possible to reduce complexity by skipping the update of such nodes. The results shown in [49] reveal that LBP and BP-FC can greatly reduce the computational complexity of the detector without severe degradation of their corresponding BER performance. Approximate message passing (AMP) methods have also been used to derive new massive MIMO detectors [50, 51]. In [50], the optimality of the AMP algorithm is investigated, while in [51] the impact of transmitter impairments, such as amplifier non-linarites, quantization artifacts, and phase noise is considered. In [53], an advanced approach has been proposed to utilize advantage of multiple antennas in signal modulation and detection methods. The quasi-quadrature amplitude modulation (QQAM) has been proposed to increase the energy efficiency of mobile network. Good results have been obtained by associating different sets of QAM signal constellation points with different antennas.

4. Channel Models for Massive MIMO

The channel model plays an important role on system analysis as well as in a performance evaluation. One factor that critically determines the channel model is an antenna array configuration. Every measurement is performed based on a given array, and there are several typical antenna configurations that can be placed into three different groups: one-dimensional, two-dimensional, and three-dimensional arrays.

Each of those configurations as well as their size affects the channel properties assigning different Massive MIMO performances. For example, the distance between the antenna elements basically dictates mutual coupling and the correlation matrix, affecting the performance of Massive MIMO.

We can list two kinds of channel models found in the literature, namely, correlation-based channel models and geometry-based stochastic channel models [54]. The correlation-based models are mainly used for theoretical evaluations of system performance.

A correlation-based channel model can be sorted into three different kinds of channel models. They are, namely,

- i.i.d. Rayleigh channel model: It assumes that no correlation among transmission antennas or reception antennas. As in Eq. (2), the elements of the fast fading matrix are i.i.d. complex Gaussian random variables. And, the most important property of such a model is given by increasing the number of antennas $N_t \to \infty$, which causes the rows of matrix $\mathbf{H}$ to become nearly orthogonal [1], implying

$$\frac{\mathbf{G}\mathbf{G}^{\mathrm{H}}}{N_t} \to \mathbf{I}_{\mathrm{N_r}}. \tag{10}$$

  Such a property is known as channel hardening and mitigates the impact of fast fading, which simplifies the complexity of scheduling schemes.

- Correlation channel model: This model inserts the antenna correlation due to antenna spacing and scattering environments. The fast fading vector of the k-th UE can be expressed mathematically as

$$\mathbf{g}_{\mathrm{k}} = \mathbf{R}^{1/2}{}_{\mathrm{k}}\mathbf{h}_{\mathrm{k}}, \tag{11}$$

  where $\mathbf{R}_k$ is the covariance matrix, and h_{k} has the same distribution as in Eq. (2).

- Mutual coupling channel model: As the number of antennas increases, the effect of mutual impedance rises as well. Moreover, the load impedance and antenna impedance should also be characterized in order to reflect a more realistic channel. The channel model can be mathematically expressed as

$$\mathbf{g}_{\mathrm{k}} = \mathbf{Z}\mathbf{R}^{1/2}{}_{\mathrm{k}}\mathbf{h}_{\mathrm{k}}, \tag{12}$$

  where $\mathbf{Z}$ represents an $N_t \times N_t$ coupling matrix, $\mathbf{R}_{\mathrm{k}}$ is the covariance matrix, and $\mathbf{h}_{\mathrm{k}}$ has the same distribution as in Eq. (2). The mutual coupling is expressed as

$$\mathbf{Z} = \left(Z_A + Z_L\right)\left(\mathbf{\Gamma} + Z_L\mathbf{I}\right)^{-1} \tag{13}$$

  with

$$\Gamma = \begin{bmatrix} Z_A & Z_M & 0 & ? & 0 \\ Z_M & Z_A & Z_M & ? & 0 \\ 0 & Z_M & Z_A & ? & 0 \\ 0 & 0 & 0 & & \\ M & M & M & 0 & 0 \\ 0 & 0 & \ldots & Z_M & Z_A \end{bmatrix}, \tag{14}$$

where Z_A, Z_L, and Z_M represent the antenna impedance, load impedance, and mutual impedance, respectively. Other structures can also be considered for $\mathbf{\Gamma}$, but it is out of the scope of this paper, as it basically involves a discussion based on electromagnetic theory. The reader can find a detailed discussion about the construction of $\mathbf{\Gamma}$ in the references [54].

Another category of channel models comprises those that are used for practical wireless communication system evaluations. The geometry-based stochastic channel models are cluster-based models that define the propagation channel containing several clusters with different delays and power factors. In the case of a 3D channel model, the two strongest clusters are spread in three sub-clusters with a fixed delay offset [54].

According to the discussion in [55], the massive MIMO channel has a “death-and-birth” phenomenon, which means that some clusters appear and disappear over the time. This phenomenon creates a non-stationary channel behavior, which has not been considered in conventional MIMO channel models. The study of accurate channel models that capture such a phenomenon is a current hot topic.

5. Scenarios and Challenges of Massive MIMO in Heterogeneous Networks

In this section, we discuss some futuristic scenarios for Massive MIMO deployments in HetNets, and discuss some key challenges in 5G networks. We consider two possible scenarios for Massive MIMO implementation: Massive MIMO as backhaul for small cells, and Massive MIMO as a multipurpose station for macro BS and small cell backhauls. The interference problem in heterogeneous networks is also discussed in this section.

5.1. Massive MIMO as Backhaul for Small Cells

The capacity of a wireless network is significantly limited by the backhaul network. Although optical backhaul can theoretically provide unlimited capacity, they are not feasible for heterogeneous networks. In order to achieve the best performance from HetNet, small cells are deployed in places with high user density. In such cases, small cell transceivers can be placed on any wall or pillar, where deployment of an optical backhaul would be expensive. On the other hand, a line-of-sight (LOS) wireless backhaul is also difficult to implement in a large city environment, because of the many high buildings that block signal trajectories. Massive MIMO can be a promising solution for non-line-of-sight (NLOS) backhaul. With a large number of transmitted antennas and a large number of small cell transceivers, we can, for instance, apply the multiple-input distributed-output (MIDO) scheme developed in [56]. MIDO allows multiple distributed single-antenna receivers to operate together as a single multi-antenna receiver, regardless of their location and distance between them. In [57], it is claimed that the throughput for each receiver in this system is limited only by the available spectrum and is not influenced by the number of receivers. Using advanced channel estimation and pre-coding techniques [56,57], Massive MIMO allows one to create a nearly interference-free NLOS backhaul, where each small cell fully utilizes the available bandwidth. The functional scheme of this system is shown in Fig. 6.

First, each transmission antenna at the Massive MIMO backhaul broadcasts pilot signals for channel estimation. The receiver on each small cell demodulates the pilot, estimates the channel, and sends the result via a feedback control channel. Second, the Massive MIMO transmitter analyzes the CSI information from each small cell to understand interference conditions in the wireless network environment. Note that this step is simpler to a backhaul network compared to a typical MIDO network because of the location of the transceiver of the fixed small cells. Note that the channel between the BS and the receivers on each small cell is characterized by a large coherence time.

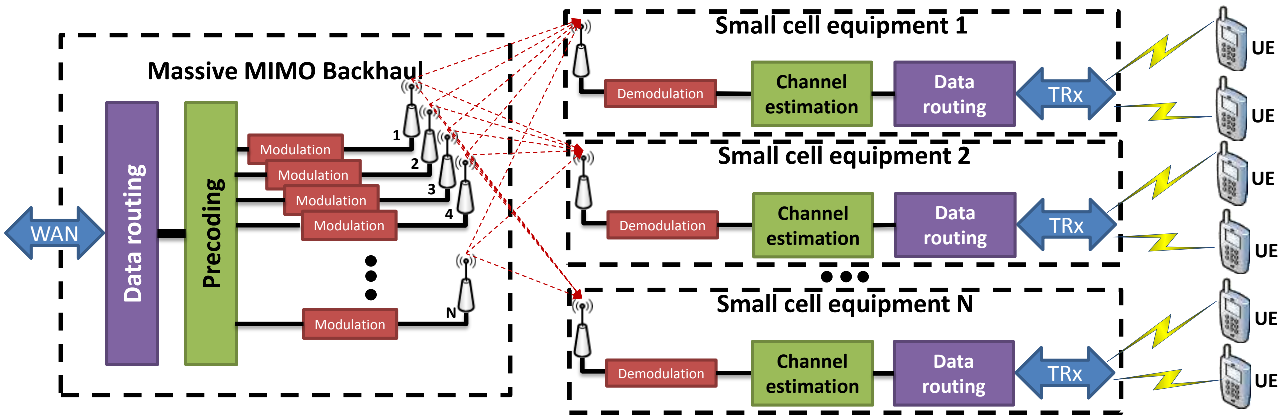

Figure 6.*Functional scheme of Massive MIMO backhaul.*

As proposed in [36], by allowing a feedback channel and using efficient closed-loop channel estimation, it is possible to further improve the CSI estimate with low pilot overhead. More specifically, the receiver at the small cell exploits the spatial and time correlation of the channel to smartly infer things about the CSI. By using the CSI, the small cells can optimize the pilot sequence and send the new sequence to the BS. Third, data routing and pre-coding is carried out according to the obtained CSI. Finally, each antenna sends its own predefined waveform into the wireless channel. Each small cell receives the sum of the radio signals, which results in a clean modulated waveform carrying the data intended for that particular small cell [58]:

$$y_{SCi} = x_1 H_{i1} + x_2 H_{i2} + \ldots + x_N H_{iN}, \tag{15}$$

Where $\mathbf{x}_i$ is the signal transmitted by the i-th antenna, and H is the channel matrix.

Afterwards, the transceiver serves UEs within the small cell area. In addition, fixed links allow the system to achieve outstanding performance from pre-coding, provide a high SINR that allows it to use high order Quadrature Amplitude Modulation (QAM) modes (i.e. 2048 QAM or 4096 QAM) with extremely high spectral efficiency. The quasi-static channel between the backhaul and the small cell harbors a favorable situation to reduce pilot overhead and the amount of information on the feedback channel. Therefore, the combination of M-MU-MIMO and small cells is a very attractive solution to drastically increase the data rates on the UE.

5.2. Interference Cancellation in Heterogeneous Networks

Sharing the same spectrum for an entire heterogeneous network can be a tricky task. The usage of advanced spatial multiplexing techniques can particularly solve this problem, as described in the previous two sections. In [58], a new Device-to-Device communication architecture was proposed that brings significant improvements in terms of radio access network flexibility and radio resources utilization. However, multiple device-to-device (D2D) links in HetNet give rise to irregular interference [59]. Therefore, interference can be a big problem in HetNet when multiple D2D connections are established. The use of Wi-Fi for D2D communications prevents the interference between D2D and cellular communication. However, the number of channels and the protocol efficiency in Wi-Fi is limited, and existing solutions to avoid interference still lead to a decrease in service quality. On the other hand, the utilization of the same spectrum for cellular and D2D networks increases spectral efficiency, but requires a new solution to deal with additional interference.

High interference between neighboring devices decreases the performance of D2D channels and degrades user quality of experience. The SINR determines the quality of wireless channel, so therefore

$$SINR_i = P_{R_i} \left[\sum_{j \neq i} P_{R_j} + N_i \right]^{-1}, \tag{16}$$

where P_{Ri} is the power of the data signal received by user i, P_{Rj} is the power of interference signals received by user i, and N_i is the power of additive Gaussian noise received by user i. Note that for scenarios with high user density, the influence of additive noise can be neglected, because in such cases the interference is the main limiting factor. Thus, the equation for user SINR can be written as follows:

$$SINR_i = P_{T_i}\alpha_i\left[\sum_{j\neq i}\left(P_{T_j}\alpha_j\right)\right]^{-1}, \tag{17}$$

where P_{Ti} denotes the power of the transmitted signal to the i-th user, αi denotes the path loss exponent in the channel between the transmitter and i-th receiver, P_{Tj} is the power of interfering signals to the i-th user, and αj is the path loss exponent in channels between interfering transmitters and i-th receiver. A path loss exponent is defined as follows:

$$\alpha_i = \left[20\log\left(4\pi dfc^{-1}\right)\right]^{-1}, \tag{18}$$

where *d* is the distance between the transmitter and receiver, f is the carrier frequency, and *c* is the velocity of an electromagnetic wave in the vacuum ($3\cdot10^8$ m/s).

The main problem for D2D communications is the dynamic user behavior that results in dynamic D2D groups, which causes D2D cells to appear and disappear dynamically. In [59], we consider a network-assisted D2D communication configuration. We assume that each D2D channel is created in a manner that new channels will not interfere with existing links. We assume that Massive MIMO can be implemented in situations when SINR conditions are not satisfied.

Let $SINR_{min}$ equal the minimal SINR value, which satisfies the D2D channel quality. The optimal conditions for D2D communication can be calculated using the following equation:

$$\begin{aligned} &\max\left(\sum_i SINR_i\right), \\ &\text{s.t. } \min\left(SINR_i\right) \geq SINR_{\min}. \end{aligned} \tag{19}$$

Due to the random user movement, it is possible for two or more D2D cells that use the same spectrum to be close enough to create harmful interference against each other, as shown. We assume two different approaches, full reallocation and CoMP reallocation, to avoid the interference between D2D cells with assistance from Massive MIMO BS.

Fig. 7 depicts the processes of proposed interference avoidance protocols in three steps. Each step is indicated by its sequence number in Fig. 7a and Fig. 7b, respectively. As shown in Fig. 7a.1 and Fig.7b.1, when two cells operating on the same spectrum move closer to each other due to user mobility, interference appears. In the full reallocation approach, the BS connects all devices within interfering cells, eliminating all existing D2D connections (Fig. 7a.2). The BS keeps serving all devices until they restore D2D cells in separate spectrum bands or create new D2D cells with other nearby devices to satisfy the requirements in (19), as shown in Fig. 7a.3.

Another approach is CoMP reallocation between Massive MIMO and D2D with time division multiplexing. In this case, a TDM frame with duration T_s is divided into M sub-frames, where M is the number of interfering D2D cells. As shown in Fig. 7b.2 (in this case M=2), the first D2D cell is allowed to transmit in the first sub-frame during a T_s/2-long interval, while the second D2D cell is served by the Massive MIMO system. During the next T_s/2-long sub-frame, the first D2D cell is served by the Massive MIMO system, while the second D2D cell uses a direct connection between devices, as shown in Fig. 7b.2. This type of transmission continues until D2D cells are reallocated to separate spectrum bands and requirement (28) is satisfied. Neighboring D2D cells will be separated by different spectrum bands as shown in Fig.7b.3. In practice, both approaches can be useful depending on the situation. In future work, we will provide a detailed efficiency comparison of full reallocation and CoMP, as well as other interference cancellation approaches for HetNet.

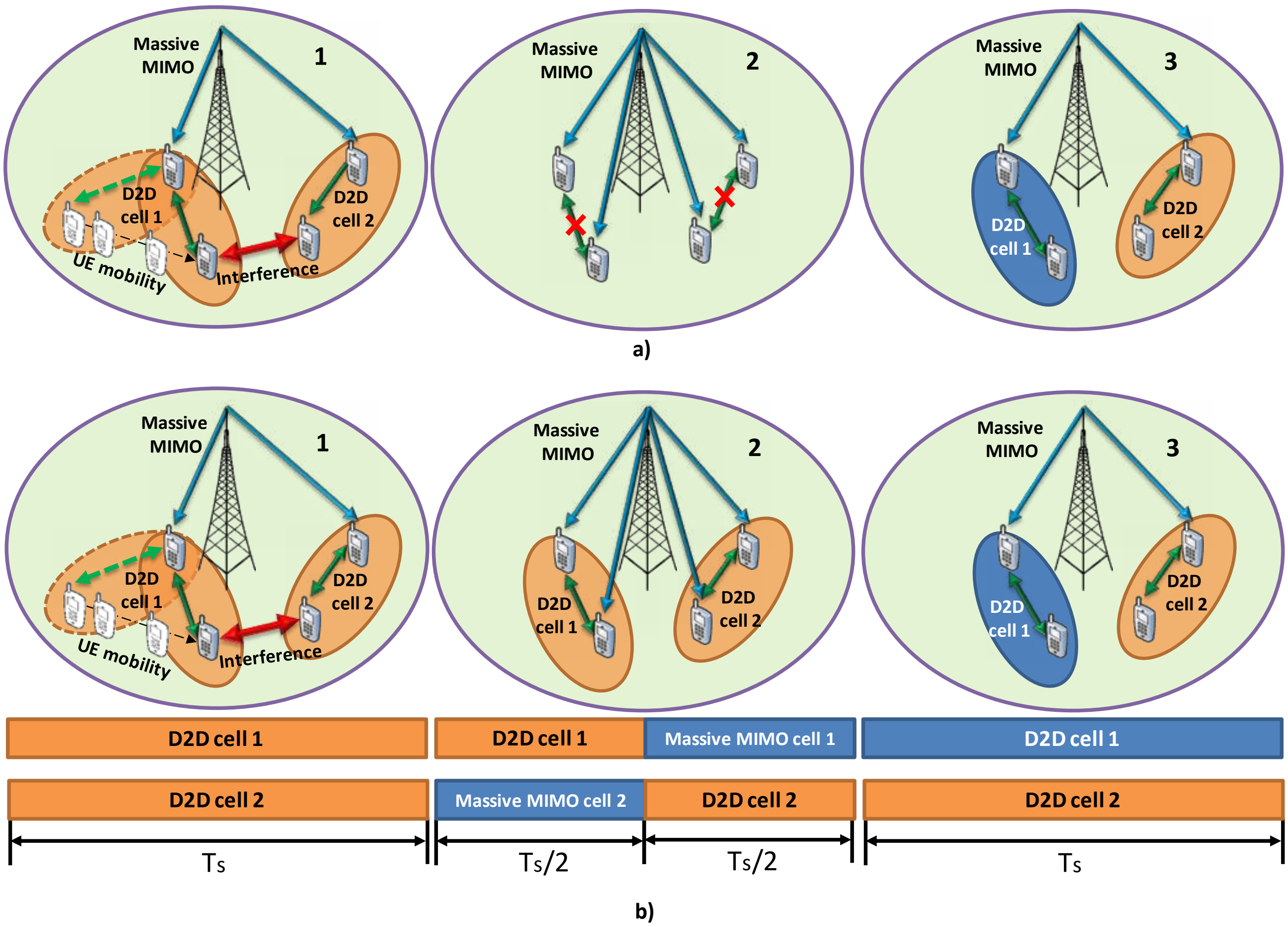

Figure 7. *Interference cancellation in HetNet: a) full reallocation, b) CoMP with TDM.*

6. Conclusion

There is great potential in scaling up the number of antennas at the BS in “beyond LTE” wireless communication standard. It allows to improve spectral efficiency and to implement parallel low-cost power amplifiers, while making the system more robust and reliable. For next generation wireless communications, we discussed futuristic scenarios where Massive MIMO meets potential applications such as wireless backhaul for small cells or interference management in network-assisted D2D communications. Although Massive MIMO enjoys several advantages, there are still plenty of challenges that need to be overcome to fully exploit its promised benefits. For instance, issues related to TDD and FDD operations, new low-complexity detection algorithms, and new pre-coding schemes that take into account restrictions on the number of RF chains must be investigated. Such important research problems have pushed both academia and industry to focus on the Massive MIMO track as a strong potential technology for a 5G communication system.

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