A Systematic Review on Challenges in Massive MIMO Based 5G and Beyond Wireless Networks and Their Solutions

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ABSTRACT

In the new era of wireless communication networks, ubiquitous connectivity with high quality multimedia services is the key requirements of high data rate transmission. In view of this, fifth generation (5G) wireless systems has been defined to handle new and enormous communication traffics efficiently for massive number of devices. 5G wireless network marks the start of real digital era for the use cases like Ultra-Reliable and Low Latency Communications (URLLC), enhanced Mobile Broadband (eMBB) and massive Machine-Type Communications (mMTC) that support low latency and high data rates for diverse range of connected devices. Currently on-going deployment and testing of 5G wireless systems is revealing its inherent limitations and needs to redefine the challenges faced by it. Massive Multiple Input and Multiple Output (MIMO) technology plays major role in 5G in which large antenna arrays are implemented at the base station. Massive MIMO facilitate spatial multiplexing for enhancing the capacity and spectral efficiency (SE) of the network. This survey is focused on the massive MIMO related issues. Channel Estimation (CE) is one of the important factors influencing the receiver performance. To get perfect CE in spatially correlated channels advanced detectors are to be designed to optimize performance and complexity. Besides CE, due to increased number of antennas, the signal processing for the detection of transmitted signal becomes more complicated. In this review paper, a framework for CE and signal detection techniques in implementation scenario of massive MIMO in 5G networks is presented. Moreover, various techniques and challenges among existing solutions in terms of their respective advantages and limitations are elaborated. This survey emphasizes on solutions suggested by researchers and open research issues in channel estimation and signal detection in massive MIMO systems for 5G and beyond wireless networks.

Keywords: Spectral Efficiency, Ultra-Reliable and Low Latency Communications, Enhanced Mobile Broadband, Massive MIMO, Channel estimation, Signal Detection

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1. INTRODUCTION

We have seen from past decade that the wireless network evolution was driven by constant need for higher data rates and to increase the network capacity in terms of devices and services. New emerging technologies defined in 5G like device-centric architectures, mmWave, massive MIMO, smarter devices, and support of machine-to-machine (M2M) communication led to both architectural and component design changes are explored in [1]. In fully connected intelligent digital world where we need to connect everything, from people to vehicles, sensors, data, and cloud resources, the mobile networks are the major data traffic carriers. 5G wireless network marks the milestone of real digital society and achieves vital breakthroughs in terms of latency, data rates, mobility, and range of connected devices in distinction to previous generations [2, 3].

5G has mainly three service scenarios, i.e., eMBB, uRLLC and mMTC. eMBB to support stable connections with very high peak data rates, as well as moderate rates for cell-edge users, uRLLC to support low-latency transmissions of small blocks with very high reliability from a limited set of terminals, and mMTC to support massive number of Internet of Things (IoT) devices [4]. The advanced 5G infrastructure is a revolution in the information and communication technology (ICT) field which will enable new secure, dependable, ultra reliable, and delay critical services to everyone and everything, such as cognitive objects and cyber-physical systems (CPSs) [5].

The framework and trends of the development of IMT (International Mobile Telecommunications) for 2020 and beyond were clearly defined in Report ITU M.2083-0 [6], where ITU-R stands for International Communications Union - Radio (ITU-R). The performance evaluation of new technologies, we need to understand the evolution of the traffic load in the next decade. So we referred the report ITU-R M.2370-0 [7] which analyses trends impacting future IMT traffic growth beyond the year 2020 and presented in Fig. 1.

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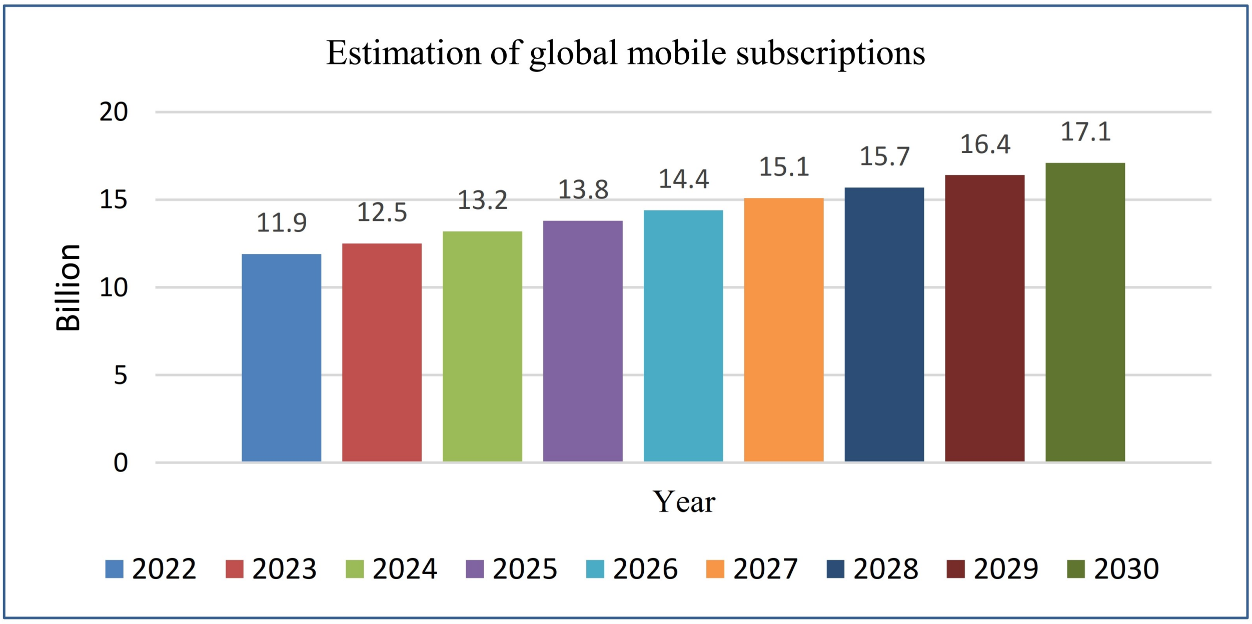

***Fig. 1**: Estimation of global mobile subscriptions Rep. ITU-R M.2370-0 [7].*

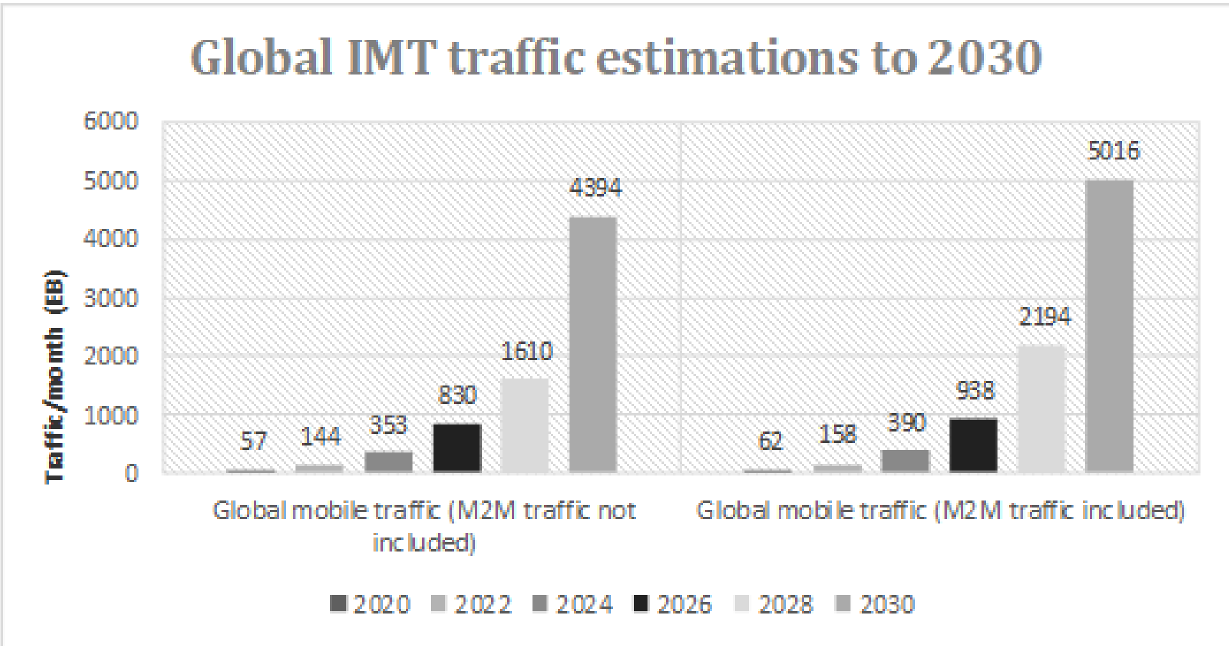

***Fig. 2**: Estimations of global mobile traffic in 2020-2030 [7].*

According to this report, the main drivers influencing the growth of future IMT traffic are video usage, Device proliferation and Application uptake. The number of global mobile subscriptions has reached 11.9 billion in 2022. According to the statistical estimation the number of global mobile subscriptions would be 17.1 billion devices in 2030 and global mobile data traffic will reach 5 zettabytes by 2030, refer figure 1, 2. As per the forecast report, the global mobile traffic per month is estimated to 4394 (Exabyte) EB which can reach up to 5016 EB with including M2M traffic in 2030.

With an immense growth in demand for high throughput, large capacity, and low latency, the on-going deployment of 5G systems is continuously exposing the inherent limitations of the system.

2. EVOLUTION OF WIRELESS COMMUNICATION NETWORKS

A new wireless network generation have been introduced approximately every 10 years. The first-generation mobile network dedicated for voice services with a data rate up to 2.4 kbps, introduced in the 1980s. It utilized analog signal to transmit information. During the 2G era that lasted from 1980's to 2003, Digital modulation technology was its fundamental part along with few advancements made within the spectrum such as Time Division Multiple Access (TDMA) and Code Division Multiple Access (CDMA). 2G systems included Global System for Mobile Communication (GSM), General packet radio service (GPRS) and Enhanced Data rates for GSM Evolution (EDGE) and IS-95 CDMA. But above-mentioned technologies had limited mobility and hardware capability. 2G supported maximum data rate of 64kbps with better voice services. 3G was big revolution which provided advanced services including Web browsing, TV streaming, and video services with speed capabilities of up to 2 Mbps [8].

4G improves spectral efficiency and reduces latency, accommodating the requirements set by advanced applications like Digital Video Broadcasting (DVB), High-Definition TV content and video chat. 4G provides terminal mobility at anytime and anywhere. Long Term Evolution-Advanced (LTE-A) and Wireless Interoperability for Microwave Access (WiMAX) are some of 4G standards for increasing efficiency and data rate on the network. The multiple access schemes enhanced MIMO channel transmission techniques. The major technique for extensive coordination among multiple cell sites is coordinated multipoint (CoMP) transmission/reception was introduced in LTE [9].

The major objectives for future 5G wireless networks include significantly faster speeds (1 Gbps-10 Gbps) and lower power requirements to support massive numbers of internet of Things (IoT) devices [10]. 5G utilize various new techniques and technologies, such as Carrier Aggregation (CA), Cognitive Radio (CR), device-centric architecture, small cell-based Heterogeneous Networks (HetNet), Massive M-MIMO, beam forming, full-duplex technology, CoMP, Wireless Sensor Networks (WSN), Device-to-Device (D2D) communication, millimetre wave (mmWave) or Terahertz wave, and visible light communication. But with the evolution of this new generation critical challenges like increasing Spectral efficiency and energy efficiency needs to be resolved [11]. These drawbacks of 5G are currently leading in activities focused on defining the next generation Sixth generation (6G) wireless system that can integrate applications ranging from autonomous systems to extended reality. The emergence of the Internet of Everything (IoE) system will be supported by IoE services like eXtended reality (XR), telemedicine, haptics, flying vehicles, brain-computer interfaces, and connected autonomous systems will disturb the original 5G goal [12].

This survey is focused on massive MIMO technology towards 5G, the main identified area of wireless communication process needs to be studied is Signal detection as signal detection needs advanced signal processing. Here an effort is made to present the challenges in detection algorithms in concise manner with existing research works and their comparison. The outline of this review article is organized as follows:

- Firstly, in section 3, discussion about the Massive MIMO technology exploring its implementation and capability to meet the requirements of 5G. The evolution of massive antenna technology and leads towards the advantages and challenging aspects of this technology.
- Following with the section 4, where we discuss the different existing areas in massive MIMO communication technology where challenges are identified, and research works in the respective domain are presented with comparison. In the area of signal detection, the detailed literature survey is done with the available techniques, proposed solutions, and their comparison.
- In section 5, overall summarized report of the survey is presented and along with future research directions are elaborated. This section concludes the paper with remarking points.

3. MASSIVE MIMO: KEY ENABLING TECHNOLOGY FOR 5G NETWORKS

Massive MIMO is the key enabling antenna technology to fulfil the needs of 5G and beyond networks. This technology is about bringing together antennas, radios, and spectrum together to enable higher capacity and speed to meet the demands of 5G [13]. It involves using hundreds and even thousands of antennas attached to a base station (BS) to improve spectral efficiency and throughput. Many issues and challenges need to be solved in the massive MIMO technology. Some of the fundamental challenges in massive MIMO systems are discussed in [2] are related to Channel Estimation, pilot contamination and signal Detection which is the basis of this literature survey.

MIMO systems are a natural extension of developments in antenna array in which impact to fading is reduced by the spatial diversity provided by multiple spatial paths. The use of multiple antennas greatly increases the achievable rates on fading channels if the channel parameters can be estimated perfectly at the receiver and if the path gains between different antenna pairs behave [14, 15]. The concept of multiuser MIMO (MU-MIMO) system where many user terminals are served by an antenna array simultaneously was introduced in [16].

In 2010, the concept of massive MIMO in the context of multiple cell and Time Division Duplex (TDD) scenario was introduced by T.L. Marzetta, who concluded that asymptotically as $M \to \infty$, where M are the number of antennas at BS and under realistic propagation channel, drastic improvement in throughput without cooperation among the BSs is achieved [17]. Massive MIMO technology refers to that the BS is equipped with a huge number of antennas, usually a hundred or several hundred antennas simultaneously serve many single antenna users and improves the capacity, the throughput, the reliability, the diversity gain, the performance gain,

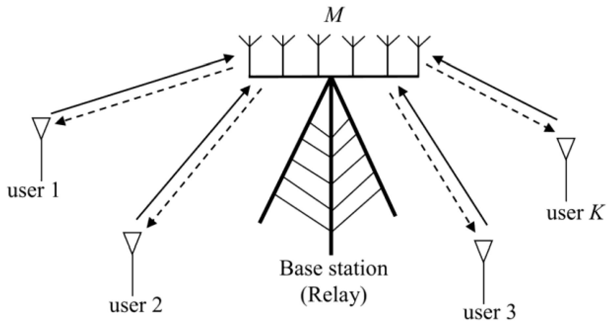

***Fig. 3**: Massive MIMO techniques.*

and the spectral efficiency to meet the 5G use case scenarios. The basic model of massive MIMO is shown in figure 3 [18, 19].

The use of multiple antennas at the Base Station opens a new spatial dimension and serves the following advantages [20]:

- Increase the transmission rate via Multiplexing gain.
- Increase the SNR called as Array or coding gain.
- A massive BS antenna array does not have to be practically large.
- Massive MIMO is scalable.
- All the complexity lies at the BS.
- It can increase the capacity by 10 times or more as compared to current MIMO deployment.
- Massive MIMO improves the radiated energy-efficiency.
- System can be realized with inexpensive, low-power components.
- Massive antenna array enables a significant reduction of latency on the air interface.
- It simplifies the multiple-access layer.
- It increases the robustness both to unintended man-made interference and to intentional jamming with Diversity gain.

4. MASSIVE MIMO CHALLENGES AND SOLUTIONS

For massive MIMO based wireless systems, multi-user pre-coding in the downlink and detection in the uplink require channel characteristics at the BS. These channel information needs to be retrieved by BS with some resource block which is proportional to the number of the transmit antennas. Channel estimation is vital requirement to improve link performance in wireless systems. Due to massive number of antennas, channel estimation becomes a challenging aspect in its practical implementation. One way to deal with this challenge is to use reference signals called as pilots for estimating exact channel conditions but massive antenna array at BS leads to pilot contamination because of inter cell interference. Therefore, pilot contamination has become challenge to deal with and mitigating techniques are to be studied to cope with the performance loss in massive MIMO systems. Accurate detector is required to estimate the transmitted signal. Huge signal processing is required with large antennas which lead towards the signal detection complexity. So comprehensive survey is to be done to find the way to enhance performance and reduce computational complexity in detection strategy.

4.1 Challenges in Channel Estimation:

In wireless fading channel, the accurate estimate of the Channel State Information (CSI) is to be done for exact signal demodulation. Also, the equalization and decoding is to be implemented irrespective of channel model employed [21]. For signal detection and decoding, massive MIMO relies on CSI, the information of the state of the communication link from the transmitter to the receiver. Channel characteristics are the combined effect of fading, scattering, reflections and mobility [8]. The most important challenge is to reduce redundancy in acquisition of CSI at the BS. The channels between the massive BS antenna array and the user terminals (UTs) are quite affected by fading. CSI is done by sending reference signals called as pilots [22]. But the large number of pilots adversely affects spectral efficiency of the massive MIMO systems so some blind techniques are also available. In the literature, there are three types of channel estimation (CE) methods. These are Pilot based (PBCE), Semi-blind (SBCE) and Blind (BCE) CE techniques. The detailed classification is shown in Fig. 4.

4.1.1 Pilot Based Channel estimation (PBCE):

In PBCE technique, each user sends the pre-allotted or pre-assigned pilot sequence (training signals) to the BS. The pilot signals are orthogonal to each other. The BS has the prior knowledge of the pilot sequences transmitted from all users, and then estimates the channels based the received pilot signals. In Large-Scale Antenna Systems, Time Division Duplexing (TDD) is the better mode for CE operation in the massive MIMO scenario. A single uplink pilot is sufficient for estimating the channel between the massive antenna array and the user for both the uplink and downlink data transmission [17]. For a system using Frequency Division Duplexing (FDD), CSI needs to be estimated separately for downlink and uplink while in TDD, by exploiting the channel reciprocity property, the base station can estimate the downlink channel using channel information of uplink [8]. Refer figure 5 to understand the TDD and FDD system.

In TDD mode, only the BS needs to know the CSI to coherently process the antenna signals. Also, in TDD the uplink CSI overhead depends on the number of users (K), and not on number of antennas at BS (M), thus making the system fully scalable. In contrast to TDD system, in an FDD system, the uplink and downlink transmissions use different frequency spectrum consequently channels are not reciprocal in FDD, and this scheme requires M pilot symbols per coherence block in the downlink, and K pilot symbols along with feedback of M channel coefficients per UT on the uplink. Concluding that it is the (M + K) uplink symbols per coherence block that is

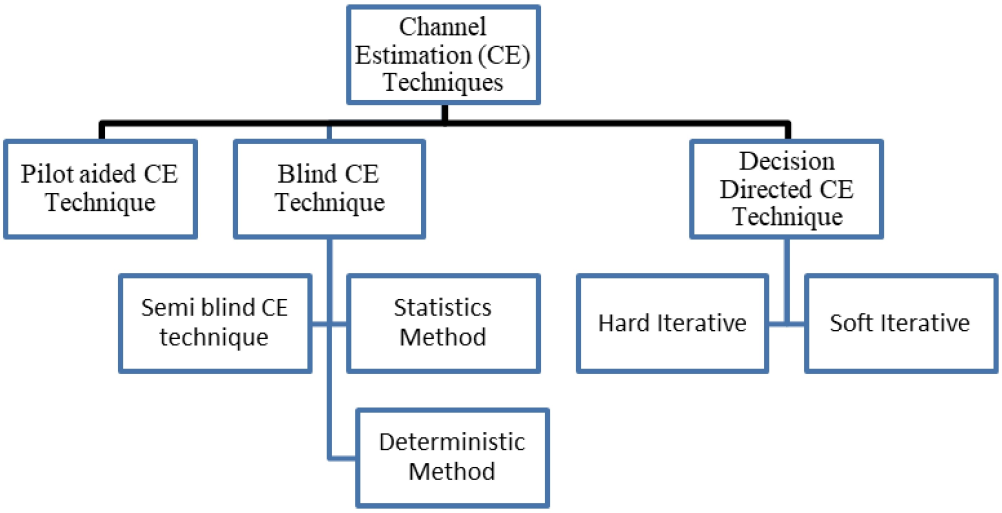

***Fig. 4**: Channel Estimation techniques [21].*

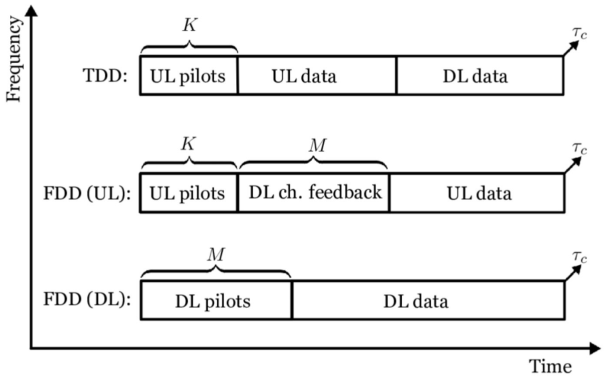

***Fig. 5**: TDD versus FDD pilot transmission and protocol.*

the limiting factor in FDD [23].

4.1.1.1 Literature for TDD versus FDD for Massive MIMO

A lot of research efforts on TDD and FDD modes particularly in Massive MIMO system is going on and to what extent FDD mode can be applied in Massive MIMO scenario is an open research topic mentioned in [23]. TDD and FDD protocol are presented in figure 5. Despite all the advantages discussed in previous section, one of the limitations for TDD is justified in [24], that TDD massive MIMO system is more prone to data jamming attacks as compared to the FDD mode because the probability of acquiring information about the channels for smart jammer is more in TDD mode. Although the relative performance of both the modes is controversial, the comparison of the performance in Massive MIMO for TDD and FDD beam forming based on feedback of CSI is presented in [25], concluding that performance depends on the existence of propagation conditions i.e., Line-of-Sight (LOS) and high Rician factors. In Non-Line of Sight (NLOS) scenarios TDD beam forming outperforms significantly FDD mode [25]. Channel sparsity can be utilized for reducing pilot overhead in the channel estimation problem in 5G. FDD Multi-user massive MIMO systems as proposed in [26] to reduce the pilot overhead, by using the spatial correlation between multiuser channels to split the channel matrix into two sparser channel matrices and then use compressed sensing technology to estimate the two parts of the channel separately. Comparative analyses are made between TDD-based massive MIMO and FDD-based MIMO deployments in recent research in [27] and experiments results proved that TDD-based massive MIMO has higher cell throughput than FDD-based MIMO in 10 and 20 MHz bandwidth.

So, we can conclude from above survey that the underlying sparsity assumptions made in FDD, are so far only hypotheses and are open for research to find some alternate ways to reduce the overhead signalling. On the other hand, some solution for anti-jamming needs to be proposed for TDD mode of operation.

4.1.1.2 Concluding remarks of pilot scheme

In TDD architecture, the use of channel reciprocity and pilot in the Uplink (UL) are key features for its application. To increase the spectral efficiency in cellular network requires appropriate frequency or time or pilot reuse factors to maximize system throughput [28].

To get effective working of pilot signal sequences, these pilots need to be orthogonal, and the pilot duration is bounded to coherence time [20]. Major drawback in implementation of pilot-based technique is wastage in the communication bandwidth. To cope with spectral efficiency, concept of pilot reuse was suggested. Two major points in pilot-based techniques is that, firstly, depending on pilots for channel estimation is not worthy and secondly, the interpolation techniques can't be perfect; hence, there would be error introduced into the estimation process [21]. Pilot reuse feature introduces co-channel interference and pilot contamination becomes a major challenge in massive MIMO systems which limit its performance. So it's important at this point to mention the pilot decontamination techniques are needed to be studied to improve the CE accuracy.

4.1.2 Blind Channel Estimation Techniques

Blind CE technique uses the structural properties of transmitted signal and predict the channel based on inherent information in the received signals. The pilot contamination problem can be mitigated, as there is no pilot sequence is used. Blind channel estimation techniques can be classified as described in Table 1 [21, 29, and 30].

4.1.2.1 Concluding remarks of Blind CE scheme

The blind techniques utilize bandwidth efficiently as it does not require training symbols for the channel estimation. The major limitation of blind estimation techniques is that channel needs to be time-invariant or static as a result blind CE technique is not suitable for fast time-varying channel. But to deal with the mobile wireless communications systems where the channel changes frequently with time due to mobility of UTs further optimized estimation technique need to be identified. This method has higher computational complexity than pilot-based methods but combats with pilot contamination problem. Space alternating generalized expectation (SAGE), multiple signal classification (MUSIC), estimation of signal parameters via rotational invariance techniques (ESPIRIT), a posteriori probability (APP), and Viterbi algorithm are different blind techniques [31].

4.1.3 Semi blind channel estimation (SBCE) technique:

The semi-blind channel estimation techniques are blended form of the PBCE and blind channel estimation methods which uses shorter pilot signal sequences than pilot-based methods. SBCE can potentially enhance the performance by using smaller pilot symbol pay loads. Combining the small pilots with blind statistical information, avoids the convergence problems faced in blind techniques [32].

4.1.3.1 Concluding remarks of Semi-Blind CE scheme

Computation complexity in SBCE is more as compared to Blind CE, as it uses singular value decomposition (SVD) based estimation. But it still uses pilot sequence; probability of pilot contamination is there but is reduced compared to PBCE scheme [33, 34].

4.1.4 Decision directed channel estimation (DDCE) technique:

In the DDCE techniques, the re-modulated detected message symbols along with the pilot symbols are considered for channel estimation. This technique provides a more accurate channel estimate and assuming zero transmission errors, it could be viewed as a PBCE scheme with sparse to act as perfectly pilot assisted estimation. Usually, DDCE method demodulates the received data using hard decision. But hard decision along with iterative decoding procedure is called soft decision feedback is also implemented [35, 36, 37]. It is time varying channel estimation method but has major drawback of high probability of error decision [38]. Table 2 represents various CE strategies and applications.

4.2 Challenges in signal detection:

In massive MIMO systems, the uplink scenario results in multiuser interference at the receiver due to the overlapping of transmitted signals by the users. So, the demodulation at the receiver side is difficult due to the interfering signals. To separate the data streams transmitted by the different users, we need to focus on multiuser detection techniques mentioned in [49]. So, accurate and instantaneous CSI is needed at the BS to perform pre-coding in a downlink and detection in uplink. In massive MIMO signal processing requires a computational cost for transmit and receive processing that increases with number of antennas. So, we must lead for solutions for both transmit and receive processing tasks, which will require significant research effort in the next years for next generation cellular networks.

Complexity of massive MIMO detection algorithm defined by the following factors: number of antennas at transmitters and receiver terminals, the matrix-by-matrix multiplication, and the matrix inversion [50]. The most challenging task is at the receiver side for designing reliable and energy-efficient detectors because of the implementation complexity of the signal detection due to the interference. The signal detection problem refers to finding the most expected transmitted symbols based on the CSI available at the receiver and the received signal [51].

4.2.1 Optimal detector:

The maximum likelihood (ML) detector is an optimal detector and the most straightforward approach to solve the detection problem in multiple antenna scenarios. It performs an exhaustive search and examines all possible signals illustrated by Eq. (1), where $\hat{x}$ is the estimated received signal, given that y is received signal, H is channel matrix:

$$\hat{x} = \operatorname{argmin}\|\mathrm{y} - \mathrm{Hx}\|_2^2 \tag{1}$$

But the ML detector can be complex even for a small-scale MIMO detection. It has a complexity cost that grows exponentially with the number of transmit antennas, K, and modulation order used, which makes it very complex to be implemented in massive MIMO systems [52].

4.2.2 Linear detector

In the case where M is much larger than K, i.e., 1 << K << M, linear detectors perform accurately and

***Table 1**: Blind channel Estimation techniques.*

Blind CE Method	How it estimates the channel properties	Limitation
Statistical blind channel estimation Method	In this method, cyclic statistic properties of the received signals are examined	When we transmit extremely short sample sequence, this estimation method is prone to finite data effect.
Subspace-based channel estimation Method	Finite alphabet structure, symbol rate, correlation or higher order statistics is applied	
Recursive adaptive channel estimation methods	Each sample adaptively estimated	For successive adaptation and estimation, sufficient memory space is needed to compare previously received symbols at each antenna of the BS
Deterministic blind channel estimation Method	In this estimation technique, the received signals and the channel coefficients are assumed to be deterministic rather than random	It converges much faster than statistical method and have high computation complexity

able to asymptotically achieve capacity as M grows with low complexity. Linear detectors can be represented as multiplying the received signal y with the equalization matrix A^H, $\hat{x} = S(A^H y)$, followed by a slicer S (.), which quantizes each signal. The most conventional low complexity linear detectors are the matched filter (MF), the Zero forcing (ZF) algorithm and the Minimum mean-square error (MMSE) algorithm.

4.2.2.1 Matched filter:

MF handles the interference from other sub-streams as purely noise. MF, also called the maximum ratio combining (MRC), tries to maximize the received SNR of each stream by neglecting the effect of multiuser interference. For the worst-case scenario of channel, its performance is severely degraded for a square MIMO system. Let A be an $M \times K$ linear detector matrix which depends on the channel H. The estimated received signal using MF is given by:

$$\hat{x}_{MF} = S(H^H y) \tag{2}$$

By making A = H works properly when K is much smaller than M.

4.2.2.2 Zero forcing detectors:

It aims to maximize the received signal-to-interference ration (SINR). The ZF mechanism is based on inverting the channel matrix H and thus, removing the effect of the channel. Firstly, the ZF solves the Eq. (1), so that the problem becomes convex optimization. The equalization matrix of the ZF detector [53] is given by:

$$A_{ZF}^{H} = (H^H H)^{-1} H^H \tag{3}$$

It is called as the left Moore-Penrose pseudo-inverse. The pseudo-inverse is used because H is not always a square matrix (the number of users is not equal to the number of antennas at BS). Then, the constraint on x is reintroduced by quantizing the vector accordingly to the constellation in use. This quantization should lead to a good estimation. The estimated signal is given as follows.

$$\hat{x}_{ZF} = S\left(A_{ZF}^{H} y\right) \tag{4}$$

4.2.2.3 Minimum mean-square error detector:

The MMSE linear detector chooses A to minimize the mean squared error e.

$$e = E\left\| x - H^H y \right\|^2 \tag{5}$$

It achieves an optimal balance of noise enhancement and interference suppression. The equalization matrix of the MMSE detector is as follows:

$$A_{MMSE}^{H} = \left(\left(H^H H \right) + \frac{K}{SNR} I \right)^{-1} H^H \tag{6}$$

Here 'I' is the identity matrix. The output of the MMSE detector can be obtained by

$$\hat{x}_{MMSE} = S\left(A_{MMSE}^{H} y\right) \tag{7}$$

Table 3 gives the insight for the comparative analysis of linear detection techniques.

4.2.3 Decision-driven detection

To improve further the performance, it is necessary to drop the linear detector approach and look for more elaborate decoding algorithms. These are non-linear methods which generally achieve a better performance than linear detectors.

4.2.3.1. Successive interference cancellation (SIC) detector:

SIC detection is used in the Vertical-Bell Laboratories Layered Space-Time (VBLAST) systems. The SIC detectors have a two-step iterative process: first, a decision is taken on the first single symbol at a time. Then the interference imposed by this symbol on the other symbols is subtracted after recreating the interference upon generating the modulated signal corresponding to this symbol. In this scheme, it is most important to cancel the effect of the strongest interfering signal before detecting the weaker signals [54]. It outperforms the ZF method and the MMSE method but has high computational complexity.

***Table 2**: Literature survey of CE methods in massive MIMO systems.*

CE Strategy	Implementation scenario	Detail/Limitations	References
Compressive Sensing	Massive MIMO FDD systems, sparsity update CoSaMP (SUCoSaMP) CE algorithm	It reduces the pilot overheads but has a limited accuracy and a high computational complexity	[39], [40], [41], [42]
SBCE using Expectation Maximization (EM)	EM with the Gaussian prior of data in Single cell Massive MIMO systems	SBCE-EM performance was better than the training-based ML channel estimation, and its accuracy increases with the increase of data length.	[43] [44]
Beam Domain CE	Massive MIMO hybrid architecture with phase shifters and limited RF chains.	Here beam steering vectors are estimated from the direction -of-arrival (DOA) and beam gains estimated from small length pilots	[45]
Semi-blind iterative space-alternating generalized expectation maximization (SAGE)	Massive MIMO with pilot based MMSE estimator	Channel estimate is obtained from the received samples converges almost in one iteration and reduces pilot overhead	[46]
Parafac-based blind channel estimation	multi-user massive MIMO uplink system	constrained bilinear alternating least squares Algorithm it performs better than traditional Least square method	[47]
Semi-blind channel-and-signal estimation (SCSE) scheme	Uplink massive MIMO system	This method uses integration of pilot sequences and message passing algorithm for sparse matrix factorization	[48]

4.2.3.2. Parallel interference cancellation (PIC) detector:

In the PIC based detector, all symbols are detected simultaneously, and the algorithm start by using a simple detector with poor performance, generally a linear one, and cancel the interference on all antennas at once based on the assumption. If better performance is required, then this PIC detection process may be repeated for several iterations. [55]. The PIC detector has lower processing delay and is more robust to inter-stream error propagation.

4.2.3.3. Multistage interference cancellation (MIC) detector:

MIC is another alternative of SIC where the initial stage consists of the linear ZF/MMSE detector, the SIC detector or any other suboptimum detector [56]. The subsequent stages apply the initial stage results as inputs and employs sub-optimal detection as well for the sake of cancelling the multi-user interference.

4.2.4 Decision feedback (DF) detectors:

The first DFD scheme was proposed in [57, 58] for asynchronous DS-CDMA systems which also relies on the SIC concept. DF detectors employ feed-forward

Table 3: *Literature survey of CE methods in massive MIMO systems.*

Detection Technique	Strategy	Drawback	Concluding Remarks
ML	Optimum detector uses exhaustive search and examines all possible signals	High computational cost which increases exponentially with the M, K, and modulation order used	ML detection is impractical
MF(MRC)	Handles the interference from other sub-streams as purely noise, and tries to minimize noise	It fails to treat interference	MRC complexity is much less than the one for both ZF and MMSE detectors
ZF	It eliminates interference completely, regardless of noise enhancement and it aims to maximize the received SINR.	ZF detector ignores the effect of noise.	It works properly in interference-limited scenarios in expense of computational complexity
MMSE	It aims to minimize the mean-square error between the transmitted and the estimated signal	Low performance in the ill-conditioned channel matrix.	It achieves an optimal balance of noise enhancement and interference suppression

and feedback matrices for interference cancellation. It represented mathematically as Eq. (8), where x_0 is initial decision vector, which is usually performed by the linear section of the decision-feedback receiver, and then it is applied to the feedback section. The receiving filters, W and F can be computed using design criteria and optimization algorithms.

$$\hat{x} = S\left(W^H r[i] - F^H \hat{x_0}[i]\right) \tag{8}$$

When we talk about DF/SIC detector, here F have a strictly lower triangular structure for performing successive cancellation and for DF/PIC F have zeros on the main diagonal when performing parallel cancellation. The adaptive technique proposed in [59], is simpler to implement based on the generalized decision feedback equalizer (GDFE) with time-varying channels. This algorithm adaptively follows least square error (LSE) criterion.

4.2.5 Approximate inversion based linear detectors

In the massive MIMO system, high computational complexity being one of the major problems in the linear and simple non-linear detectors. Although linear precoding is less complex, but complexity in computation is found in deriving pseudo inverses of large matrices. The approximate inversion based linear detectors have been introduced due to challenge in (a) matrix inversion when the channel matrix is nearly singular and (b) when the system becomes ill-conditioned. So, approximation is best choice for inversion of matrices by making use of special properties of the matrices, thereby reducing the cost of hardware [60].

As we have seen in linear detectors, matrix inversion of the Gramian or Gram matrix is required to equalize the received signal, where the Gram matrix is given as follows:

$$G = H^H H$$

All proposed approximations are summarized in Table 4.

4.2.6 Tree-search based detectors:

Tree-search-based detectors can either be optimal with a non-polynomial or quasi-optimal yet not optimal with a polynomial convexity [51]. Especially in the massive MIMO systems, this is very promising approach because of the introduction of the powerful sphere decoding (SD) algorithm. SD technique has design flexibility in terms of trade-off between approaching the optimum ML performance and reducing the computational complexity [53]. All tree-search-based detectors use the pre-processing using QR decomposition of the channel matrix with Q a unitary matrix and R an upper triangular one. The decomposition is computed only once per coherence block leading to a negligible overhead of the complexity per received symbol. Different types of tree search algorithms are summarized in Table 5.

4.2.7 Detectors based on local search

In the local search, the search focuses on a local region and gradually approximates the optimized the neighbouring vectors [81]. These algorithms are categorized in two subsections: Likelihood ascent search (LAS) algorithm and reactive tabu search (RTS) algorithm. The concept of LAS is based on starting with an initial solution and keeps searching the neighbourhood for a better solution where the initial solution is computed by a ZF or a MMSE detector [82]. The RTS algorithm also starts with an initial solution vector. In defining the neighbourhood in each iteration, the RTS algorithm seeks to avoid cycling by making moves to solution vectors of past little iteration as "tabu". RTS can find better minima as it involves several parameters such as the stopping criteria parameters, initial tabu period, and maximum number of iterations [83].

***Table 4**: Literature survey of CE methods in massive MIMO systems.*

S. No	Approximation Method	Description	Remarks
1	Neumann series (NS) approximation	In this method G can be decomposed into G = D+E, where D is the main diagonal matrix and E is the non-diagonal matrix [61]. The NS expansion of G is $G^{-1} = \sum_{n=0}^{\infty}(-D^{-1}E)^n D^{-1}$ (9)	Its convergence is slow and more complex
2	Newton Iteration or Newton-Raphson method	It is an iterative method estimation of the matrix inversion at nth iteration is given by (10) which converges quadratically to the inverse matrix if $\left\|I - GX_0^{-1}\right\|$ [62] $X_n^{-1} = X_{n-1}^{-1}(2I - GX_{n-1}^{-1})$ (10)	A fast convergence can be achieved but requires more calculations to obtain the initial estimation
3	Successive Over-Relaxation (SOR) method	The detected signal using this method is described by: $\hat{x} = (\frac{1}{\omega}D + L)^{-1}(\hat{x}_{MF} + ((\frac{1}{\omega} - 1)D - U)\hat{x}^{n-1}$ (11) SOR method outperforms the NS approximation method in terms of performance and complexity reduction [63]	It is not readily implemented on parallel computing platforms
4	Gauss-Seidel (GS) or Liebmann or successive displacement method	Here the G matrix can be decomposed as A = D+L+U, where D, L and U are the diagonal component, the strictly lower triangular component, and strictly upper triangular component, respectively. The estimation of x signal is: $\hat{x} = (D + L)^{-1}(\hat{x}_{MF} - U\hat{x}^{n-1}$ (12) Where n is the number of iterations and $\hat{x}_{MF}$ is the output of matched filter. The GS method is a special case of the SOR method by setting $\omega = 1$	It is not applicable in parallel implementation but have better performance than the NS detector with lower complexity
5	Richardson method	It utilizes the residual vector y−H x where H, y and x are channel matrix, received vector and transmitted vector respectively. The estimation of x signal is: $x^{(n+1)} = x^n + \omega(y - Hx^n)$ (13) Where n presents the number of iterations. The initial solution $x^{(0)}$ can be identified as $2K \times 1$ zero vector without loss of generality [65]	This method is a hardware-friendly
6	Jacobi method	It is also iterative method for determining the solution of a diagonally dominant system where the estimated signal is given by: $\hat{x}^n = D^{-1}(\hat{x}_{MF} + (D - A)\hat{x}^{n-1})$ (14) which holds if can be met in a very high probability [66, 67]	It can be easily implemented for parallel computation. Convergence speed is slower than the GS and SOR methods
7	Conjugate Gradients (CG) method	It solves the linear equations through nth iterations as mentioned in [68], [69]. The estimated signal can be obtained using. $\hat{x}^{(n+1)} = \hat{x}^n + \alpha^n p^n$ (15) Where $p^{(n)}$ is the conjugate direction with respect to A and α^n is a scalar parameter.	It achieves a near-optimal performance when M>>K but at the cost of increasing number of iterations
8	Lanczos method	It is a Krylov subspace method to solve large sparse linear equations by generating the orthogonal basis of the co-efficient matrix and finds the solution whose residual is orthogonal to Krylov subspace [70], [71]. The estimated signal is given by: $\hat{x} = Q^n F^{n-1} Q^{nH} gx + Q^n F^{n-1} Q^{nH} H^H n$ (16) Where Q and F are the matrix formed by orthogonal basis, and the tri-diagonal matrix, respectively.	The initial solution plays an important role in the convergence rate and detection accuracy; high computational complexity under time-varying channels
9	Residual method	This iterative method focuses on minimizing the residual norm rather than approximating the exact solution, whose generalized version is called generalized minimal residual (GMRES) as mentioned in [72]. The symbol detection is done by computing the MMSE filter without a matrix inversion.	No bounded limit on M but requires a pre-conditioning algorithm to improve BER performance
10	Coordinate Descent method	It is an iterative method that inverts the high-dimensional linear system at low complexity. It obtains an approximate solution of many the convex optimization using series of simple, coordinate-wise updates [73].	Performs well even when BS antennas are larger than UTs but have high complexity in computing inverse.

***Table 5**: Tree-Search Based Detectors.*

Depth-first tree-search detection: sphere decoding	SD is the transposition of the mathematical Fincke-Pohst algorithm to define an upper-bound for the objective function named the radius r^2 and then to use it to clip paths as early as possible [74], [75]
Breadth-first tree-search detector: K-best and M-algorithm	Breadth-first detectors can provide soft-output using the max-log approximation and a list. This list approach is used by several detectors, including some other tree-search algorithm and detectors from other families. [76-78]
Best-first tree-search detector: Metric First	The concept is that the node with the best partial Euclidean distance (PED) is expanded. First, the pool is initialized with the root node. Then, iteratively, the node with the lower PED is popped out from the pool, and all its children are computed and pushed in the pool unless they are leaves. [79], and in [80] its performance and complexity was analysed.

***Table 6**: Overview of detection techniques.*

Technique of signal detection in Massive MIMO	Advantage	Challenge	References
Decision-driven detection	The first detected signal affects the algorithm performance	Outperforms linear detectors but with high computation complexity	[54-56]
Local Search based signal detection	It achieves almost ML performance, but computational complexity increases with modulation order.	Complexity depends on the size of the neighbourhood which is not optimum.	[81]
Approximate inversion-based detection	This algorithm is applied to avoid direct matrix inversion to reduce complexity	This technique is challenging when the channel matrix is singular, and the system becomes ill-conditioned. Also, it is not hardware-compatible	[62]
Matrix decomposition algorithm	Complexity is based on the QR, Cholesky, and LDL decomposition algorithms.	Complexity increases with number of antennas at BS.	[90]
Approximate message passing (AMP) Algorithm	Realization and implementation of this algorithm is suitable for large systems	Perfect initialization improves the convergence rate.	[91]
Sphere Decoding with tree search-based detection	Based on QR decomposition	This technique has high complexity with large number of antenna element.	[92]

4.2.8 Lattice-reduction aided detectors

LR aided detectors constitute another important class of MIMO detectors, which rely on the algebraic concept of "lattice" originating from classic geometry. A lattice typically has multiple sets of basis vectors; LR is basically the process of finding a basis closer to orthogonality. Some of LR algorithms in literature are Gaussian reduction, Minkowski reduction and Korkine-Zolotareff (KZ) reduction. These methods are capable to find the optimal basis for a lattice, and Lenstra-Lenstra-Lov´asz (LLL) algorithm, Seysen's algorithm and Brun's algorithm, which are all suboptimal [51].

4.2.9 Miscellaneous detectors:

Detectors Based on Belief Propagation proposed in [84] used in massive MIMO systems using graphical models such as factor graphs, Bayesian belief networks and Markov random fields. Sparsity based algorithms can achieve the ML performance and its complexity is lower than local search algorithms. Using compressive sensing (CS), a channel matrix H can be estimated by exploiting the sparse structure of H. The sparse signals can be reconstructed from compressed measurements through a convex programming [85, 86]. Probabilistic Data Association Based Detectors is a statistical approach applicable to channel estimation of MIMO systems first applied in [87] showing a near-optimum performance at a significantly lower computational complexity than the ML detector. In [88, 89], BOX constrained detection method is mentioned which uses ML decoder for the signal recovery through the efficient convex optimization followed by a hard thresholding.

4.2.10 Concluding remarks on signal detection in Massive MIMO systems

A lot of signal detection schemes are analysed in literature and the objective particularly in massive MIMO scenario is to achieve adequate level of trade-off between the performance and computational complexity. So, the concluding points regarding the above-mentioned techniques can be summarized in Table 6:

5. CONCLUSION

Massive MIMO is the key to achieve the vision of 5G use cases but at the same time the signal processing with huge number of BS antennas faces a lot of complexity. So, to give an in-depth overview of the problems associated with primary requirements of data transmission are explored in this survey. In this paper, an overview of TDD and FDD schemes in massive MIMO systems is presented and firstly focused on the basic channel estimation problems. We have also categorized the channel estimation methods based on the approach used in estimating channel information. A systematic analysis for the reasons and impact of pilot contamination is presented. We have explored some broader perspectives, for signal detection techniques. As far as the signal processing is concerned, it needs improving the SNR or SINR to cancel the interference but in terms of procedure, the detection problem is the trade-off between performance and the complexity that relies on algorithms.

From this survey we concluded that channel estimation along with the effects of pilot contamination are to be analysed properly for symbol detection in a massive array of antennas at the receiver since a change in the estimation technique affects the performance of a given massive MIMO receiver. Proper pilot assignment schemes need to be implemented for mitigation of pilot contamination and the uplink signal detection becomes computationally complex in massive MIMO systems. So, we need advance processing to detect the transmitted signal and the achievable throughput. Relevant insights and comparisons are abstracted from the literature and summarized for the mentioned challenges.

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