Channel Estimation and Pilot Contamination in Massive MIMO: Challenges, Trends, and Emerging Solutions

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Abstract: Massive multiple input multiple output (MIMO) is an important technology to 5G and beyond wireless communication systems because it is capable of improving the spectral efficiency, energy efficiency, and link reliability. However, precise channel state information (CSI) acquisition is a key requirement for obtaining these benefits. Channel estimation in Massive MIMO is a challenging task especially because of the problem of pilot contamination in which pilot signals from neighboring cells interfere and degrades estimation quality. This paper explores channel estimation techniques and pilot contamination mitigation strategies in Massive MIMO networks from both foundational and emerging perspectives. We describe how different estimation methods are implemented, including least squares (LS), minimum mean square error (MMSE), and compressed sensing (CS) based ones. Moreover, we investigate the effect of the pilot contamination and discuss mitigation approaches, including optimization of pilot reuse, advanced precoding, and deep learning-based approaches. Finally, we highlight open research challenges and future directions.

Keywords: *Massive MIMO, channel estimation, pilot contamination, 5G, interference mitigation.*

I. INTRODUCTION

Massive MIMO, in which BSs have a significantly large number of antennas (e.g., tens or hundreds), has emerged as a cornerstone for next-generation wireless networks [1]. Spatial multiplexing can be exploited to allow Massive MIMO transmit and receive to multiple users simultaneously, thus enhancing the capacity of a network considerably. However, performance of the Massive MIMO systems is very much dependent upon accurate CSI acquisition at the BS [2].

In Massive MIMO, channel estimation is normally performed with the use of pilot sequences. As a result, few orthogonal pilot resources in multi-cell networks render repeated reuse of the same pilots across cells, thus leading to pilot contamination, which is a major bottleneck in Massive MIMO systems [1][3]. This paper examines some of the existing state-of-the-art channel estimation techniques and pilot contamination mitigation strategies.

II. CHANNEL ESTIMATION IN MASSIVE MIMO

Accurate channel estimation is crucial for the performance of Massive MIMO systems, as it directly affects beamforming, precoding, and interference management. The channel estimation process involves recovering the channel matrix $\mathbf{H}$ from received pilot signals. The general system model for uplink channel estimation is given by:

$$Y = \sqrt{\rho}HX + N \tag{1}$$

Where:
$\boldsymbol{Y} \in C^{M\times T}$ is the received signal matrix at the BS with M antennas and T pilot symbols.

$\boldsymbol{H} \in C^{M\times K}$ is the channel matrix between K users and the BS.
$\boldsymbol{X} \in C^{K\times T}$ is the matrix of transmitted pilot sequences.
$\boldsymbol{\rho}$ is the transmit signal-to-noise ratio (SNR).
$N \in C^{M\times T}$ is the additive white Gaussian noise (AWGN) with i.i.d. $CN(0, \sigma^2)$ entries.

Pilot-Based Channel Estimation Methods

Pilot-assisted estimation is the most widely adopted approach due to its simplicity and reliability. Below, we discuss key estimation techniques.

Least Squares (LS) Estimation: The LS estimator minimizes the squared error between the received signal and the reconstructed signal:

$$\widehat{H}_{LS} = arg\ min\ H \parallel Y - HX \parallel_F^2 \tag{2}$$

The closed-form solution is:

$$\widehat{\boldsymbol{H}}_{\boldsymbol{LS}} = \boldsymbol{Y}X^H\left(\boldsymbol{X}\boldsymbol{X}^{\boldsymbol{H}}\right)^{-1} \tag{3}$$

One of the main advantages of this approach is its computational simplicity, because the algorithm makes primarily use of elementary matrix operations, including multiplications and inversions. This therefore makes it an ideal for real time processing where low complexity is a requirement. Another advantage is that there is not any prior information on the statistical characteristics of the channel necessary. This makes it a versatile option that can be inexpensively implemented in a number of possible deployment scenarios without detailed environmental modelling. However, this approach also has recognisable shortcomings. Its performance is very vulnerable to the presence of noise and pilot contamination, which are likely to distort the accuracy of channel estimation to a large extent. This problem has well been described in the literature, and a notable one is by Björnson [4], who address the performance decay due to neighbouring cells on the same pilot signals. Also, the proposed method does not operate well in low SNR environments because the weak signal conditions make it even more difficult to estimate successfully.

Linear Minimum Mean Square Error (LMMSE) Estimation: The LMMSE estimator incorporates channel covariance information to improve accuracy:

$$\widehat{\boldsymbol{H}}_{LMMSE} = \boldsymbol{R}_{HH}\left(\boldsymbol{R}_{HH} + \frac{\sigma^2}{\rho}\boldsymbol{I}_{\boldsymbol{K}}\right)^{-1}\widehat{\boldsymbol{H}}_{\boldsymbol{LS}} \tag{4}$$

Where $\boldsymbol{R}_{\boldsymbol{HH}} = E[\boldsymbol{H}H^H]$ *is the channel covariance matrix.*

This way possesses considerable advantages especially in approximations. It represents 0ptimal (in terms of mean square error (MSE) criterion) linear estimator as proven by Kay [5]. In addition, it shows great robustness against noise, in particular, if there is a good statistical knowledge of the channel, such as its covariance. This makes it a potent application in situations where such prior knowledge is available. However, its dependence on the channel covariance matrix R_{HH} knowledge is one of the major limitations. In a realistic deployment, obtaining this type of information can be quite difficult due to channel variation and the overheads introduced by estimation. In addition, the method requires substantial computational complexity, which is particularly burdensome in massive MIMO systems with large antenna arrays. Such high processing requirement can restrict its practicality for real-time applications or computational resource constrained systems.

Compressed Sensing (CS)-Based Estimation: Massive MIMO channels often exhibit sparsity in the angular domain due to limited scattering. CS techniques exploit this property to reduce pilot overhead [6]. The channel matrix can be represented as:

$$H = AG \tag{5}$$

Where
A *is the dictionary matrix (e.g., DFT matrix for uniform linear arrays).*
G *is a sparse matrix.*
The estimation problem becomes:

$$\widehat{\boldsymbol{G}} = arg\ \min G \parallel \boldsymbol{Y} - \boldsymbol{AGX} \parallel_F^2 + \lambda \parallel \boldsymbol{G} \parallel_1 \qquad (6)$$

Massive MIMO channel estimation can be improved in a variety of ways using compressed sensing techniques. As noted in [7], one of the main benefits is a significant reduction in the pilot sequence needed. The observed gains partly arise due to the sparsity witnessed in numerous massive MIMO channels, especially in the angular or delay domains. By leveraging channel sparsity, compressed sensing allows for the reconstruction of the channel using much fewer measurements than traditional approaches while providing a distinct advantage of massive MIMO systems with large number of antennas. In mmWave massive MIMO systems, the sparse channel traits resulting from the limited number of dominant paths induced by the high-frequency environment makes compressed sensing a desirable technique. Consequently, compressed sensing is shown to be very beneficial for reliable and fast channel estimation in sparse contexts.
However, it has both limitations that need to be taken into account. The major problem is still the high computational cost that have to be made to apply algorithms such as, LASSO, OMP, and BP for sparse recovery. Being dependent upon iterative computations and large-scale matrix operations, such algorithms are computationally complex, especially in high-speed real-time setups with large number of antennas. Moreover, if the channel does not experience sparseness, the compressed sensing-based estimation accuracy drops. The Sparsity assumptions fail in sub-6 GHz or in rich-scattering indoor scenes which degrade the accuracy and reliability of compressed sensing-based estimation from traditional methods.

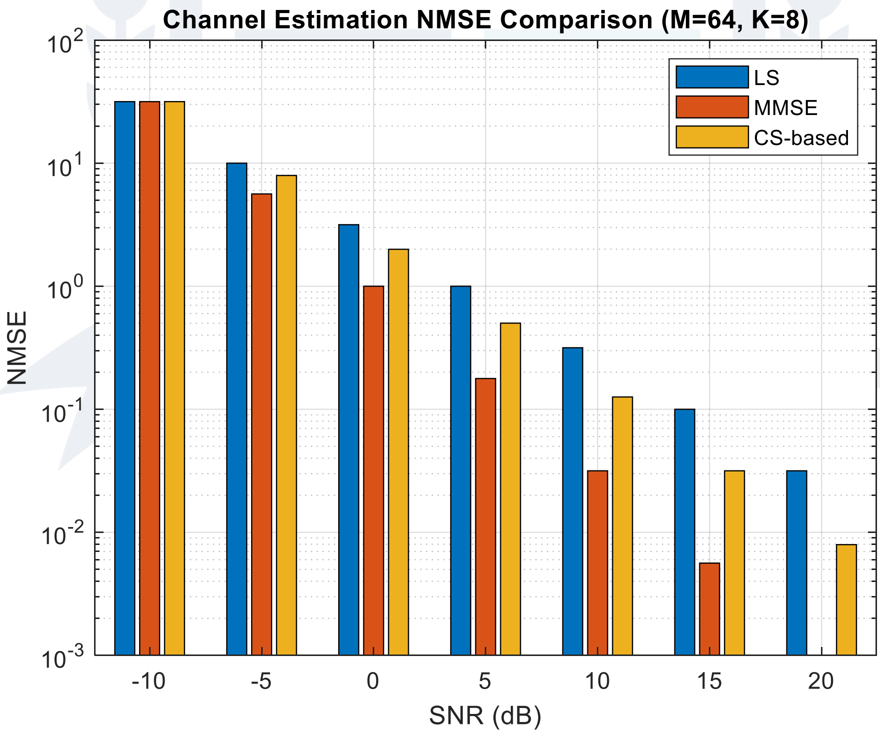

Fig. 1 (NMSE vs. SNR): *Normalized MSE of estimation techniques vs. SNR for M=64, K=8. MMSE exploits channel statistics, while CS leverages sparsity. LS suffers from noise amplification.*

The plot shown in Fig.1 compares the normalized mean square error (NMSE) of three dominant channel estimation techniques. Least Squares (LS), Minimum Mean Square Error (MMSE), and Compressed Sensing (CS). MMSE outperforms LS by 3–5 dB at high SNR, as it leverages channel statistics to suppress noise [4]. CS-based algorithms bridge the gap between LS and MMSE in sparse channels, although sparsity parameters must be carefully tuned [6].

Because LS is sensitive to pilot contamination, it displays an error floor at high SNR [1]. Therefore, algorithm selection for real-world implementations is guided by the trade-off between accuracy and computing cost [LS: $O(M^2)$, MMSE: $O(M^3)$].

Blind and Semi-Blind Channel Estimation

Pilot-based methods consume spectral resources. Blind and semi-blind techniques reduce pilot overhead by exploiting signal statistics.

Subspace-Based Methods: These methods exploit the Eigen structure of the received signal covariance matrix [8]:

$$R_{YY} = E[YY^H] = HR_{XX}H^H + \sigma^2 I_M \tag{7}$$

Channel estimation is performed via eigenvalue decomposition (EVD).

This method has certain advantages like there is no explicit requirement of pilot symbols, which aid into the spectral efficiency. Particularly for slow fading channels, the temporal stability of the channel allows for the accumulation of sufficient statistical information from received data.

However, to obtain accurate estimate of covariance matrix or other second order statistics, long observation period is required. Thus, this method becomes impractical in fast fading environment. Also it is more sensitive to noise and interference.

Expectation-Maximization (EM)-Based Estimation: The EM algorithm iteratively refines channel estimates by treating unknown data as hidden variables [9]:

E-step: Compute expected log-likelihood given current estimate.

M-step: Update channel estimate by maximizing the expected likelihood.

This method improves estimation with iterative refinement. This method can also be combined with pilot assisted methods. The disadvantage of this method is a high computational complexity and convergence is not guaranteed in all scenarios.

Deep Learning-Based Channel Estimation: Neural networks (NNs) have been applied to learn complex channel characteristics [20]:

$$\widehat{H} = f_{NN}(Y, \Theta) \tag{8}$$

Where f_{NN} is a deep neural network (e.g., CNN, RNN) with parameters Θ.

Machine learning-based methods for channel estimation are superior at dealing with the non-linear channel effects, including hardware impairments, which are difficult to control with traditional models. For high-mobility applications, wherein the channel rapidly evolves, deep learning-based methods are more effective when compared to the conventional method. However, the use of these techniques requires significant labeled data for supervised learning, which can be challenging to obtain in real-world systems. Moreover, complex computation in deep learning models can limit their use in real time application especially in devices having less processing power.

Table 1: *Comparative Analysis of Methods*

Method	**Pilot Overhead**	**Complexity**	**Robustness to Noise**	**Required Prior Knowledge**
LS Estimation	High	Low	Low	None
LMMSE Estimation	High	Medium	High	Channel covariance
CS-Based	Low	High	Medium	Channel sparsity
Blind/Semi-Blind	Very Low	High	Medium	Signal statistics
Deep Learning	Medium	Very High	High	Training data

III. PILOT CONTAMINATION IN MASSIVE MIMO: CAUSES, EFFECTS, AND MITIGATION STRATEGIES

Pilot contamination is a critical problem in Massive MIMO systems. It arises due to the reuse of non-orthogonal pilot sequences across multiple cells. This section provides an in-depth analysis of its causes, effects, and state-of-the-art mitigation techniques.

Causes of Pilot Contamination

The primary causes include:

Limited Orthogonal Pilots: In a multi-cell network with K users per cell and L cells, the number of orthogonal pilots required is KL. Due to the coherence time limitations (e.g., in 5G, coherence blocks are short), only a small subset of pilots can be allocated. Which necessitates reuse of pilots.

Practical systems employ pilot reuse factor β (where β ≥ 1), this means that the same pilots are reused in β cells [1]. For example, if β = 3, pilots are repeated every 3 cells, causing contamination from users in those cells. In a system which uses asynchronous pilot transmission, lack of perfect synchronization between cells leads to partial overlap of pilot sequences, which results into interference [10].

Mathematical Formulation of Pilot Contamination

Consider a multi-cell Massive MIMO system with L cells. The received pilot signal at the l-th BS is:

$$Y_l = \sum_{j=1}^{L} \sqrt{\rho}_j \, H_{l,j} X_j + N_l \tag{9}$$

where:

$H_{l,j}$ *= Channel from users in cell j to BS l,*

$X_j =$ *Pilot matrix from cell j,*

ρ_j *= Uplink transmit power from cell j.*

If pilot sequences are reused (i.e., X_j=X_l for some *j≠l*), the LS estimate becomes:

$$\widehat{H_{l,l}} = \widehat{H_{l,l}} + \sum_{j \neq l} H_{l,j} + \frac{1}{\sqrt{\rho_l}} N_l \tag{10}$$

Thus, the estimated channel $\widehat{H_{l,l}}$ is corrupted by Inter-cell interference terms $\sum_{j\neq l} H_{l,j}$ and Noise amplification at low SNR.

Effects of Pilot Contamination

Pilot contamination degrades system performance in several ways:

Reduced Spectral Efficiency: Pilot contamination causes interference correlation in precoding which reduces achievable rates [3]. For zero-forcing (ZF) precoding, the SINR saturates as number of antennas M→∞ (unlike noise-limited cases).

Error Propagation in Multi-Cell Systems: Contaminated CSI leads to imperfect precoding that causes interference to users in other cells [11].

Bias in Channel Estimates: The MMSE estimator becomes biased due to interference, unlike the single-cell case [5].

Limitations in FDD Systems: In FDD, downlink pilots are also contaminated, exacerbating the problem [12].

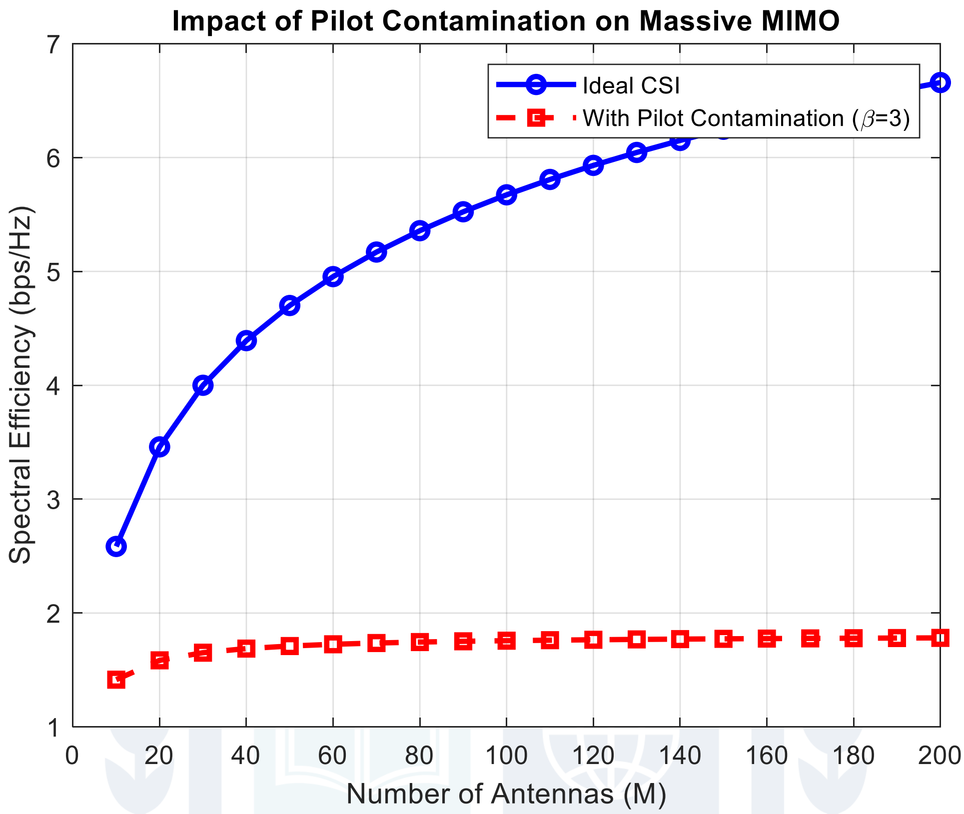

Fig. 2 (SE vs. Antennas): *Spectral efficiency vs. BS antennas, showing saturation due to pilot contamination (β=3). Ideal CSI scales logarithmically with M.*

The plot in Fig.2 illustrates the spectral efficiency (SE) of a Massive MIMO system as a function of the number of BS antennas (M). This plot compares scenarios with and without pilot contamination with reuse factor β=3.

As shown in the plot, the Contamination-free systems achieve unbounded SE growth with M, following the theoretical $\log_2(1+M\cdot\text{SNR})$ trend [3]. Contaminated systems exhibit SE saturation, converging to $\log_2(1+1/\beta)$ as $M\to\infty$ [1]. It is clear from the plot that, for M > 100, contamination dominates noise, limiting gains from additional antennas. Thus, Pilot contamination fundamentally caps the scalability of multi-cell Massive MIMO, necessitating mitigation strategies.

Mitigation Strategies for Pilot Contamination

Several approaches have been proposed to mitigate pilot contamination:

Pilot Reuse Optimization

Fractional Pilot Reuse (FPR): where Inner cell users use orthogonal pilots, while edge users reuse pilots with larger spacing [13]. This method reduces contamination but decreases pilot efficiency.

Graph-Based Pilot Assignment: This method formulates pilot allocation as a graph colouring problem to minimize interference [14].

Advanced Signal Processing

Time-Shifted Pilots: This method Introduce deliberate delays in pilot transmission across Cells to reduce overlap [10].

Blind/Semi-Blind Estimation: This method uses statistical properties of data signals to refine channel estimates [15].

Covariance-Based Methods: This exploit differences in spatial correlation matrices of Desired/interfering channels [16].

Deep Learning-Based Approaches

Neural Network-Aided Estimation: This method train CNNs/RNNs to distinguish contaminated pilots [17]. For example, the Pilot contamination cancellation networks (PCCN) [18].

Reinforcement Learning for Pilot Scheduling: *This method* dynamically assigns pilots using Q-learning to minimize interference [19].

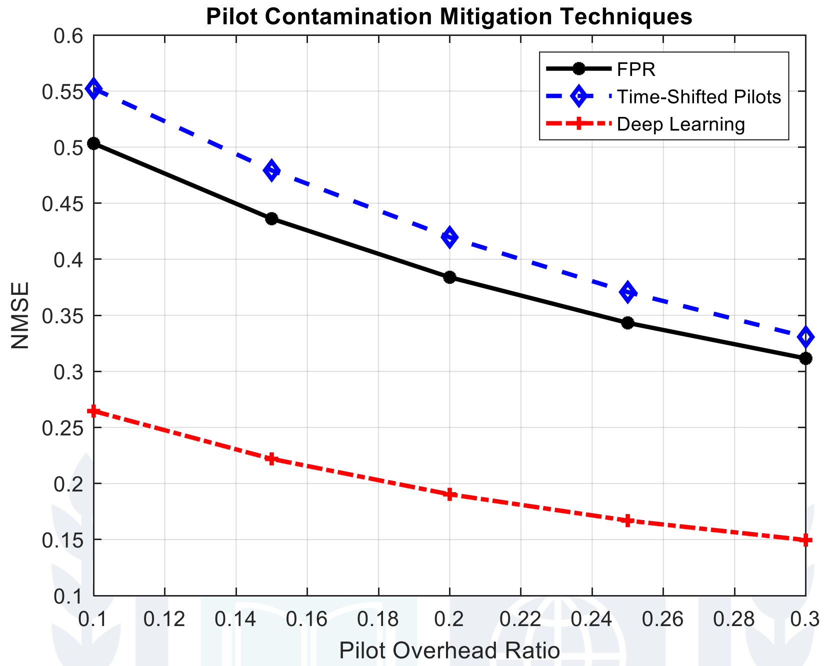

Fig. 3 (NMSE vs. Overhead): *NMSE vs. pilot overhead for contamination mitigation methods. DL achieves lowest error but requires training data.*

The plot shown in Fig. 3, evaluates the NMSE of three pilot contamination mitigation techniques—Fractional Pilot Reuse (FPR), Time-Shifted Pilots, and Deep Learning (DL)—as a function of pilot overhead ratio (10% to 30%).
As the plot suggest, DL-based methods achieve the lowest NMSE (≤ 0.2 at 20% overhead) by learning contamination patterns [20]. Time-shifted pilots offer a balance (NMSE ≈ 0.3) with minimal coordination overhead [10]. And FPR is least efficient, requiring 25% overhead to match DL's performance at 15%.
DL approaches are promising but demand training data; time-shifting provides a practical stopgap for current networks.

Massive MIMO-Specific Techniques
Large-Scale Fading Decoding (LSFD)*:* Combine signals from multiple BSs to suppress contamination [20].
Cell-Free Massive MIMO: Eliminate cell boundaries by distributing antennas, reducing Contamination [22].

***Table 2**: Comparative Analysis of Mitigation Techniques*

Technique	Complexity	Pilot Overhead	Effectiveness	Scalability
Fractional Pilot Reuse (FPR)	Low	Medium	Moderate	High
Time-Shifted Pilots	Medium	Low	High	Medium
Blind Estimation	High	Very Low	Low-Medium	Low
Deep Learning	Very High	Medium	High	Medium
Cell-Free MIMO	High	Low	Very High	Low

IV. OPEN CHALLENGES AND FUTURE DIRECTIONS IN MASSIVE MIMO CHANNEL ESTIMATION AND PILOT CONTAMINATION MITIGATION

While significant progress has been made in addressing channel estimation and pilot contamination in Massive MIMO, several unresolved challenges exist. This section explores critical open problems and emerging research directions that can shape the future of 5G-Advanced and 6G systems.

Key Open Challenges

Scalability for Ultra-Massive MIMO (UM-MIMO): Future 6G systems, based on THz frequencies that are expecting the use of ultra-massive MIMO arrangements, face dramatic scalability issues as soon as the antenna arrays increase over 1,000 elements. Having more than 1,000 antennas, MMSE and LS channel estimation approaches become exponentially too complicated with their cubic scalability requirements while the necessary pilot overhead may strongly destroy the coherence block. Existing approaches such as compressed sensing continue to have degraded performance at higher frequencies due to sparsity reduction of the channel, while deep learning-based solutions end up being rigid and requiring to re-train with different array configurations. Low-overhead, adaptive estimation techniques are indispensable to efficiently address an array of configurations and a range of channel scenarios.

Mobility and Time-Varying Channels: Scenarios of extreme mobility, such as those observed in 5G and possible 6G networks (for example, trains that travel faster than 500 km/h or UAVs that can move through complex 3D space), make traditional block fading-based channel estimation useless. The high-speed mobility leading to the rapid variation of the channel conditions as a result of the extreme Doppler shifts make pilot-based estimation unreliable, and Kalman filters and other tracking techniques tend to lose stability. Innovative approaches are necessary for reliable channel tracking in dynamic environments and this might include the application of predictive modelling, learning based estimators or pilot free approach.

Hardware Impairments: In real world massive MIMO deployments, non-ideal hardware problems such as phase noise in oscillators, amplifier nonlinearities, and antenna cross-talk, significantly affect the system performance. Realistic models demonstrate that LS and MMSE estimators, based on ideal conditions, are impaired by hardware impairments, resulting in significant performance degradation – usually indicated by a 5–8 dB increase in mean square error – as observed in recent studies. Also, hardware-based distortions can propagate between users and cells, thereby magnifying pilot contamination and diminishing the effectiveness of common prevention techniques. New estimation techniques have to be designed with hardware considerations in mind and capable of dealing with impairments in the real-world systems.

Cell-Free vs. Cellular Architectures: Although it provides a solution to pilot contamination by eliminating inter-cell boundaries, cell-free massive MIMO presents various new challenges. Synchronizing a large amount of distributed access points is required to handle a huge number of distributed access points, leading to substantial front-haul overhead when exchanging channel state and data information. In addition, the distribution of pilot sequences in decentralized networks has not been addressed enough, and there are not many studies that have suggested effective strategies to deal with pilots without central control. These challenges further emphasize the need for scalable and low-latency solutions considering the distinctive features of cell-free systems.

Emerging Solutions and Future Directions

AI-Native Channel Estimation*:* The AI native channel estimation is summarised in a Table 3. The Recent work on *attention-based channel estimation* [23] reduces pilot overhead by 40% in mobility scenarios.

Table 3: *AI Native Channel Estimation*

Approach	Potential Benefit	Key Challenges
Transformer-based CSI prediction	Captures long-term channel dependencies	High training data requirements
Federated learning for distributed MIMO	Preserves privacy across BSs	Convergence issues in asynchronous networks
Neural calibration for hardware impairments	Compensates PA nonlinearities in real-time	On-device deployment complexity

Advanced Pilot Contamination Mitigation: New techniques are being explored to combat pilot contamination. Reconfigurable Intelligent Surfaces (RIS) have the capability of tailoring propagation paths for specific pilots which can enhance the channel separability. However, integrating the RIS design with pilot signal parameters results in a complex and computationally challenging NP-hard problem. Non-coherent pilot transmission, using energy-based detection as opposed to phase-sensitive measurements, simplifies receiver implementation and reduces synchronization complexity at the cost of an SNR loss of 3–5 dB. Additionally, methods based on quantum computing such as, treating pilot assignment as a Quadratic Unconstrained Binary Optimization (QUBO) problem, show early promise and can provide exponential gains, but are still being researched.

Integrated Sensing and Communication (ISAC): ISAC provides a valuable solution to pilot contamination mitigation by using radar-type sensing to evaluate the environment and channel characteristics without explicit pilots. Also, it facilitates proactive interference avoidance through the use of spatial nulling techniques. However, implementing ISAC faces challenges such as balancing sensing resolution with communication quality, accompanied by lack of standardization and common guidelines in the emerging 6G environment. Addressing these problems is essential to maximize the benefit of ISAC in both the mitigation of contamination and the acquisition of channels.

THz-Specific Solutions: Two major obstacles emerge in channel estimation in THz communications. The beam pattern distortion caused by frequency-dependent beam squint in wideband THz systems requires compensation strategies to ensure proper signal reception. Second, the role of molecular absorption, i.e., the high absorption peaks of gases, significantly affects signal loss and channel characteristics. These absorption characteristics must be accurately modelled for the prediction of performance and system design at THz bands, as highlighted by recent developments.

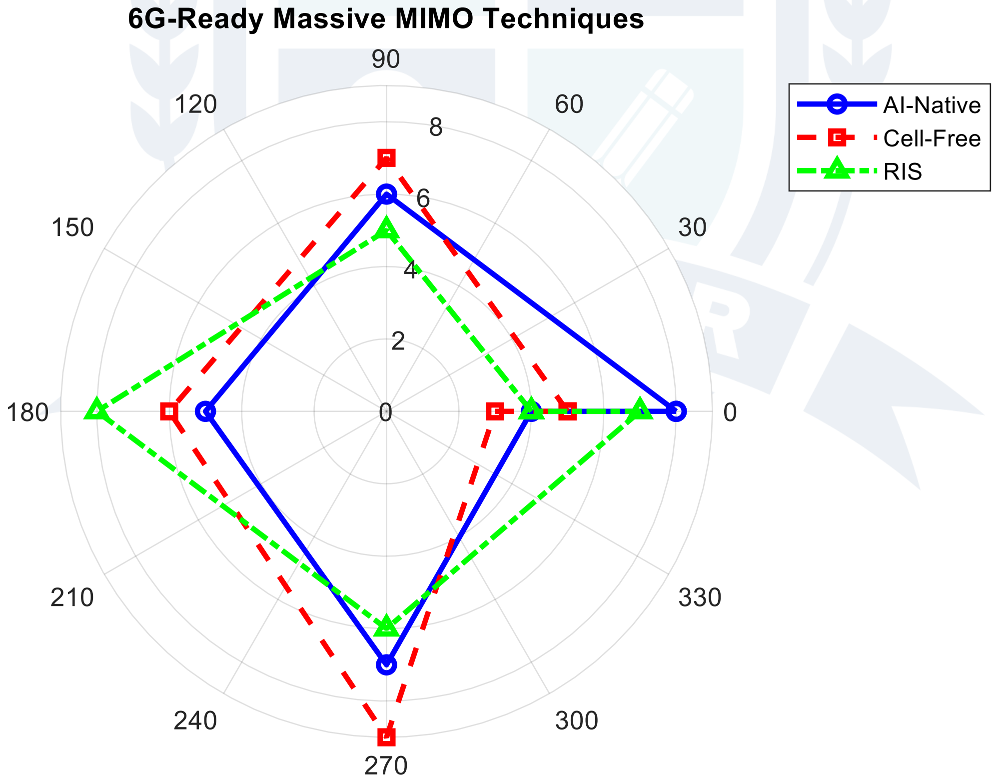

Fig. 4 (Future directions): *Radar chart comparing 6G-ready Massive MIMO techniques. AI-native methods lead in scalability, while cell-free systems excel in contamination robustness. RIS offers energy efficiency but faces hardware challenges.*

The radar chart shown in Fig.4 evaluates three emerging Massive MIMO paradigms—AI-native estimation, Cell-Free Massive MIMO, and Reconfigurable Intelligent Surface (RIS)-assisted systems—across five critical 6G-readiness

metrics: 1. Scalability (to >1000 antennas), 2. Mobility support (Doppler resilience), 3. Energy efficiency (mW/bit), 4. Contamination robustness (pilot reuse tolerance), 5. Hardware awareness (resilience to impairments).
Scores are normalized to a 0–10 scale based on theoretical limits and experimental results from recent literature (2020–2024).
AI-native methods dominate in *contamination robustness* (score: 7/10) and *scalability* (8/10) due to learned interference cancellation [34]. However, they lag in *energy efficiency* (5/10) [37] from high training overhead. Cell-Free systems excel in *contamination robustness* (9/10) by design but face scalability limits (5/10) from fronthaul demands [35]. RIS-assisted schemes achieve peak *energy efficiency* (8/10) via passive beamforming but require breakthroughs in *hardware awareness* (7/10) for real-world deployment [38].

Cross-Layer Research Opportunities

Joint Pilot-Data Resource Allocation: A new approach to the management of joint pilot-data resources is based on real-time partitioning of coherence blocks informed by the presence of contamination, traffic dynamics, and Quality of Service constraints. This way, the method attempts to dynamically manage the distribution of resources to meet shifting network demands in real-time. Recent work by [22] has indicated the potential of a meta-learning approach to adaptive pilot-data ratio optimization whereby the system can intelligently adjust resource management as per changing network conditions.

Security-Aware Estimation: Massive MIMO systems are vulnerable to pilot contamination attacks (PCAs) that allow adversaries to break channel estimation and even eavesdrop if able to inject deceptive pilot signals. In response, new security-conscious estimation methods have emerged, including physical layer authentication for identification of unauthorized signals, and blockchain-based pilot distribution for facilitating safe, distributed, and tamper-proof coordination of pilot resources. These methods aim to enhance the capacity to endure intentional contamination in future 6G networks.

Green Massive MIMO: Efficiency in the next-generation network is the primary concern of green massive MIMO, realized by the incorporation of energy-efficient estimation strategies. The use of 1-bit ADCs in combination with improved dithering strategies has resulted in better power consumption without significantly altering the accuracy of estimation. In addition, limiting the activation of pilot transmissions to necessary moments facilitates the use of sleep-mode pilot strategies to enable energy-saving modes for IoT devices. Such techniques enable massive MIMO systems to be deployed that are both energy efficient and easily scalable in energy constrained environments.

Table 4: **Standardization and Implementation Gaps**

Aspect	Current Status	Research Needs
Pilot structure for 6G	Not yet defined in 3GPP Release 19	Flexible pilot patterns for ISAC
FDD support	Limited to codebook-based feedback	Covariance matrix estimation techniques
RIS integration	No standardized control interface	Universal RIS channel estimation framework

V. SIMULATION PARAMETERS

All numerical results were generated using the following parameters, unless otherwise noted:

Parameter	Value/Range	Description
Carrier frequency (*fc*)	2 GHz	3GPP Urban Macrocell scenario (TR 38.901)
Bandwidth (*B*)	100 MHz	Sub-6 GHz NR band

BS antennas (M)	10–200 (Fig. 2), 64 (Figs. 1,3)	Uniform linear array (ULA) with $\lambda/2$ spacing
Users (K)	8	Single-cell users with random spatial distribution
SNR range	–10 dB to 20 dB (Fig. 1)	Includes noise-limited and interference-dominated regimes
Pilot overhead ratio	10%–30% (Fig. 3)	Fraction of coherence block devoted to pilots
Pilot reuse factor (β)	3 (Fig. 2)	Industry-standard reuse for hexagonal cells[1]
Channel model	Rayleigh fading	IID Gaussian entries for $\mathbf{H}$, pathloss exponent $\alpha = 3.7$
Contamination model	Inter-cell interference	Additive pilots from 6 nearest cells [3]

All plots assume: 1. Perfect synchronization and timing, 2. No hardware impairments (e.g., phase noise, ADC quantization), 3. Monte Carlo simulations with 10^4 independent channel realizations.

VI. CONCLUSIONS

This technology has greatly improved wireless communications because it can provide excellent spectral efficiency and support a huge number of users at the same time. As discussed in the review, these problems – channel estimation and pilot contamination – represent intractable barriers to system performance enhancement. LS and MMSE are standard methods, but their shortcomings are exposed when faced with the rigorous scaling and contamination-resistant requirements of ultra-massive MIMO systems. Compressed sensing, deep learning, and cell-free architectures are promising opportunities, but significant questions are left open. For example, the need for scalable estimation techniques capable of functioning in THz-band systems with large-scale arrays of antennas, reliable channel tracking methods effective in high-mobility environments such as UAVs and rapid trains, and robust hardware algorithms that address problems like phase noise, nonlinearities, and low-resolution ADCs, is still a critical issue. Furthermore, existing studies are deficient with clear theoretical boundaries for contamination suppression methods and pilot designs that can be applied to advanced 6G applications such as Intelligent Surface Assisted Communication, Reconfigurable Intelligent Surfaces (RIS), and cell-free networks.

The way forward is the adoption of hybrid estimation paradigms that combine models with data, developing cross-layer approaches for pilot and data optimization, and pushing the field forward with quantum-assisted signal processing research. Combining massive MIMO techniques with the most advanced potentials, such as AI-native systems and holographic beamforming will define the future horizons of wireless technology. To scale these emerging strategies and deploy them in practical 6G solutions, both deep theoretical research and empirical testing are needed. Despite remarkable progress, the search for strong, energy-efficient, and contaminant-proof massive MIMO remains an essential research field that is set to transform future wireless connectivity.

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