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AI-BASED CHANNEL ESTIMATION AND INTERFERENCE MITIGATION IN B5G/6G

A Comprehensive Review on Advanced Physical-Layer Processing

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Abstract—B5G and prospective 6G systems are expected to use large antenna arrays, wider bandwidths, higher carrier frequencies, and increasingly dynamic network configurations. These features make channel state information (CSI) more difficult to acquire and maintain, particularly when users or propagation conditions change rapidly. This review examines channel estimation and interference management methods, beginning with least-squares (LS), linear minimum mean-square-error (LMMSE), and compressed-sensing approaches, and then considering neural estimators, untrained networks, CSI-feedback autoencoders, and score-based generative models. The discussion covers massive MIMO, millimeter-wave (mmWave) links, reconfigurable intelligent surfaces (RIS), and orthogonal time-frequency-space (OTFS) systems. It also considers learning-assisted interference control, including neural approximations of weighted-MMSE optimization and deep reinforcement learning. The reviewed studies indicate that learning methods can exploit channel structure and reduce selected computational or feedback burdens; however, their performance depends on the channel model, training-data coverage, pilot design, and implementation constraints. Model-driven and hybrid methods are therefore relevant when physical structure can be incorporated into the learning process, although their robustness must be established through evaluation under representative operating conditions.

Index Terms—B5G/6G, channel estimation, channel state information (CSI), CSI feedback, deep learning, interference mitigation, massive MIMO, reconfigurable intelligent surfaces (RIS), OTFS.

I. INTRODUCTION

B5G and 6G research considers combinations of large antenna arrays, millimeter-wave (mmWave) and sub-terahertz operation, and different waveform and network architectures. These developments increase the importance of accurate channel state information (CSI), but they also make its acquisition more demanding. In frequency-division-duplex (FDD) systems, the base station (BS) transmits downlink reference signals; the user equipment (UE) estimates the downlink channel and returns CSI, often after quantization or compression. In time-division-duplex (TDD) systems, channel acquisition commonly uses uplink pilots and relies on reciprocity between uplink and downlink channels, with calibration needed to account for transceiver-chain differences. Mobility, blockage, and beam misalignment can further reduce the useful lifetime of a channel estimate, especially at high carrier frequencies [1], [2].

For an unstructured block-fading MIMO channel with Nt transmit dimensions, identifying all channel coefficients requires a sufficient number of linearly independent pilot observations. Under the pilot model used in this paper, the pilot matrix must provide full column rank, which generally requires at least Nt pilot channel uses. A shorter training sequence is possible when additional structure is available, for example angular or delay-domain sparsity, low-rank correlation, or temporal correlation. RIS-assisted links introduce a cascaded BS–RIS–UE channel; separating the constituent channel components therefore depends on the adopted observation model and the design of the RIS training patterns [3], [4]. Learning-based estimators may exploit correlations across antennas, frequency, and time, but they do not remove the identifiability requirements imposed by the measurement model. The review consequently treats channel estimation, CSI feedback, and interference management as related but distinct tasks.

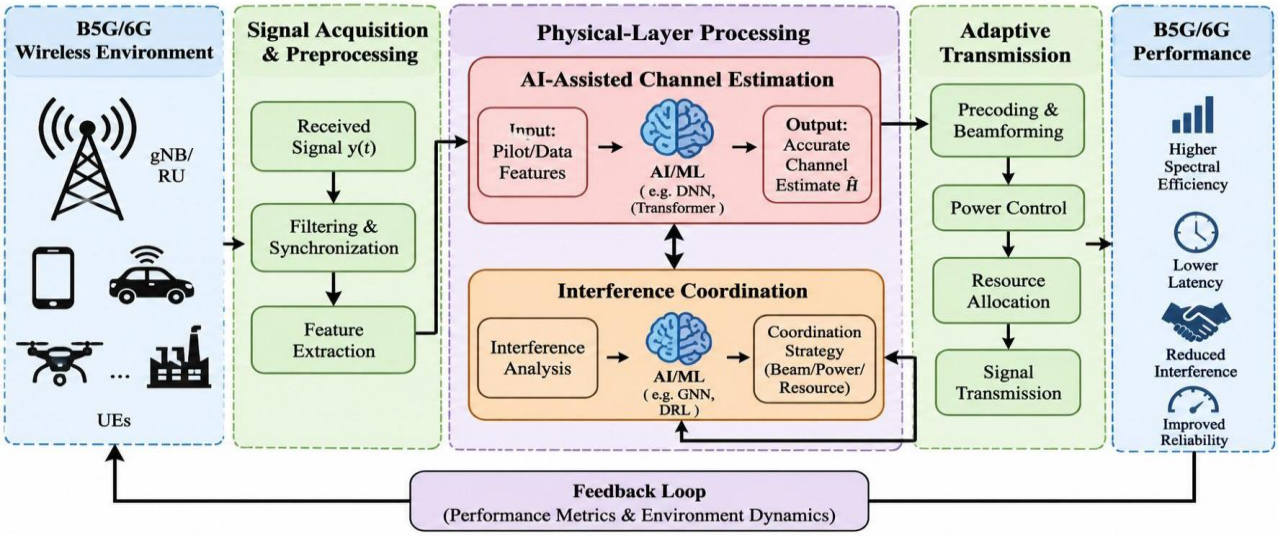

Fig. 1. General architectural workflow of B5G/6G physical-layer processing integrating AI-assisted channel estimation and interference coordination.

II. CHANNEL MODEL AND CONVENTIONAL ESTIMATION

Consider a narrowband, block-fading MIMO link with Nt transmit antennas and Nr receive antennas. During a training interval of Np pilot channel uses, the received pilot matrix is modeled as:

$$Y_p = H X_p + W_p \quad (1)$$

Here, $H \in \mathbb{C}^{(NrxNt)}$ is the channel matrix, $X_p \in \mathbb{C}^{(NtxNp)}$ is the known pilot matrix, and $W_p \in \mathbb{C}^{(NrxNp)}$ is additive white Gaussian noise. Assuming that the channel remains constant over the training interval, vectorization gives the linear observation model:

$$y = vec(Y_p) = (X_p^T \otimes I_{nr})h + vec(W_p) = Ah + n \quad (2)$$

In this expression, $h = vec(H)$, $A = X_p^T \otimes I_{nr}$, and y, h, and n have dimensions $NrNp \times 1$, $NrNt \times 1$, and $NrNp \times 1$, respectively. Identifiability of the unrestricted channel vector requires $rank(A) = N_rN_t$. Since A has NrNp rows, this condition also requires $N_p \geq N_t$.

A. Least-Squares and LMMSE Estimators

The least-squares (LS) estimate is obtained by minimizing the squared residual between the received pilot observations and the model prediction. If A has full column rank, the solution is:

$$h_{ls} = (A^H A)^{-1} A^H y \quad (3)$$

The LS estimator does not require prior channel statistics, but its error is affected by noise and by the conditioning of the pilot matrix. If the channel covariance $R_h = E[hh^H]$ and the noise covariance is $R_n = \sigma_n^2 I$, the linear minimum mean-square-error (LMMSE) estimate is:

$$h_{lmmse} = R_h A^H (A R_h A^H + \sigma_n^2 I)^{-1} y \quad (4)$$

The LMMSE estimator uses second-order channel statistics and minimizes the mean-square estimation error among linear estimators under the stated statistical model. Its performance depends on the accuracy of the assumed covariance and noise statistics. Its implementation may also require substantial matrix operations, particularly when the observation dimension is large.

B. Compressed Sensing Approaches

When a channel has a sparse representation in an appropriate angular- or delay-domain basis, it can be written as $h = Ds$, where D is a known dictionary and s contains a relatively small number of significant coefficients. The observation model then becomes $y = ADs + n$. Methods such as orthogonal matching pursuit (OMP) and approximate message passing (AMP) estimate the sparse vector from the available measurements. Their effectiveness depends on the degree of sparsity, the coherence of the sensing dictionary, and how well the chosen basis represents the physical channel. Off-grid paths, diffuse scattering, and wideband beam-squint effects can weaken these assumptions [1], [5].

C. Comparative Summary

Table I summarizes the main strengths and limitations of the conventional and learning-based estimation approaches considered in this review.

Estimation Method	Primary Advantage	Key Operational Limitation
Least Squares (LS)	No prior statistics required; computationally lightweight	Sensitive to noise; requires a full-column-rank pilot matrix.
LMMSE	Minimizes MSE utilizing channel covariance	High matrix inversion complexity; covariance mismatch
Compressed Sensing	Exploits spatial/delay sparsity effectively	Sensitive to dictionary mismatch and off-grid propagation
Supervised CNNs	Learns complex nonlinear channel correlations	Vulnerable to distribution shift and out-of-domain data
Model-Driven DL	Blends analytical domain knowledge with neural fitting	Higher architectural design complexity

Table I. Comparative Evaluation of Channel Estimation Methodologies

III. AI-BASED CHANNEL ESTIMATION AND CSI FEEDBACK

Learning-based estimators use received pilot observations or an initial estimate, such as an LS estimate, to infer the channel. Convolutional neural networks (CNNs) and residual networks can exploit local structure in channel matrices, but their accuracy depends on whether the training data represent the SNR range, mobility, and propagation conditions encountered during operation [6]. In beamspace massive MIMO, lens-based transformations can concentrate channel energy into a smaller set of angular components, which may support sparse estimation [5]. Untrained deep-prior methods instead optimize a network for an individual observation and therefore reduce reliance on a large offline training set; this per-instance optimization can, however, increase processing time [7].

In FDD systems, the estimated downlink CSI must be conveyed from the UE to the BS. CsiNet uses an encoder at the UE to map the channel representation to a compact codeword and a decoder at the BS to reconstruct the CSI [8]. Score-based generative methods provide another way to model channel distributions by learning score functions at different noise levels. Their iterative sampling procedures can be computationally demanding, so the trade-off between reconstruction quality and inference cost needs to be assessed for the intended application [9].

A. Emerging Channel Paradigms: RIS and OTFS

For an RIS-assisted link, a commonly used cascaded-channel model is y = (h_r^H diag(θ) G + h_d^H)x + n, where G denotes the BS-to-RIS channel, h_r is the RIS-to-UE channel, h_d is the direct BS-to-UE channel, and θ contains the RIS reflection coefficients. The received signal depends on the combined channel, so the training design must provide enough information to estimate the required channel parameters. Two-timescale methods exploit the relatively slow variation of the BS–RIS link and the faster variation of the RIS–UE link [3], [4]. OTFS represents symbols in the delay–Doppler domain and is intended for channels with significant time variation. Channel estimation in this domain must account for Doppler effects, including leakage associated with non-integer Doppler shifts [10], [11].

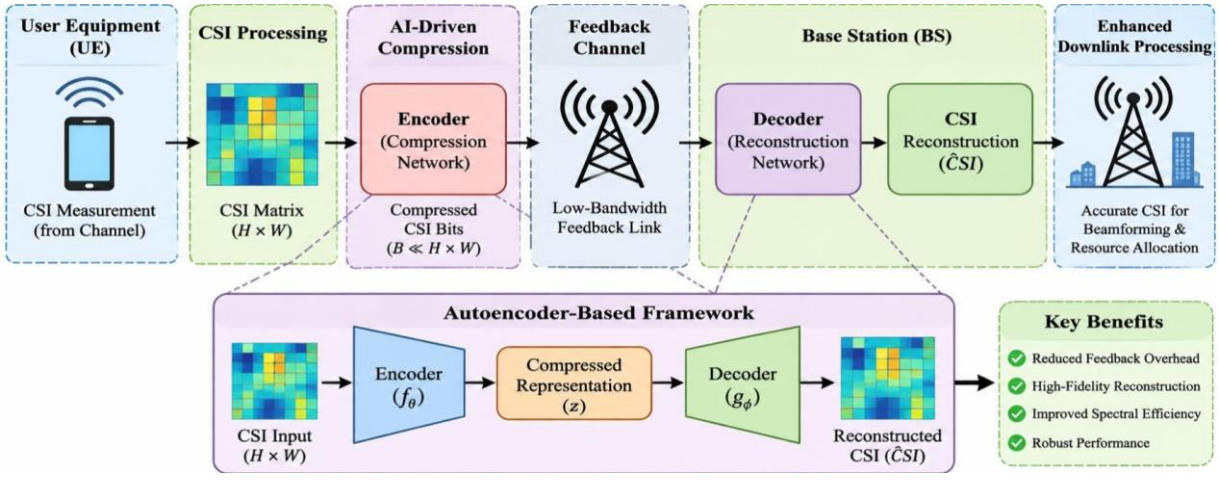

Fig. 2. Conceptual framework of AI-driven CSI feedback compression and autoencoder-based base station reconstruction.

IV. AI-BASED INTERFERENCE MANAGEMENT

In a multi-user downlink, beamforming vectors and transmit powers affect both the desired signal and the interference received by each user. For user k, the signal-to-interference-plus-noise ratio (SINR) can be written as:

$$\mathrm{SINR}_k = (P_k\,|h_k^H w_k|^2) \,/\, (\textstyle\sum_{j\neq k} P_j\,|h_k^H w_j|^2 + \sigma_k^2) \qquad (5)$$

Here, h_k denotes the channel vector for user k, w_j is the precoder for stream j, P_j is its transmit power, and σ_k² is the receiver-noise variance. The expression assumes the channel and precoder dimensions are compatible and that the precoders are normalized so that ||w_j||² = 1; otherwise, the normalization must be included in the power definition. In multicell systems, pilot reuse can cause pilot contamination and correlated channel-estimation errors. Pilot assignment and covariance-aware estimation can help address this problem, while data-phase interference is further managed through precoding and power control.

Learning-assisted interference management has been studied through both optimization-inspired neural networks and reinforcement learning. One approach trains a neural network to approximate the output of an iterative weighted-MMSE (WMMSE) optimization procedure. This can reduce the online computation required by the iterative solver in the scenarios used for training and evaluation, but it does not guarantee faster execution or identical performance in every deployment [12]. In deep reinforcement learning (DRL), an agent learns a policy by interacting with an environment and receiving rewards associated with network performance. Such methods have been investigated for joint beamforming, power control, and interference coordination; their effectiveness depends on the state and action definitions, training stability, and the realism of the environment model [13].

V. PERFORMANCE METRICS

Channel-estimation methods should be compared using metrics that describe both reconstruction quality and system-level consequences. The normalized mean-square error (NMSE) is commonly used to quantify the difference between an estimated channel and the reference channel:

$$\mathrm{NMSE} = \mathrm{E}[\|h - \hat{h}\|^2] \,/\, \mathrm{E}[\|h\|^2] \qquad (6)$$

For a multi-user system, the sum spectral efficiency under the assumed SINR model is:

$$R_{\mathrm{sum}} = \textstyle\sum_k \log_2(1 + \mathrm{SINR}_k)\ \mathrm{bits/s/Hz} \qquad (7)$$

Other useful measures include bit error rate (BER), pilot overhead, computational complexity, and inference latency. A pilot-overhead ratio may be defined as ρ_pilot = N_pilot/N_total, provided that N_pilot and N_total count the same type of time-frequency resources. Complexity is often reported in floating-point operations (FLOPs), while inference latency should be measured on the target processor or hardware platform. Results should be compared only when the channel model, SNR range, pilot configuration, antenna dimensions, and evaluation procedure are sufficiently similar.

Architecture / scenario	Evaluation focus	Representative baseline	Evidence and comparison note
Massive MIMO channel estimation	NMSE; pilot overhead	LMMSE / OMP	Reported performance depends on array size, channel model, pilot budget, and SNR [1], [5].
FDD CSI feedback	Reconstruction NMSE; feedback rate	Compressed-sensing feedback	CsiNet reports study-specific reconstruction comparisons; gains are not universal across datasets or compression ratios [8].
RIS-assisted channel estimation	NMSE; pilot overhead; achievable rate	Conventional/two-timescale estimation	Results depend on RIS training design and cascaded-channel assumptions [3], [4].
Multi-user interference management	Sum rate; SINR; outage probability	WMMSE / conventional power control	Learning-based methods approximate or optimize specific scenarios; report numerical gains only with matching test conditions [13], [12].

Table II. System-Level Performance Benchmarking Across B5G Architectures

VI. OPEN RESEARCH GAPS AND FUTURE DIRECTIONS

The studies reviewed in this paper leave several issues open. First, performance measured using synthetic channel data does not by itself establish that a trained estimator will work under measured propagation conditions. Differences in scattering, mobility, radio-frequency impairments, and antenna calibration can create a mismatch between training and deployment. Evaluation across more than one channel model and, where possible, measured data is therefore important. Second, reductions in pilot overhead often depend on assumptions such as angular sparsity or low-rank channel structure. These assumptions may be less accurate in rich-scattering environments or when hardware and propagation effects depart from the adopted model. Third, complexity results are difficult to compare when studies use different hardware, input dimensions, and counting conventions. Reporting both algorithmic complexity and measured inference time would make practical assessments more informative.

Hybrid model-driven methods are a relevant direction because they combine known channel relationships or optimization structures with trainable components. Their ability to generalize to conditions outside the training distribution, however, must be demonstrated rather than assumed [2], [14]. Federated learning has also been considered for channel estimation in distributed and RIS-assisted networks. It can support collaborative model training without centralizing all raw local observations, but it does not automatically guarantee privacy and may introduce communication, synchronization, and non-identically distributed (non-IID) data challenges [15].

VII. CONCLUSION

This review has discussed conventional and learning-assisted approaches to channel estimation and interference management in B5G/6G-related scenarios. LS and LMMSE provide useful model-based reference methods, while compressed sensing can exploit sparse channel representations when the underlying assumptions are appropriate. Neural estimators, CSI-feedback autoencoders, and generative models offer additional ways to use structure in channel observations, but their performance depends on training coverage and inference cost. For interference management, neural approximations of WMMSE and DRL-based control have been investigated for different optimization settings. A fair assessment of these methods requires reproducible comparisons under clearly specified channel, pilot, hardware, and computational conditions.

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