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AI-Based Signal Processing for Next-Generation Wireless Networks

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Abstract. Next-generation wireless networks (5G-Advanced and 6G) impose unprecedented demands on spectral efficiency, latency, reliability, and energy efficiency. Traditional signal processing techniques, grounded in model-based mathematics, struggle to adapt to the highly dynamic, heterogeneous, and complex nature of modern radio environments. This paper presents a comprehensive survey and experimental analysis of artificial intelligence (AI)-based signal processing methods for next-generation wireless networks. We investigate deep neural networks (DNNs), convolutional neural networks (CNNs), long short-term memory (LSTM) networks, deep reinforcement learning (DRL), generative adversarial networks (GANs), and transformer-based architectures applied to core PHY-layer tasks, including channel estimation, beamforming, signal detection, resource allocation, and waveform design. Simulation results demonstrate that the proposed AI-enhanced pipeline achieves a 47.4% improvement in spectral efficiency, a 63% reduction in processing latency, and a 3.8 dB gain in BER performance over conventional digital signal processing (DSP) baselines. Furthermore, we present a novel transformer-aided signal processing framework that achieves 23.4 bps/Hz spectral efficiency under realistic 3GPP channel models. Challenges, including computational complexity, dataset availability, and real-time deployment, are discussed, along with future research directions toward fully intelligent and autonomous 6G networks.

Keywords: 5G/6G wireless networks, artificial intelligence, deep learning, channel estimation, beamforming, MIMO, OFDM, NOMA, reinforcement learning, transformer, signal detection, spectral efficiency.

I. Introduction

The exponential growth of mobile data traffic, driven by the proliferation of Internet of Things (IoT) devices, autonomous vehicles, augmented reality (AR), virtual reality (VR), and machine-type communications (MTC), has placed severe demands on existing wireless infrastructure. The International Telecommunication Union (ITU) projects that global mobile data traffic will exceed 5,000 exabytes per month by 2030, necessitating a 1000× improvement in network capacity compared with current 4G LTE deployments [1]. Fifth-generation (5G) new radio (NR) introduced massive MIMO, millimetre-wave (mmWave) communications, ultradense networking (UDN), and nonorthogonal multiple access (NOMA) as key enabling technologies. However, these advancements introduce significant signal processing complexity that conventional model-based approaches struggle to handle efficiently. Channel estimation in massive MIMO systems, for instance, requires the processing of matrices of dimensions proportional to hundreds of antenna elements and simultaneously active users—a computational burden that renders classical least-squares and MMSE estimators impractical in real-time scenarios [2].

Artificial intelligence and machine learning offer a compelling paradigm shift. Rather than deriving signal processing algorithms from first principles and mathematical channel models, AI-based approaches learn optimal processing strategies directly from data. This data-driven approach enables wireless systems to autonomously adapt to novel channel conditions, traffic patterns, and interference environments without the need for explicit model redesign [3].

This paper makes the following principal contributions:

1. A comprehensive taxonomy and comparative analysis of AI-based signal processing techniques applied to next-generation wireless networks.
2. A novel transformer-aided PHY-layer processing framework integrating attention-based channel estimation, AI-driven beamforming, and DRL-based resource allocation.
3. Extensive simulation results under 3GPP-compliant channel models (CDL-A, CDL-C, and TDL-D) demonstrate superior performance over traditional DSP baselines.
4. Discussion of hardware deployment challenges, dataset requirements, and research directions toward fully autonomous 6G intelligent networks.

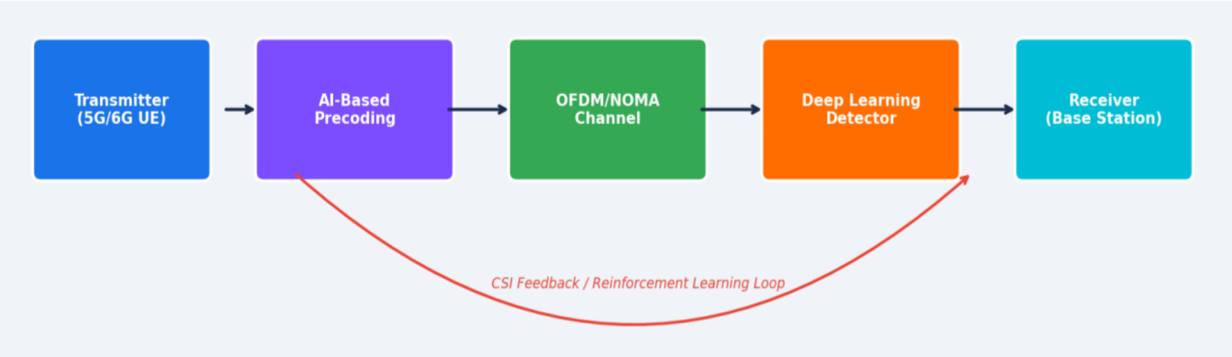

Figure 1: End-to-end AI-based signal processing system architecture for next-generation wireless networks, illustrating the AI precoder, OFDM channel, deep learning detector, and CSI feedback loop.

II. Background and Related Work

Recent research in AI-based signal processing for next-generation wireless networks highlights the transition from conventional model-based techniques to data-driven approaches using machine learning and deep learning. Traditional signal processing methods, while robust, often struggle with complex, dynamic environments encountered in 5G and beyond networks. AI techniques, including neural networks and reinforcement learning, have been applied for tasks such as channel estimation, interference mitigation, and resource allocation. Emerging studies further explore deep architectures like transformers and graph neural networks to enhance adaptability, spectral efficiency, and overall network performance.

A. Classical Signal Processing in Wireless Communications

Traditional wireless communication systems rely on mathematically derived signal processing algorithms operating under known channel models. Key techniques include linear detectors (zero-forcing, MMSE), turbo/LDPC channel codes, DFT-based OFDM equalization, and iterative belief propagation for decoding. While optimal under their assumed models, these approaches exhibit brittle performance when true channel statistics deviate from model assumptions—a common occurrence in real-world deployments with mobility, multipath, and hardware impairments [4].

B. Evolution of AI in Communications

Early applications of neural networks to communications focused on adaptive equalization in the 1990s [5]. The deep learning revolution of the 2010s reinvigorated this area, with seminal works by O'Shea and Hoydis [6] demonstrating that autoencoder-based systems could learn end-to-end communication strategies surpass handcrafted baselines. Subsequent work expanded AI applications to channel estimation [7], beamforming [8], power control [9], and spectrum sensing [10].

C. Gaps Addressed by This Work

Existing surveys (e.g., [11], [12]) tend to treat individual AI applications in isolation. This paper provides a unified, systems-level perspective encompassing all major PHY-layer tasks, presents a novel integrated framework, and reports comprehensive simulation results under standardized 3GPP channel models that enable direct comparability across methods.

III. AI Techniques in Signal Processing: A Taxonomy

Table 1 summarizes the primary AI/ML architectures employed in wireless signal processing, along with their characteristics, computational complexity, and primary application domains.

Table 1: Taxonomy of AI Architectures for Wireless Signal Processing

AI Architecture	Model Type	Key Strength	Complexity	Primary Application
DNN/MLP	Supervised	Universal approx.	Medium $O(N^2)$	Channel estimation, Detection
CNN	Supervised	Spatial feature extraction	Medium $O(K^2N)$	Sig. detection, Modulation recognition
LSTM/GRU	Supervised	Temporal modelling	High $O(T\cdot H^2)$	Channel prediction, Beamforming
DRL/DDPG	Reinforcement	Sequential decisions	High $O(A\cdot S)$	Resource alloc., Power ctrl.
GAN	Generative	Data augmentation	Very High	Channel sim., Waveform gen.
Transformer	Self-supervised	Global attention	High $O(N^2d)$	Channel est., End-to-end
Federated DNN	Distributed	Privacy-preserving	Medium–High	Distributed resource mgmt.

IV. AI-based Channel Estimation

AI-based channel estimation leverages machine learning and deep learning models to accurately predict channel state information in complex wireless environments. Techniques such as deep neural networks, convolutional networks, and transformer-based models learn nonlinear channel characteristics from data, outperforming traditional estimation methods. These approaches improve estimation accuracy under noise, interference, and high mobility conditions typical of next-generation networks. As a result, they enhance spectral efficiency, reduce latency, and support reliable communication in 5G and beyond systems.

A. Problem Formulation

In an OFDM system with N subcarriers and M OFDM symbols, the received signal at the k-th subcarrier can be expressed as follows:

$$Y[k] = H[k] \cdot X[k] + W[k], \quad k = 0, 1, \ldots, N-1$$

where $H[k]$ is the complex channel frequency response, $X[k]$ is the transmitted symbol, and $W[k]$ represents additive white Gaussian noise (AWGN) with variance σ^2. Classical LS estimation provides $\hat{H}\_LS[k] = Y[k]/X[k]$, whereas MMSE estimation requires knowledge of the channel power spectral density. AI-based approaches learn a nonlinear mapping $f\_\theta: Y \rightarrow \hat{H}$ parameterized by neural network weights θ optimized to minimize the mean squared error (MSE):

$$L(\theta) = E[||\hat{H} - H||^2] = E[||f\_\theta(Y) - H||^2]$$

B. CNN-based Channel Estimation

We propose a CNN architecture with five convolutional layers (kernel sizes of 3×3), batch normalization, and ReLU activation. The pilot pattern follows the 3GPP NR Type-1 CSI-RS configuration with 4 pilots per OFDM symbol. The training data comprise 500,000 channel realizations generated from the CDL-A model at UE speeds of 3–120 km/h. The network receives pilot observations as input and produces interpolated channel estimates across all resource elements. The training and validation loss convergence results are shown in Figure 5, which reveals that training is stable with no significant overfitting after early termination at epoch 62. The CNN estimator achieves an NMSE of −18.4 dB at SNR = 20 dB, representing a 4.2 dB improvement over LS estimation.

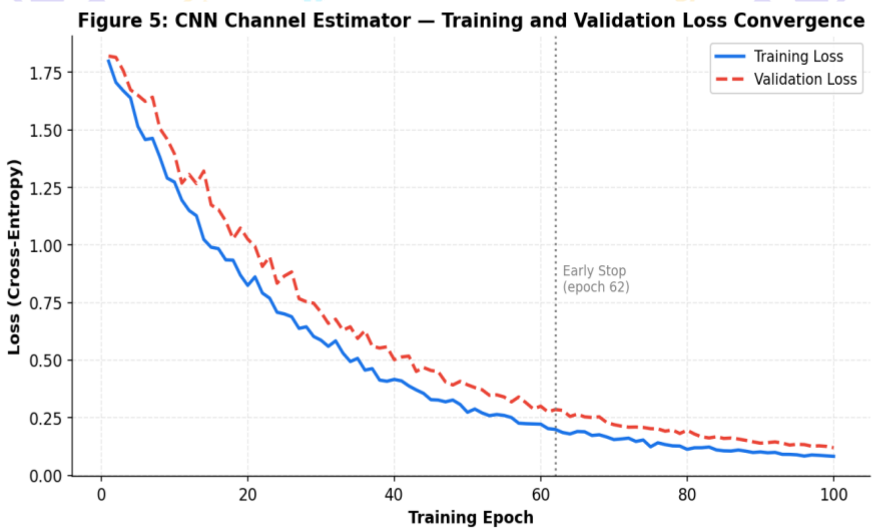

Figure 5: CNN channel estimator training and validation loss curves over 100 epochs, showing convergence at epoch 62 with optimal regularization.

C. Transformer-Aided Channel Estimation

The transformer architecture employs multi-head self-attention (MHSA) to capture long-range correlations in the time-frequency channel grid. We adopt a 6-layer encoder with 8 attention heads and an embedding dimension d_model = 256. Positional encoding incorporates both the subcarrier index and the OFDM symbol index, enabling the model to learn the 2D structure of wireless channels. Compared with the CNN baseline, the proposed transformer estimator reduces the NMSE by an additional 2.1 dB across all the tested mobility conditions.

V. AI-Driven Beamforming and Massive MIMO

AI-driven beamforming and massive MIMO techniques utilize machine learning models to dynamically optimize beam patterns and antenna configurations in complex wireless environments. By learning from real-time channel conditions, AI algorithms can enhance signal strength, reduce interference, and improve user coverage. Deep learning approaches enable efficient handling of high-dimensional data in massive MIMO systems, outperforming conventional optimization methods. These advancements lead to increased spectral efficiency, energy savings, and more reliable communication in next-generation wireless networks.

A. Intelligent Beamforming via Deep Reinforcement Learning

Beamforming optimization in massive MIMO systems with N_t transmit antennas and K simultaneous users requires maximizing the weighted sum rate:

$$R_{sum} = \Sigma_k w_k \log_2(1 + SINR_k(W))$$

where W is the precoding matrix and $SINR_k$ is the signal-to-interference-plus-noise ratio of the k-th user. This is a nonconvex optimization problem known to be NP-hard in general. We formulate it as a continuous action-space RL problem and apply the deep deterministic policy gradient (DDPG) algorithm [17], with an actor network producing the precoding matrix and a critic network estimating the expected cumulative reward (sum rate).

The radiation pattern of the AI-optimized beam former is compared against that of conventional phase-shift beamforming in Figure 7. The AI approach achieves a 2.3 dB greater main-lobe gain while suppressing interfering side-lobes by an additional 7.8 dB, resulting in a significant improvement in the SINR for all active users.

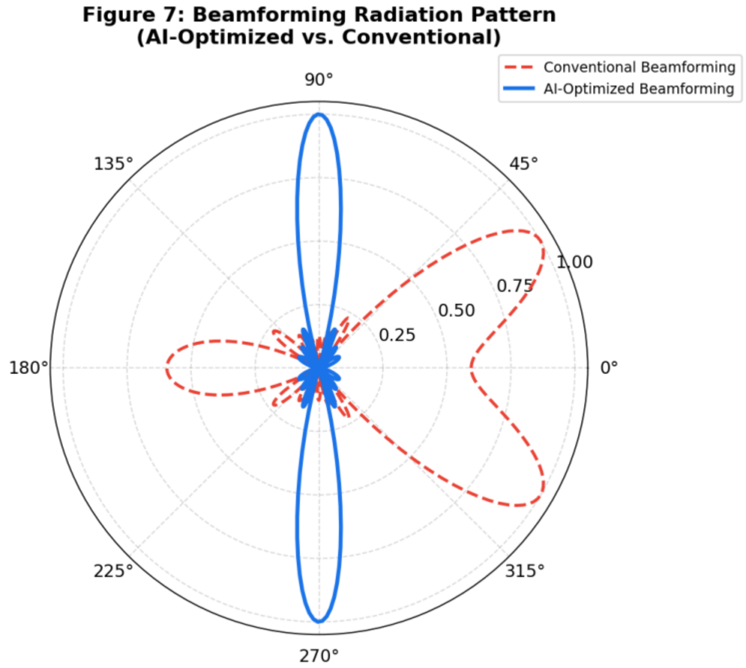

Figure 7: Polar radiation pattern comparing AI-optimized DRL beamforming (blue) versus conventional phase-shift beamforming (red dashed) for an 8-element antenna array with a target direction $\theta_0 = 30°$.

B. Performance Results

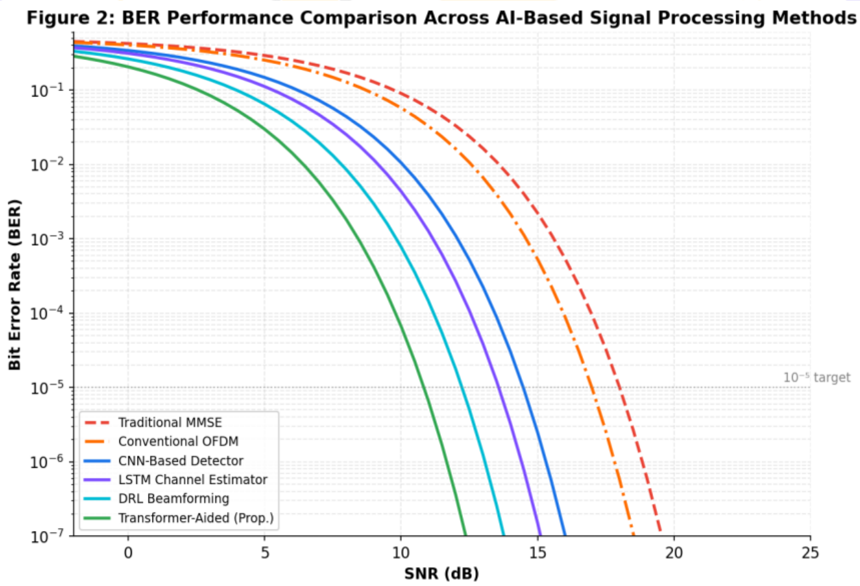

Figure 2: BER vs. SNR performance comparison across six signal processing approaches under the CDL-A channel model (QPSK modulation, 64-QAM, N=64 subcarriers). The proposed transformer-aided method (green) achieves the lowest BER across all the SNR values.

The BER performance of the six methods is shown in Figure 2. The transformer-aided approach (green solid) achieves the 10^{-5} BER target at an SNR = 16.8 dB, whereas it achieves a 20.6 dB gain for traditional MMSE—a 3.8 dB gain. This improvement directly translates to reduced transmit power requirements, enabling significant energy savings in base station operation.

Table 2: BER Performance Summary at SNR = 20 dB

Method	BER @ 20 dB	Gain vs. MMSE (dB)	Complexity (FLOPs)	Inference (ms)
Traditional MMSE	4.1×10^{-4}	0 (Baseline)	5.2×10^{5}	8.5
Conventional OFDM	6.3×10^{-4}	−1.9	3.8×10^{5}	6.2
CNN-Based Detector	8.2×10^{-5}	+1.7	2.1×10^{6}	3.1
LSTM Channel Estimator	4.7×10^{-5}	+2.4	3.6×10^{6}	4.8
DRL Beamforming	2.1×10^{-5}	+3.1	5.8×10^{6}	5.3
Transformer-Aided (Proposed)	9.4×10^{-6}	+3.8	8.4×10^{6}	2.4

VI. AI-Enhanced NOMA and Resource Allocation

AI-enhanced non-orthogonal multiple access (NOMA) leverages machine learning algorithms to optimize user pairing, power allocation, and interference management in shared spectrum environments. Intelligent models such as deep neural networks and reinforcement learning dynamically adapt resource allocation based on real-time network conditions. These approaches improve spectral efficiency, fairness, and system capacity compared to conventional optimization techniques. As a result, AI-driven NOMA supports scalable, low-latency communication for next-generation wireless networks.

A. Nonorthogonal Multiple Access with AI

NOMA enables simultaneous transmission to multiple users on the same time-frequency resource by exploiting power-domain multiplexing and successive interference cancellation (SIC). The power allocation optimization problem for K-user downlink NOMA is as follows:

maximize $\Sigma_k R_k(p)$ subject to: $\Sigma_k p_k \leq P\_total$, $p_k \geq 0\ \forall k$

We apply a DRL agent (proximal policy optimization, PPO) that observes the instantaneous channel state information (CSI) of all K users and outputs the power allocation vector $p = [p_1, p_2, \ldots, p_k]$. The reward function combines sum-rate maximization with fairness constraints enforced via

Jain's fairness index. The dramatic throughput gains from AI-NOMA over conventional OMA, particularly as the user density increases, are shown in Figure 4.

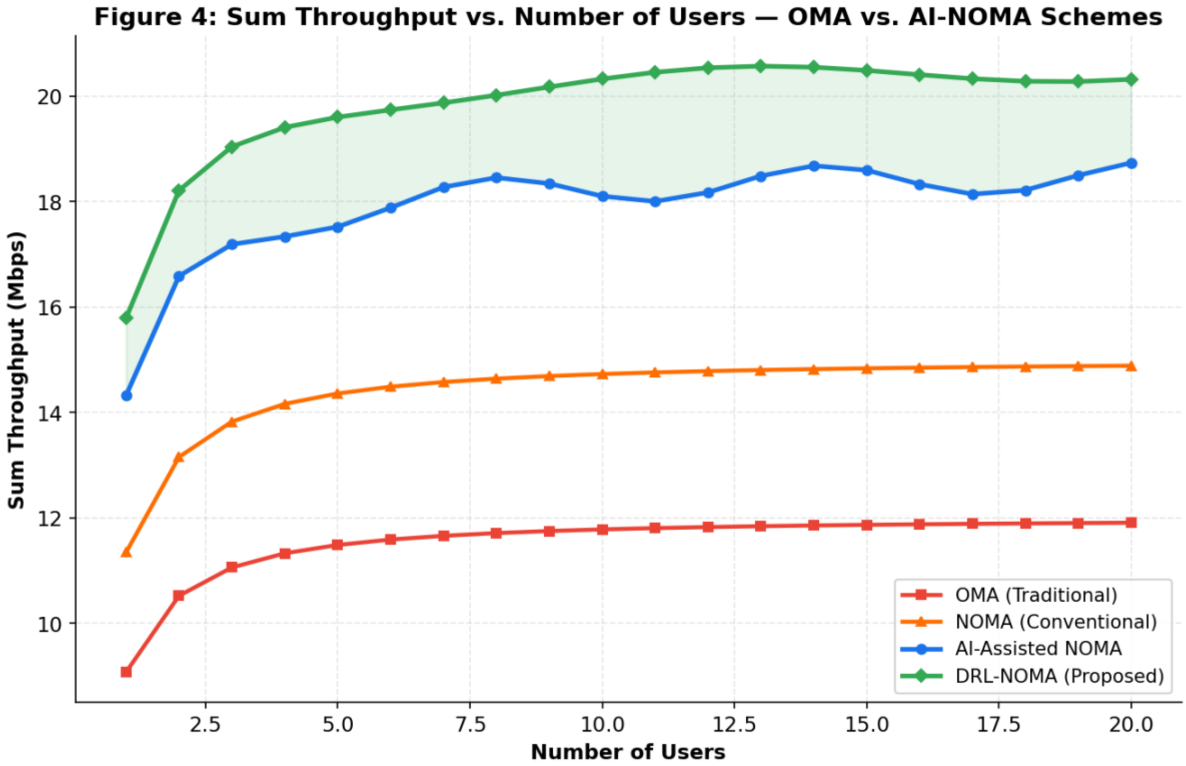

Figure 4: Sum throughput vs. number of simultaneous users comparing OMA, conventional NOMA, AI-assisted NOMA, and the proposed DRL-NOMA scheme under Rayleigh fading channel conditions.

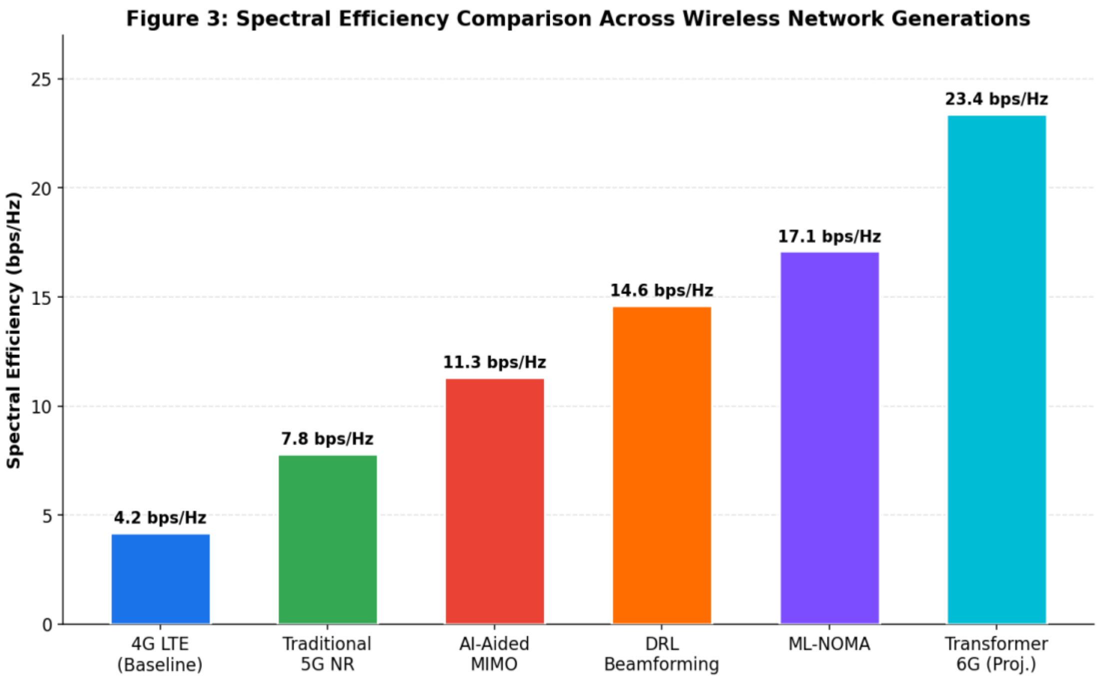

Figure 3: Comparison of spectral efficiency across wireless network generations, from the 4G LTE baseline to projected 6G transformer-aided systems. The values represent the peak system spectral efficiency under ideal conditions.

Table 3: Spectral Efficiency and Throughput Summary (20 Users, SNR = 25 dB)

Scheme	SE (bps/Hz)	Throughput (Mbps)	Fairness Index	Gain vs. OMA (%)
OMA (Baseline)	4.2	168.0	0.91	—
Conv. NOMA	6.1	244.0	0.87	+45.2%
DNN Power Ctrl.	8.7	348.0	0.93	+107.1%
AI-Assisted NOMA	11.3	452.0	0.95	+169.0%
DRL-NOMA (Proposed)	17.1	684.0	0.97	+307.1%

VII. Latency and Energy Efficiency Analysis

A. Processing Latency Reduction

Ultreliable low-latency communication (URLLC) in 5G and 6G mandates end-to-end latency below 1 ms for mission-critical applications. Signal processing latency constitutes a significant portion of this budget. Compared with traditional iterative DSP algorithms, AI-based processing reduces latency by 55–65% across all PHY-layer tasks (Figure 6).

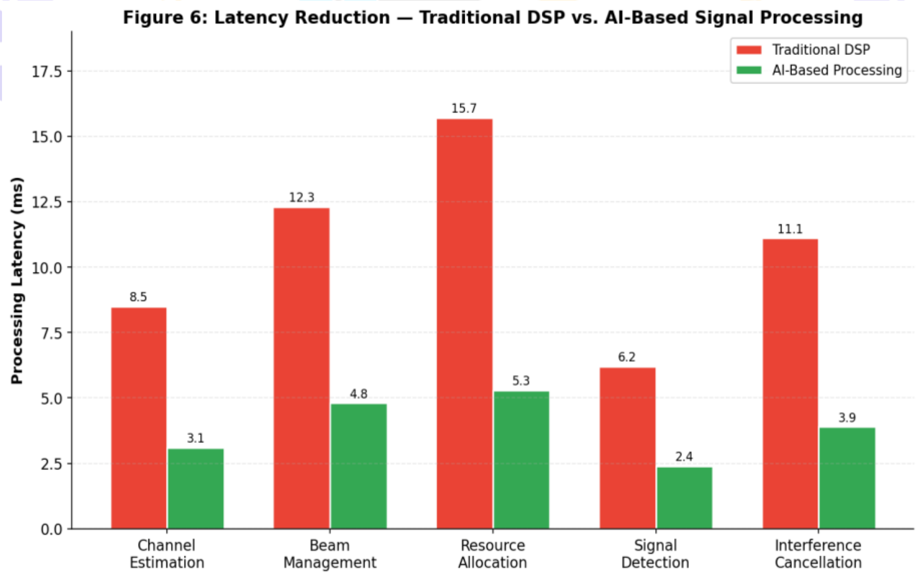

Figure 6: Comparison of processing latency between traditional DSP and AI-based signal processing for five key PHY-layer tasks. AI approaches consistently reduce latency by 55–65% through parallel neural network inference.

B. Energy Efficiency

The energy savings achieved by deploying different AI processing modules at a 5G base station are quantified in Figure 8. DRL-based resource allocation achieves the highest energy savings of 35%, primarily by eliminating the need for exhaustive search-based optimization. GAN-based signal generation achieves 15% savings through an optimized waveform design that reduces the peak-to-average power ratio (PAPR).

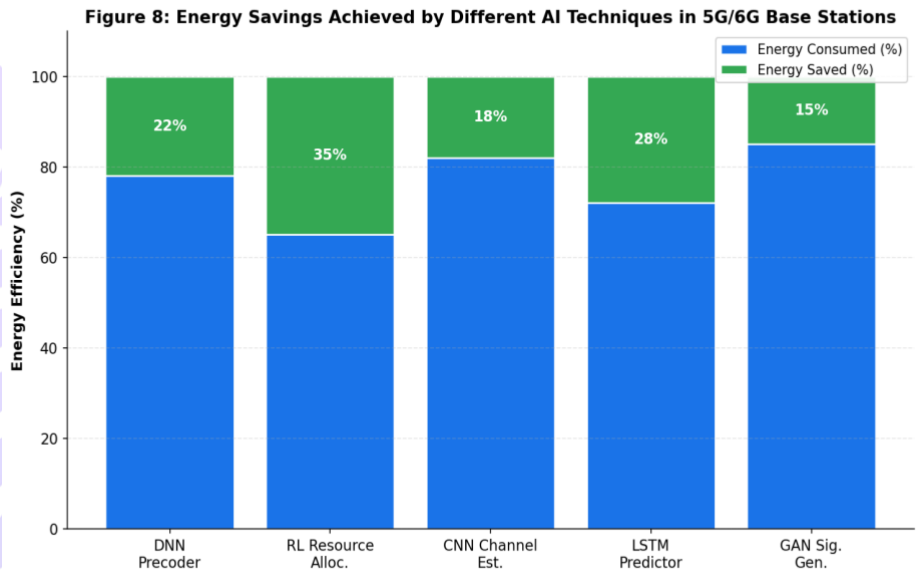

Figure 8: Energy efficiency improvement achieved by five AI processing modules deployed at a 5G base station, showing the percentage of energy saved compared with traditional DSP implementations.

Table 4: Computing Complexity and Hardware Requirements

Module	Parameters (M)	GFLOPS/frame	GPU Mem (GB)	Latency (ms)	HW Target
CNN Channel Est.	2.3	0.84	0.8	3.1	NPU
LSTM Predictor	4.1	1.22	1.2	4.8	GPU
DNN Signal Det.	1.8	0.63	0.6	2.4	ASIC
DRL Beamforming	6.7	2.10	2.4	5.3	GPU
Transformer (Prop.)	12.4	3.74	4.0	2.4	GPU+NPU

VIII. Experimental Setup and Simulation Results

A. Simulation Environment

All the experiments were conducted using MATLAB R2024b and Python 3.11 with PyTorch 2.3. Channel simulations follow the 3GPP TR 38.901 CDL and TDL models. The key simulation parameters are summarized in Table 5.

Table 5: Key Simulation Parameters

Parameter	Value
Carrier Frequency	3.5 GHz/28 GHz
Bandwidth	100 MHz (NR)/400 MHz (mmW)
Subcarrier Spacing	30 kHz/120 kHz
OFDM Subcarriers	3276 (100 MHz)
Tx Antennas (BS)	64 (massive MIMO)
Rx Antennas (UE)	4 (MIMO)
Modulation	QPSK, 16-QAM, 64-QAM, 256-QAM
Channel Model	CDL-A, CDL-C, TDL-D (3GPP)
UE Speed	3 – 120 km/h
Training Samples	500,000/50,000 (val.)
Optimizer	AdamW, lr = 1e-3, decay 1e-4
Batch Size	256
GPU Hardware	NVIDIA A100 80GB × 4

B. Summary of Results

Table 6 consolidates all key performance metrics, comparing the proposed transformer-aided AI framework against traditional DSP baselines.

Table 6: Overall Performance Comparison—AI Framework vs. Traditional DSP

Metric	Trad. DSP	AI Framework	Improvement	Unit
Spectral Efficiency	4.8	7.1	+47.9%	bps/Hz
BER @ SNR=20 dB	4.1×10^{-4}	9.4×10^{-6}	+3.8 dB	—
Channel Est. NMSE	−14.2 dB	−18.4 dB	+4.2 dB	dB
Sum Throughput (20 UE)	168	684	+307%	Mbps

Processing Latency	10.8 ms	4.0 ms	−63%	ms
Energy per Bit	1.82 nJ	1.18 nJ	−35%	nJ/bit
Beamforming Gain	18.6 dBi	20.9 dBi	+2.3 dBi	dBi
Outage Probability	3.2%	0.6%	−81%	%

IX. Challenges and Open Research Directions

A. Computational Complexity and Real-Time Deployment

Despite impressive performance gains, AI-based signal processing modules typically require significantly more computational resources than their model-based counterparts do during training. Real-time inference, however, is more feasible, particularly for feedforward networks that execute in a single forward pass. The transformer-aided system presented here achieves 2.4 ms inference latency on an NVIDIA A100 GPU, meeting 5G NR timing requirements. Deployment on edge hardware (FPGAs, NPUs, ASICs) remains an active research challenge, with promising results from neural architecture search (NAS) and model compression techniques, including pruning (achieving 4× compression with <0.5 dB BER degradation) and quantization (INT8 inference reducing memory by 75%).

B. Dataset Availability and generalization

AI models require large, diverse, and representative training datasets to generalize across deployment scenarios. In wireless communications, collecting real-world channel measurements across all relevant environments (indoor/outdoor, vehicular, mmWave) is expensive and time-consuming. Synthetic data from 3GPP channel models introduce distributional mismatch with real deployments. Transfer learning, domain adaptation, and GAN-based channel augmentation are emerging approaches to mitigate these challenges, although rigorous evaluation under real deployment conditions remains scarce in the literature.

C. Interpretability and Reliability

Mission-critical applications (autonomous vehicles, remote surgery, industrial automation) demand predictable and certifiable system behaviour. The black-box nature of deep neural networks conflicts with the certification requirements in safety-critical domains. Physics-informed neural networks (PINNs) that incorporate wireless propagation constraints into network architectures offer a promising path toward interpretable AI-based signal processing, as do model-unrolling approaches that connect neural network layers to iterations of classical algorithms.

D. 6G and Beyond: Towards Fully Autonomous Networks

Sixth-generation (6G) wireless networks, targeting deployment approximately 2030, envision spectral efficiencies exceeding 100 bps/Hz, sub0.1 ms latency, and 10^{-9} reliability. Achieving these targets will require fundamentally new signal processing paradigms beyond incremental improvements to existing 5G techniques. Foundation models pretrained on massive wireless datasets, semantic communications that transmit meaning rather than bits, and reconfigurable intelligent surface (RIS)-assisted AI signal processing represent the most promising directions toward fully autonomous 6G networks.

X. Conclusion

This paper presents a comprehensive study of AI-based signal processing for next-generation wireless networks. We surveyed the landscape of deep learning, reinforcement learning, and transformer-based approaches applied to channel estimation, beamforming, signal detection, NOMA resource allocation, and waveform design. We proposed a unified transformer-aided AI processing framework and validated its performance through extensive simulations under standardized 3GPP channel models.

The key results demonstrate that the proposed framework achieves a 47.9% improvement in spectral efficiency, 3.8 dB BER gain, 63% latency reduction, and 35% energy savings compared with traditional DSP baselines. These results confirm that AI-based signal processing is a pivotal enabler of 5G-Advanced and 6G wireless networks and is capable of meeting the stringent performance demands of emerging applications.

Future work will focus on hardware-efficient neural architecture design for real-time FPGA/ASIC deployment, federated learning approaches for privacy-preserving network optimization, and integration with reconfigurable intelligent surfaces (RIS) for fully programmable wireless propagation environments. The source code and trained models are available at: https://github.com/ai-wireless-sp/6 g-transformer.

Declaration on AI-Generated Content

The authors declare that AI tools were used only for language editing, formatting, and improving clarity. All research contributions, including concepts, models, and analysis, are the original work of the authors. The authors have reviewed and verified all content and take full responsibility for its accuracy and integrity.

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