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# AI-ASSISTED ADAPTIVE BEAMFORMING FOR ENERGY-EFFICIENT 6G WIRELESS COMMUNICATION SYSTEMS

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## Abstract

The sixth generation (6G) of wireless communication systems, envisioned for commercial deployment around 2030 under the ITU-R IMT-2030 framework (Recommendation ITU-R M.2160, November 2023), introduces unprecedented demands on spectral and energy efficiency. Conventional model-based beamforming approaches are increasingly inadequate for the ultra-dense, heterogeneous, and high-mobility environments characteristic of 6G. This paper examines AI-assisted adaptive beamforming as a transformative paradigm for 6G, integrating deep reinforcement learning (DRL), convolutional neural networks (CNNs), and long short-term memory (LSTM) networks into the beamforming pipeline for massive multiple-input multiple-output (mMIMO) arrays, terahertz (THz) frequency channels, and reconfigurable intelligent surface (RIS)-assisted propagation environments. A comparative analysis of AI-based versus conventional beamforming is presented alongside a review of India's nascent 6G research policy landscape. Recommendations are provided for accelerating AI-beamforming integration in alignment with the IMT-2030 framework.
***Keywords:*** 6G Wireless Networks, Adaptive Beamforming, Deep Reinforcement Learning, Massive MIMO, Reconfigurable Intelligent Surfaces, Energy Efficiency, Terahertz Communication, IMT-2030, Neural Beamforming, Hybrid Precoding

## 1. Introduction

Global mobile data traffic is projected to grow exponentially through the late 2020s, driven by immersive extended-reality (XR) applications, autonomous vehicular systems, holographic telepresence, and the proliferation of massive machine-type communications. The fifth generation (5G) standards, while transformative, are not architected to satisfy all of these demands at scale. The research community has therefore converged on a sixth generation (6G) of wireless systems, with commercial deployment targeted near 2030. In November 2023, the International Telecommunication Union Radiocommunication Sector (ITU-R) published Recommendation ITU-R M.2160, formally establishing the IMT-2030 Framework and defining six usage scenarios for 6G: Immersive Communication, Hyper-Reliable and Low-Latency Communication (HRLLC), Massive Communication, Ubiquitous Connectivity, AI-and-Communication, and Integrated Sensing and Communication (ISAC). [1] A defining characteristic of this framework is that artificial intelligence (AI) is embedded as a native design principle rather than an optional overlay, reflecting its anticipated role in automating and optimizing every layer of the network stack.

Beamforming, the spatial signal processing technique by which antenna arrays concentrate radiated energy toward intended receivers, is a foundational capability for meeting 6G's spectral and energy efficiency targets. Massive MIMO technology, employing tens to hundreds of antenna elements per base station, demonstrated approximately twenty-fold capacity gains over 4G systems and reached more than 45% global population coverage in 5G deployments by end of 2023. [2] For 6G, the evolution is toward ultra-massive and gigantic MIMO arrays at terahertz (THz) frequencies between 100 GHz and 10 THz, enabling terabit-per-second data rates but introducing severe propagation challenges: high path loss, sparse multipath, near-field channel effects, and hardware impairments at phase shifters and analog-to-digital converters. [3]

Classical optimization-based beamforming, including alternating optimization, convex relaxation, and semi-definite programming, becomes computationally intractable at the dimensionality of 6G arrays under real-time slot constraints. Hybrid beamforming architectures, which partition processing between analog phase-shifter networks and a reduced number of digital RF chains, offer a practical compromise, but optimal design of both the analog and digital components jointly under partial channel state information (CSI) remains a hard non-convex problem. [4] Reconfigurable Intelligent Surfaces (RIS), programmable planar arrays of reflecting meta-material elements that reshape the propagation environment, further expand the optimization space by coupling active base station beamforming with a high-dimensional passive phase configuration. [5]

AI and machine learning (ML) methods address these challenges by learning near-optimal beam selection and phase configuration policies directly from data, obviating the need for explicit analytical channel models. Deep neural networks have been applied to beam prediction from CSI feedback, substantially reducing exhaustive codebook search overhead. DRL agents learn adaptive control policies through environmental interaction, enabling real-time beamforming in dynamic channels. Recent studies report that deep learning-assisted RIS systems achieve data rate improvements of approximately 97% over reference baselines and approximately 115% over no-RIS cases, while gradient-based meta-learning beamforming in RIS-aided systems achieves energy consumption reductions of two orders of magnitude relative to standard alternating optimization methods. [6][7] This paper surveys, synthesis, and critically evaluates these advances, identifies remaining challenges, and provides recommendations for their integration within India's 6G research trajectory.

The remainder of this paper is organized as follows: Section 2 presents the literature review. Section 3 describes the theoretical framework. Section 4 details the methodology. Section 5 provides analysis and discussion. Section 6 concludes with policy recommendations and future research directions.

## 2. Literature Review

### 2.1 Beamforming Evolution: From 5G Massive MIMO to 6G Ultra-Massive Arrays

Massive MIMO beamforming has been the defining radio access technology of 5G, providing spatial multiplexing, interference suppression, and array gain through base station configurations of 16, 32, or 64 antenna branches. Analog beamforming, which uses RF-domain phase shifters to direct a single beam per stream, maximises array gain with minimal hardware but lacks the flexibility to serve multiple spatially separated users simultaneously. Digital beamforming provides full flexibility at the cost of requiring one RF chain per antenna element, leading to prohibitive power consumption at large scale. Hybrid beamforming bridges these extremes: a smaller digital baseband precoder feeds a larger analog phase-shifter network, with typical configurations reducing RF chain count by an order of magnitude while approaching the performance of full digital systems. [4]

For 6G, the transition toward THz frequencies introduces qualitatively different channel physics. High-frequency THz channels exhibit extreme path loss, low molecular scattering diversity, and propagation conditions that shift from far-field plane-wave to near-field spherical-wave when array apertures are large. Jiang et al. (2022) addressed practical THz hybrid beamforming with a dynamic-subarray and fixed phase-shifter (DS-FPS) architecture, which circumvents the power consumption of adjustable phase shifters at THz frequencies and handles partial CSI, demonstrating spectral efficiency competitive with full-CSI algorithms. [8] Murshed et al. (2023) proposed a CNN-LSTM fusion-separation deep neural network for 6G ultra-massive MIMO hybrid beamforming that approaches the performance of the computationally intensive Alt-Min algorithm in spectral efficiency while requiring substantially lower computational effort, confirming that learned beamformers can decouple accuracy from complexity. [9]

### 2.2 Deep Learning and Reinforcement Learning for Adaptive Beamforming

The application of deep learning to beamforming accelerated from 2020 onward, catalogued comprehensively in Mao et al.'s (2022) IEEE Communications Surveys & Tutorials article on AI models for green communications toward 6G. [10] CNNs applied to CSI-to-beam mapping reduce the pilots and feedback overhead associated with exhaustive codebook search; LSTM networks model temporal channel dynamics, enabling proactive beam switching before channel quality degrades below threshold. Elbir et al. (2021) established theoretical and practical baselines for model-free hybrid beamforming at THz frequencies using deep neural architectures, demonstrating that model-free approaches can match the spectral efficiency of model-based methods while handling the non-stationarity inherent in ultra-massive MIMO channels. [11]

Deep reinforcement learning (DRL) offers a complementary paradigm: rather than learning a mapping from CSI to beam index (supervised), a DRL agent learns a policy by maximizing a reward signal that encodes system objectives such as sum rate, energy efficiency, or SINR. Huang et al. (2020) demonstrated the applicability of DRL to RIS-assisted multi-user MISO systems, showing that the learned policy substantially outperforms alternating-minimization baselines under partial CSI and user mobility, establishing a foundational framework widely extended in subsequent work. [5] Nashwan (2024) applied DRL to energy-harvesting RIS (EH-RIS) assisted drone communications in a 6G context, using DRL to allocate resources dynamically across time and space to maximize harvested energy while sustaining communication quality, demonstrating the versatility of DRL across heterogeneous 6G deployment scenarios. [12]

The channel estimation problem in RIS systems is particularly acute: with tens to thousands of passive elements, pilot-based estimation incurs prohibitive overhead. Nguyen et al. (2023) proposed a CNN-LSTM framework for channel estimation in RIS-assisted NOMA 6G networks, achieving substantially reduced estimation error compared to classical least-squares methods while maintaining low pilot overhead, illustrating how deep learning can restructure the estimation pipeline rather than merely accelerating existing algorithms. [13]

### 2.3 Reconfigurable Intelligent Surfaces (RIS) and AI Beamforming

RIS technology has rapidly transitioned from a conceptual proposal to an active experimental and standardization topic within the 6G timeframe. A RIS comprises a planar array of low-cost passive or semi-active elements whose electromagnetic response—amplitude and phase of the reflected signal—is programmable via a smart controller. By intelligently shaping the propagation environment, a RIS can create constructive interference at intended receivers and destructive interference at unintended ones, improving coverage and energy efficiency without requiring additional RF chains or active amplification.

Megahed (2024, Wiley Transactions on Emerging Telecommunications Technologies) demonstrated a deep-learning-assisted RIS framework for 6G mobile networks in which the trained neural architecture selects optimal RIS configurations from a learned codebook. The proposed model improved the achievable data rate by approximately 97% above the reference model and approximately 115% above a no-RIS baseline, underscoring both the significance of RIS-enabled propagation control and the effectiveness of data-driven configuration selection. [6] The study further confirmed that spectral energy efficiency (SEE) improves commensurately with data rate, validating RIS as a joint spectral-and-energy efficiency enabler.

For scenarios requiring adaptation across diverse mobility conditions without expensive pre-training, gradient-based meta-learning beamforming (GMLB), proposed in an arXiv study submitted November 2023, feeds the gradient of the sum-rate objective—rather than raw channel information—into neural networks, enabling fast adaptation to new propagation conditions. The approach designs a differential regulator for RIS phase-shift optimization and achieves energy consumption two orders of magnitude lower than alternating optimization algorithms, while maintaining competitive sum-rate performance. [7] The multi-hop extension of deep learning beamforming, explored in subsequent literature for two or more cascaded RIS elements in a relay topology, achieves sum-rate gains of approximately 1.8 bit/s/Hz in two-user scenarios compared to conventional beamforming, with gains growing as user count increases. [14]

### 2.4 Hybrid Beamforming for Spectral-Energy Efficiency in Massive MIMO

Sundar et al. (2024, Heliyon) proposed a dual deep-learning model for spectral energy balancing in massive MIMO-based hybrid beamforming for 6G, combining a beamforming prediction module with a resource scheduling module. Evaluated across dense network configurations, the approach demonstrated improved balance between spectral efficiency and energy consumption compared to single-model or classical hybrid precoding baselines, illustrating how multi-objective DL architectures can navigate the spectral-energy trade-off intrinsic to 6G design. [15] The neuro-inspired approach of Lin et al. (2024, Frontiers in Computational Neuroscience) explored echo state networks (ESN)—a reservoir computing paradigm—for symbol detection in massive MIMO-OFDM systems, a critical pre-processing step for beamforming pipeline efficiency in 6G, demonstrating that neuromorphic computing principles can provide energy-efficient alternatives to standard deep learning inference on dedicated hardware. [16]

### 2.5 AI for Green Communications and 6G Policy

Mao et al. (2022) provided a systematic survey of AI models for green communications toward 6G in IEEE Communications Surveys & Tutorials, covering model-driven, data-driven, and hybrid approaches across physical layer, resource management, and network orchestration. The survey identified energy efficiency as the dominant motivation for AI adoption in 6G radio access networks, noting that the RAN accounts for a disproportionately large fraction of total cellular network energy consumption. [10] The ITU-R M.2160 framework (November 2023) explicitly codifies this imperative, defining energy efficiency as one of the fifteen enhanced IMT-2020 capabilities to be extended in IMT-2030, alongside new capabilities specific to AI-and-Communication and ISAC. [1] India's Telecommunications Standards Development Society India (TSDSI) participates in ITU-R WP5D standardization, and the Department of Telecommunications' Bharat 6G Vision document acknowledges AI-native air interface design as a national research priority, though specific beamforming standardization contributions remain nascent at the time of this writing. [17]

## 3. Theoretical Framework

This study draws on three established theoretical constructs to frame the analysis of AI-assisted adaptive beamforming for 6G.

### 3.1 Markov Decision Process (MDP) Formulation.

Adaptive beamforming in time-varying wireless channels is naturally modelled as a Markov Decision Process. The state encodes instantaneous CSI, interference levels, user positions, and mobility indicators. The action space comprises beam codebook index selections or continuous-valued phase configurations for hybrid and RIS-assisted systems. The reward function encodes the system objective—commonly a linear combination of weighted sum rate and negative transmit power, or energy efficiency in bits per joule. DRL agents (e.g., Deep Q-Network, Deep Deterministic Policy Gradient, Proximal Policy Optimization) learn a stationary policy mapping states to actions by interacting with the wireless environment, circumventing the need for closed-form channel models or convex approximations.

### 3.2 Information-Theoretic Capacity and Energy Efficiency.

The achievable rate of the massive MIMO downlink under zero-forcing (ZF) or regularized ZF precoding converges deterministically as the number of antennas N grows large relative to users K, a regime known as favorable propagation. Energy efficiency (EE), measured in bits per joule, captures the trade-off between throughput and power consumption: EE = R_sum / P_total, where P_total includes transmit power, circuit power of RF chains, and static hardware power. At THz frequencies, the near-field channel model replaces the far-field planar-wave approximation with a spherical-wave formulation, rendering classical codebook-based beamforming suboptimal and motivating data-driven approaches capable of learning the geometry of near-field channel manifolds.

### 3.3 Multi-Objective Optimization and Pareto Analysis.

Energy-efficient beamforming inherently involves competing objectives: maximizing sum rate and minimizing total power draw are conflicting in general. Pareto front characterization provides a rigorous framework for understanding these trade-offs: the Pareto front defines all achievable operating points from which no objective can be improved without degrading another. Multi-objective DRL and Pareto-conditioned neural architectures offer practical methods to trace the Pareto front under operational time constraints that preclude classical semi-definite programming or exhaustive search, making them particularly relevant for 6G systems requiring sub-millisecond beam management decisions.

## 4. Methodology

This research employs a mixed-methods approach combining a systematic literature review, comparative quantitative analysis of reported performance metrics, and a policy review of India's 6G research ecosystem.

### 4.1 Systematic Literature Review.

A structured review of peer-reviewed publications from 2020 to November 2024 was conducted across major databases including IEEE Xplore, Wiley Online Library, MDPI Open Access, Springer Nature Link, Nature Scientific Reports, and arXiv (cs.IT, eess.SP). Search terms included combinations of 'adaptive beamforming', '6G', 'deep reinforcement learning', 'massive MIMO', 'reconfigurable intelligent surface', 'energy efficiency', 'terahertz', 'hybrid precoding', and 'neural beamforming'. Journal articles from IEEE Transactions on Wireless Communications, IEEE Journal on Selected Areas in Communications, IEEE Access, IEEE Communications Surveys & Tutorials, Wiley Transactions on Emerging Telecommunications Technologies, and IET Signal Processing were prioritized. Preprints from verified academic groups on arXiv, including the GMLB meta-learning study (November 2023), were included where peer-reviewed counterparts were unavailable.

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### 4.2 Comparative Performance Analysis.

Quantitative performance metrics—spectral efficiency (bit/s/Hz), energy efficiency (bit/J), data rate improvement (%), SINR gain, and computational complexity reduction—reported in selected studies were extracted and synthesized. Only studies with clearly defined simulation parameters, reproducible baselines, and explicit performance comparisons against classical methods were included in the quantitative synthesis. Where multiple studies addressed the same technique, results were cross-referenced to assess consistency. Results are presented in Tables 1 and 2.

### 4.3 Policy Review.

India's 6G policy landscape was assessed through review of the ITU-R M.2160 recommendation (November 2023), publicly available documents from the Department of Telecommunications (DoT), and published accounts of TSDSI's participation in ITU-R WP5D. The analysis identifies alignment with and gaps relative to the IMT-2030 framework for AI-native beamforming.

### 4.4 Limitations.

The review is bounded by the literature available before December 2024; simulation results may not fully reflect real-world channel conditions; and the policy review is limited to publicly available documents.

## 5. Analysis And Discussion

### 5.1 Performance Gains of AI-Assisted Beamforming: Synthesis

The comparative synthesis of reviewed studies reveals consistent and substantial improvements attributable to AI-driven beamforming relative to classical baselines. Table 1 summaries key quantitative findings from the literature reviewed.

**Table 1: Performance Summary of AI-Assisted Beamforming Techniques in 6G (Literature up to Nov. 2024)**

| Technique / Study | AI Method | Key Performance Gain | Reference |
|---|---|---|---|
| DL-RIS for 6G mobile networks (Megahed, 2024) | Deep Learning (Codebook Selection) | ~97% data rate gain over reference; ~115% over no-RIS baseline | [6] |
| RIS Meta-Learning BF (GMLB, arXiv Nov. 2023) | Gradient-Based Meta-Learning | 100× less energy vs. alternating optimization; competitive sum rate | [7] |
| CNN-LSTM Hybrid BF (Murshed et al., 2023) | CNN-LSTM Fusion Separation DNN | Approaches Alt-Min SE; significantly lower compute | [9] |
| DRL for RIS-MISO (Huang et al., 2020) | Deep Deterministic Policy Gradient (DDPG) | Outperforms alternating-min under partial CSI and user mobility | [5] |

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| Technique / Study | AI Method | Key Performance Gain | Reference |
|---|---|---|---|
| Multi-hop RIS BF (Deep Learning, 2024) | Deep Learning Joint BF (DLBF) | +1.8 bit/s/Hz sum rate vs. conventional BF (2-user) | [14] |
| DS-FPS THz Hybrid BF (Jiang et al., 2022) | Analytical + ML Partial CSI Design | Competitive SE vs. full-CSI; low phase-shifter power | [8] |
| DRL EH-RIS Drone 6G (Nashwan, 2024) | Deep Reinforcement Learning (DRL) | Maximized EH while sustaining communication quality | [12] |
| CNN-LSTM for RIS-NOMA (Nguyen et al., 2023) | CNN-LSTM Channel Estimation | Significantly reduced NMSE vs. classical LS estimation | [13] |

### 5.2 Energy Efficiency as a First-Class Design Objective

The ITU-R M.2160 framework explicitly identifies energy efficiency as both a performance capability to be enhanced from IMT-2020 and a sustainability design principle for IMT-2030. [1] This policy signal is reinforced by the technical reality that the RAN accounts for a large majority of a cellular network's energy draw, and that 6G's densification—orders of magnitude more base station antenna elements than 5G—will exacerbate this challenge without architectural countermeasures. AI-assisted beamforming directly addresses this through three mechanisms: (i) intelligent antenna sub-array activation and sleep scheduling that powers down elements when not needed; (ii) dynamic power allocation calibrated to instantaneous traffic demand and channel quality; and (iii) interference-aware beam shaping that minimizes radiated power directed toward non-intended users, reducing both interference and wasted energy.

The GMLB approach of the November 2023 arXiv study exemplifies mechanism (iii): by optimizing the sum-rate gradient flow through the neural network rather than raw channel parameters, the method achieves orders-of-magnitude energy savings in the beam update process itself, not merely in RF power allocation. [7] The dual deep learning model of Sundar et al. (2024) pursues mechanism (ii) by jointly training spectral efficiency and energy consumption objectives, demonstrating that multi-task learning architectures can navigate the SE-EE trade-off more effectively than single-objective optimization. [15]

### 5.3 Key Challenges and Barriers to Deployment

Despite the compelling performance results, several substantive barriers must be addressed before AI-assisted adaptive beamforming can be deployed at scale in 6G networks.

Channel Estimation Overhead: Large-scale RIS and ultra-massive MIMO arrays dramatically increase the dimensionality of the channel estimation problem. A RIS with N_RIS elements introduces N_RIS additional channel coefficients per user, making traditional pilot-based schemes prohibitively expensive. Deep learning approaches, such as the CNN-LSTM framework of Nguyen et al. (2023) for

RIS-NOMA networks, restructure the estimation pipeline to achieve lower normalized mean squared error (NMSE) at reduced pilot overhead, but require careful co-design with the beamforming module. [13]

Real-Time Inference Latency: 6G HRLLC applications targeting sub-millisecond latency impose stringent constraints on neural network inference time. Large DRL policies with millions of parameters may not satisfy these budgets on embedded hardware platforms. Model compression, quantization-aware training, and hardware-software co-design—such as the neuromorphic ESN inference demonstrated by Lin et al. (2024) on FPGA—represent active research frontiers for closing the latency gap. [16]

Hardware Impairments: Phase-shifter precision, ADC quantization noise, and non-linear amplifier characteristics introduce systematic errors that degrade beamforming accuracy. Jiang et al. (2022) explicitly designed around THz phase-shifter limitations by adopting fixed rather than adjustable phase shifters, accepting a small SE loss in exchange for substantial power savings and manufacturing feasibility. [8] AI models trained without accounting for such hardware impairments may experience significant performance degradation in deployment.

Model Generalisation: AI beamforming models trained on specific channel distributions—for example, outdoor urban macro THz channels—may fail to generalize to indoor pico-cell or rural macro environments. Transfer learning and domain adaptation are active research approaches, but their effectiveness in beamforming contexts across diverse deployment scenarios (rural, urban, indoor, vehicular) remains an open research problem.

Standardisation Gap : The ITU-R M.2160 framework establishes AI as a native IMT-2030 principle, but the specific interfaces, evaluation methodologies, and conformance tests for AI-based physical-layer beamforming have not yet been defined by 3GPP or TSDSI. This regulatory uncertainty creates adoption risks for manufacturers and operators and may slow industry investment in AI beamforming IP.

## 5.4 India's 6G Ecosystem and AI-Beamforming Opportunities

India is actively building its 6G research infrastructure. The Department of Telecommunications has articulated a Bharat 6G Vision that positions India as both a technology developer and a lead adopter, with emphasis on AI-native networks, indigenized hardware, and inclusive connectivity. TSDSI participates in ITU-R WP5D standardization, and research institutions including the Indian Institutes of Technology, National Institutes of Technology, and C-DAC have established wireless systems research programs addressing 5G-Advanced and 6G. [17]

India's deployment environments—dense urban cores such as Mumbai and Delhi, rural hinterlands with low cell density, and high-mobility corridors—constitute a uniquely diverse testbed for validating AI beamforming algorithms under real-world heterogeneity. This diversity is both a challenge and an asset: it demands robust, generalizable AI beamforming policies, but successful demonstration under these conditions would carry significant evidential weight for global standardization. Prioritizing investment in AI-beamforming testbeds at academic institutions, and establishing collaborative frameworks with global equipment vendors for RIS and massive MIMO experimentation, represents a high-leverage strategy for India's 6G program.

**Table 2: IMT-2030 Capabilities and Corresponding AI Beamforming Enablers (based on ITU-R M.2160, November 2023)**

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| IMT-2030 Capability (M.2160) | 6G Target (vs. IMT-2020) | AI Beamforming Enabler |
|---|---|---|
| Energy Efficiency | Significant enhancement; sustainability by design | DRL sleep scheduling; meta-learning power control; multi-objective EE-SE DNN |
| Spectral Efficiency | Enhanced beyond 5G NR | MARL multi-user precoding; CNN/DNN hybrid BF |
| Peak Data Rate | Terabit/s range (THz spectrum) | DNN hybrid BF for THz sparse channels (Elbir 2021, Murshed 2023) |
| User Experienced Data Rate | 300-500 Mbps or higher ubiquitously | RIS-aided AI BF for cell-edge users; DL RIS codebook selection |
| Latency (HRLLC) | Sub-millisecond user plane | Model-compressed neural beam prediction; ESN inference on FPGA |
| AI-Native Operation | Foundational design principle | End-to-end AI beamforming pipeline; DRL policy-driven beam management |
| Sensing Integration (ISAC) | Joint communication and sensing | AI dual-function BF waveform optimization |
| Ubiquitous Connectivity | TN-NTN interworking | AI beam handover for satellite-terrestrial hybrid scenarios |

## 6. Conclusion

This paper has surveyed and analyzed AI-assisted adaptive beamforming as a transformative enabler for energy-efficient 6G wireless communication systems. The literature review of studies published up to November 2024 demonstrates consistent and substantial performance improvements from AI-driven approaches relative to classical optimization-based methods. Deep-learning-assisted RIS systems have achieved data rate improvements of approximately 97–115% over reference baselines; gradient-based meta-learning beamforming reduces energy consumption in the beam update process by two orders of magnitude; CNN-LSTM hybrid beamforming for ultra-massive MIMO approaches Alt-Min spectral efficiency at substantially lower computational cost; and DRL-based approaches have demonstrated effectiveness across RIS-MISO, EH-RIS, and multi-user scenarios under partial CSI and user mobility.

These gains are grounded in the theoretical properties of MDP-based adaptive control, near-optimal traversal of the spectral-energy Pareto front, and the capacity of deep neural networks to learn channel

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manifold geometry without explicit model assumptions. They align directly with the energy efficiency, spectral efficiency, peak data rate, AI-nativity, and HRLLC latency capabilities codified in ITU-R Recommendation M.2160 for IMT-2030.

Significant challenges remain channel estimation overhead in high-dimensional RIS-massive MIMO systems, real-time inference latency under HRLLC constraints, hardware impairment robustness, cross-environment model generalization, and the absence of finalized 3GPP/TSDSI standards for AI-native physical-layer beamforming interfaces. Overcoming these barriers requires coordinated effort across academia, industry, and standards bodies.

For India specifically, three strategic priorities are recommended: (i) establishing AI-beamforming testbeds at major research institutions validated against India's diverse deployment environments; (ii) strengthening TSDSI contributions to IMT-2030 physical-layer AI standardization; and (iii) fostering joint academic-industry programs targeting hardware-efficient neural beamforming for low-cost massive MIMO platforms suited to India's market. Future research should investigate federated learning across distributed base stations for collaborative beamforming model training, quantum-inspired optimization for large-scale RIS phase configuration, and integrated ISAC beamforming waveforms optimized jointly for communication and sensing objectives.

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