

Artificial Intelligence Techniques for Air-Interface Optimizations and Future Research Directions in 6G Networks

Nidhi Chahal^{1*}, Tarun Singhal², Ramanpreet Kaur³, Varsha Sood⁴, Tinu Anand⁵

Abstract

This paper is the second instalment of a two-part review on artificial intelligence (AI) for sixth-generation (6G) wireless networks. Where the companion paper traced the generational evolution of mobile networks and the Digital Twin architecture that underpins 6G, this paper narrows the focus to the specific AI techniques expected to drive 6G's autonomous operation and to the air-interface problems those techniques are being asked to solve. We review machine learning, deep learning, reinforcement learning, and the emerging field of quantum reinforcement learning, examining how each contributes to resource allocation, network-traffic prediction, and control-policy learning under the extreme dimensionality of terahertz and massive-MIMO systems. We then turn to three concrete air-interface problems—Channel State Information (CSI) feedback compression, AI-based beam management, and AI-assisted wireless localization—describing how learning-based methods outperform classical statistical approaches in each case. A representative smart-city use case illustrates how multi-agent reinforcement learning coordinates large numbers of autonomous decision-makers in a shared environment. The paper closes with a structured set of research directions covering computational efficiency, big-data analytics, hardware development, energy management, and AI-enabled 6G IoT, supported by original comparative tables and illustrative figures summarizing reported performance trends.

Keywords: Artificial intelligence, machine learning, deep learning, reinforcement learning, quantum reinforcement learning, CSI feedback, beam management, wireless localization, 6G IoT

*Author for Correspondence

Nidhi Chahal
E-mail: nidhi.ece@cgce.edu.in

¹Assistant Professor, Department of Electronics and Communication Engineering Chandigarh Engineering College-CGC, Landran, Mohali, Punjab, India

²⁻⁴Associate Professor, Department of Electronics and Communication Engineering Chandigarh Engineering College-CGC, Landran, Mohali, Punjab, India

⁵Student, Department of Electronics and Communication Engineering Chandigarh Engineering College-CGC, Landran, Mohali, Punjab, India

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INTRODUCTION

The first paper in this series described how 6G networks are organized around a Digital Twin that maintains a live, synchronized model of the physical network for prediction and control. That architecture is only as capable as the AI methods that populate it, and this paper is dedicated to those methods [1]. Resource allocation in 6G is fundamentally a high-dimensional optimization problem that classical mathematical modelling struggles to keep up with, particularly once the network starts operating in terahertz (THz) and millimeter-wave (mmWave) bands, where molecular absorption, rapid path loss, and frequent blockage make the physical layer behave in ways that are difficult to capture with fixed formulas [2–4].

Machine learning, particularly its deeper architectures, offers a way around this bottleneck by learning patterns directly from data rather than relying on handcrafted heuristics [5]. This paper works through the main families of learning techniques being applied to 6G—supervised and unsupervised machine learning, deep learning for traffic and channel modelling, reinforcement learning for autonomous network control, and the still-emerging quantum-assisted variants of reinforcement learning—before applying them to three concrete air-interface challenges that any 6G deployment will have to solve well: compressing channel feedback, selecting beams accurately in dense multi-antenna systems, and locating users precisely enough for industrial and indoor applications [6, 7].

ARTIFICIAL INTELLIGENCE TECHNIQUES FOR 6G

Machine Learning

Resource allocation in 6G systems involves optimization problems whose dimensionality routinely exceeds what closed-form mathematical models can handle efficiently [8–10]. As networks push into higher-frequency THz and mmWave bands, the physical layer becomes increasingly sensitive to environmental dynamics, such as molecular absorption, path loss, and sudden blockage. Machine learning supplies the predictive modelling and dynamic optimization frameworks needed to work around this complexity, uncovering patterns in large datasets that heuristic, rule-based algorithms cannot see [11].

Deep Learning for Network Traffic Prediction

6G applications range from the tactile Internet to holographic telepresence, and the resulting traffic is far more volatile and non-stationary than anything earlier generations had to forecast. Deep learning (DL) architectures are well-suited to this volatility because they can capture both the temporal dependencies and spatial correlations that arise in ultra-dense network deployments. Classical forecasting tools, such as ARIMA and Kalman filters, assume a largely fixed network topology, which breaks down once base stations, edge servers, and users are in motion [12].

Spatio-Temporal Graph Neural Networks (ST-GNN) address this limitation by representing the network as a dynamic graph $G = (V, E)$, where V is the set of nodes (base stations and edge servers) and E represents the links between them. Graph Convolutional Networks (GCNs) extract the spatial influence that traffic at one node exerts on its neighbors, and this is combined with LSTM or GRU units to capture how traffic evolves over time, allowing the network to anticipate local congestion and trigger proactive load balancing. Reported evaluations of ST-GNN models in 6G-like settings show better prediction accuracy and lower latency than recurrent-only baselines [13].

The second architecture, Trafficformer, applies the multi-head self-attention mechanism of the transformer family to focus simultaneously on multiple positions within a traffic sequence. By layering spatial masks derived from road network topology and travel time on top of this attention mechanism, Trafficformer filters out irrelevant noise and concentrates on traffic nodes that are strongly spatially connected, producing accurate short-term speed predictions that are directly useful for real-time route guidance in autonomous transportation systems [14]. NetGPT, a related model built on causal and dilated convolutions with autoregressive flow tokens, focuses on preserving the semantics of encrypted traffic while expanding the effective receptive field without a proportional increase in computational cost, as shown in Figure 1 and Table 1.

Table 1. Comparison of representative deep learning architectures for 6G traffic prediction.

Model	Key module	Traffic representation	Primary benefit
ST-GNN	GCN + LSTM integration	Dynamic graph topology	Captures inter-node traffic influence
Trafficformer	Multi-head self-attention + spatial masks	Sequential flow embeddings	Handles long-range temporal dependencies
NetGPT	Causal & dilated convolution	Autoregressive flow tokens	Expands receptive field at low added complexity; preserves encrypted-traffic semantics

Reinforcement Learning for Network Optimization

Reinforcement learning (RL), particularly its deep extension (DRL), provides the intelligence required for autonomous network operations. By framing network-management tasks as Markov Decision Processes (MDPs), RL enables an agent to learn an optimal control policy purely through repeated trial-and-error interactions with the network environment, without requiring an explicit analytical model of how the network behaves. This makes RL attractive for problems such as dynamic spectrum allocation, adaptive power control, and traffic-light-style scheduling of network resources, where the underlying dynamics are too complex or fast-changing to model manually [15].

Quantum Reinforcement Learning (QRL) and Future Optimization

As 6G research progresses through the 2025–2030 period, Quantum Reinforcement Learning (QRL) is being explored as a response to the "curse of dimensionality" that ultra-massive MIMO and THz systems impose on classical DRL. QRL replaces classical neural networks inside an actor-critic architecture with variational quantum circuits (VQCs), which exploit quantum superposition to explore high-dimensional decision spaces far faster than a classical network [16]. As an example, a quantum-enhanced framework built around the quantum approximate optimization algorithm (QAOA) can perform massive MIMO beamforming for 32 antennas with polynomial complexity $O(pM^2)$, compared with the exponential $O(2^M)$ complexity of a classical exhaustive search. Early QRL implementations reported in the literature show a latency reduction of approximately 36.8% and an energy efficiency increase of approximately 24.7% relative to state-of-the-art classical DRL models [17]. Full commercial deployment still awaits mature quantum error correction; however, quantum-inspired techniques derived from this line of work are already being used to improve the stability and convergence of otherwise classical 6G controllers, as shown in Figure 2.

Multi-Agent Reinforcement Learning in Smart Cities

In shared environments, several learning agents pursue their own rewards simultaneously, which is exactly the situation presented by a smart city. Sixth-generation (6G) networks that support AI-driven smart city applications lean heavily on Multi-Agent Reinforcement Learning (MARL): its adaptive decision-making lets each agent autonomously optimize and adjust its own behavior, improving the collective user experience across many simultaneous applications. For large-scale traffic signal control, for example, a multi-agent recurrent DDPG algorithm has been proposed to manage traffic-light phasing in real time using Internet-of-Vehicles data, easing congestion even in complex, only partially observable road networks [18].

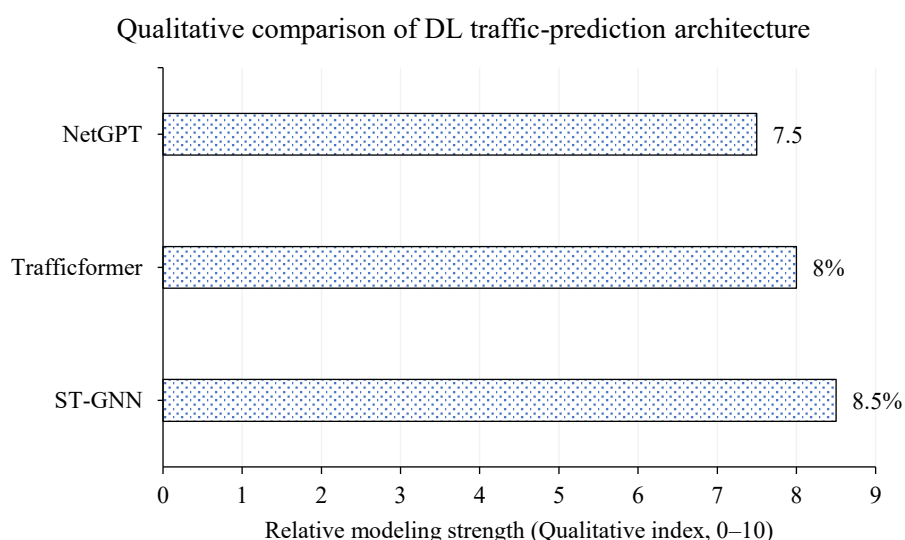


Figure 1. Qualitative comparison of deep learning traffic-prediction architectures on a relative modelling-strength index (illustrative synthesis for comparison purposes).

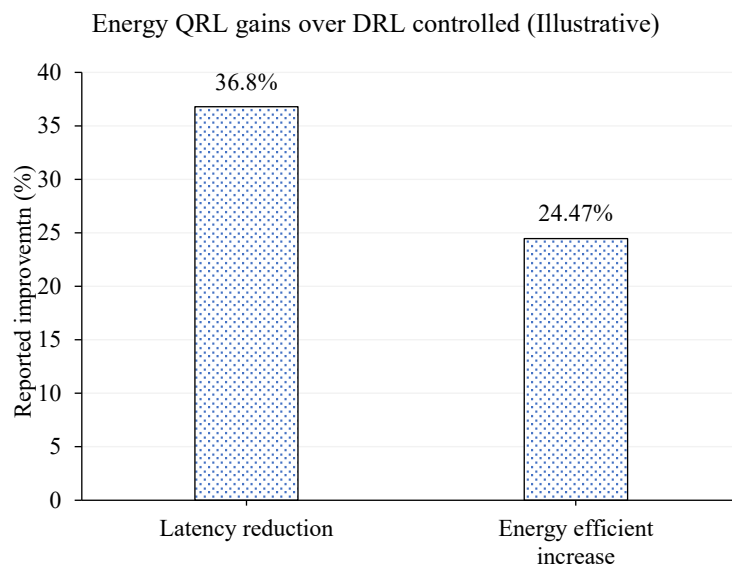


Figure 2. Reported early-stage gains of quantum-assisted reinforcement learning over classical DRL controllers (illustrative summary of literature-reported figures).

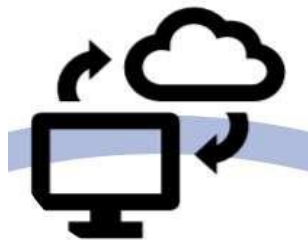


Figure 3. Smart-city connectivity concept coordinated through multi-agent reinforcement learning.

The broader smart city concept knits together telecommunications and a wide range of connected devices to increase connectivity throughout a city, spanning waste management, transportation, resource usage, and public health, while aiming to remain intelligent, economical, and cost-effective [19]. As wireless networks push toward lower latency, wider connectivity, stronger security, and higher quality of experience, this same MARL-driven approach is expected to spread to other demanding sectors beyond transportation (Figure 3).

ENHANCING AIR-INTERFACE EFFICIENCY

AI-Based CSI Feedback

Reconstructing the channel accurately while keeping the Channel State Information (CSI) feedback overhead low remains one of the more difficult open problems in wireless system design. AI offers an effective route to a solution by enabling a deeper analysis of complex channel behavior. Trained on large volumes of labelled data, AI models learn to recognize patterns across different fading conditions, interference levels, and multipath environments. Compared with traditional CSI estimation methods, which rely mainly on statistical assumptions, AI-based approaches provide more adaptive and accurate modelling, translating directly into better performance and efficiency [20].

Several specific architectures illustrate this progress. Smaller convolution kernels have been shown to extract finer CSI features and exploit CSI sparsity more effectively; a deep-learning-based CSI compression and quantization method has been developed to achieve high compression ratios; a multi-rate CSI compression framework has improved model generalization for transfer-learning settings; a non-local neural network built on the CsiNet architecture captures a wider range of dependencies and

improves channel-recovery accuracy over the original CsiNet; and CRNet, which mixes convolution kernels of different sizes for feature extraction and recovery, reduces computation while improving reconstruction accuracy [2]. The deployment of these AI-based CSI feedback models in real-world wireless environments still leaves open questions regarding model monitoring, model updating, and AI-aware signaling-process management, all of which remain active areas of study.

AI-Based Beam Management

Existing beam-selection research for multi-antenna systems generally falls into three categories: beam-scanning-based, position-prediction-based, and hierarchical search-based methods [9]. Traditional beam-management approaches struggle in millimeter-wave massive MIMO systems, mainly because real-world propagation environments are complex and change quickly. As beams narrow, transmission becomes more vulnerable to blockage, and a larger number of beams means more search operations during alignment, making it genuinely difficult to select the optimal beam accurately and instantaneously [6].

A deep-learning-based beam-alignment method addressing this problem jointly trains the probing codebook and beam predictor. Simulation results show that this approach can achieve high beam-alignment accuracy while reducing beam-sweeping complexity by approximately a factor of ten. This body of work demonstrates the advantage of AI over purely geometric or exhaustive search methods, although practical deployment still requires attention to acquiring high-quality training labels in complex environments and improving how well a trained model generalizes across different base-station environments without excessive retraining overhead [3].

AI-Based Wireless Localization

6G networks are expected to support highly accurate wireless positioning across a wide range of applications, typically expressed as the geographic coordinates of a mobile user relative to known reference points. Many emerging use cases, such as industrial automated guided vehicles, asset tracking, and indoor positioning, demand high precision that satellite-based GPS cannot provide indoors. LTE positioning reference signals do not meet these accuracy requirements either, given the limited precision and the roughly 100 m spacing typical between base stations, even with a 20 MHz bandwidth, whereas Bluetooth and Wi-Fi-based approaches can achieve better accuracy but at a high deployment cost and with limited universality [5].

AI techniques can help close this gap. Random forest models can divide large areas into smaller grids for classification or predict user coordinates directly through regression, whereas multilayer perceptron models apply to both classification and regression variants of the localization problem. AI models can also learn and recognize signal fingerprints tied to specific locations and fuse data from multiple sensors to further improve accuracy. With the adoption of massive MIMO, AI-based localization has an additional advantage: in mixed line-of-sight (LoS) and non-line-of-sight (NLoS) environments, machine learning models trained on large volumes of channel data can map the relationship between channel responses and physical position, achieving indoor positioning precision as fine as approximately 20 mm without significant added cost. The remaining challenge is ensuring that these models remain robust and reliable, given the complexity and variability of real-world channel data actually is Table 2.

RESEARCH DIRECTIONS

Enhancing Computational Efficiency and Accuracy

The sheer volume of data and complexity of 6G networks pose a real problem for AI training: the available computing power often falls short of what large, intricate datasets require for accurate model training, and deep learning methods, in particular, are resource hungry. Consequently, making AI learning faster and more accurate is a priority, and researchers are exploring feature matching, GPU-accelerated processing, residual network designs, and offline training as ways to converge faster, reduce complexity, and improve training accuracy without demanding proportionally more hardware.

Big Data Analytics for 6G

Future wireless communication will require higher data speeds and markedly more dependable transmission links to keep pace with the growing multimedia demand while maintaining service quality. To reach data speeds projected at 100–1000 times those of 5G, 6G is likely to draw on a higher-frequency spectrum than any prior generation, and deep learning applied to big data analysis—by stacking algorithms and identifying patterns in complex, abstract datasets—offers one practical way to make sense of the resulting data volumes.

Hardware Development

Operating in the millimeter-wave and THz bands requires hardware components that are power-hungry and expensive, and some devices and terminals cannot operate without consuming a significant amount of energy. AI learning algorithms are bound by finite processing and storage capacities. Although their recognition and learning capabilities have improved considerably, they still typically demand high computational complexity, notable power consumption, and ample computing resources. Closer collaboration between hardware design and AI algorithm design is needed, and GPUs, which are well suited to matrix computation and transfer learning that adapts one learning framework across different hardware constraints, are likely to remain central to this effort.

Energy Management

Terrestrial 6G devices can generally be charged using conventional power sources; however, many sensors and infrastructure elements operating in the air, at sea, and in space cannot. Combined with the sheer number of small, low-power smart devices that 6G is expected to support, this makes efficient energy use a genuine challenge, as these devices must continue to work reliably without constant recharging. Artificial intelligence is central to addressing this issue because it can allocate energy resources intelligently, improve power usage efficiency, and support energy harvesting strategies, thereby extending the operating life of devices, even as network-wide energy management becomes more complex.

AI-Enabled 6G for IoT

Building AI-powered 6G IoT responsibly requires transparent, understandable AI systems so that people can see how network decisions are made, along with active efforts to identify and correct bias so that the technology serves all use cases fairly. Strong, clearly defined rules for AI use are needed to protect personal data and keep users in control, alongside robust IoT security, real-time threat detection, and strong encryption to protect sensitive data and keep the network running reliably. Involving prospective users in the design process helps ensure that these systems are genuinely usable, and global standards are necessary to hold deployments accountable, regardless of where they operate.

Looking ahead, AI-enabled 6G IoT is expected to drive several concrete advances, including AI-based network management for greater efficiency and resilience, integration with VR/AR and autonomous systems to unlock new applications, sustainable IoT solutions that reduce environmental impact, stronger security mechanisms that build user trust, and user-centric application design that improves usability and satisfaction (Table 3).

Table 2. Representative wireless-localization approaches and their reported characteristics.

Approach	Typical indoor accuracy	Relative deployment cost	Main limitation
Standalone GPS	Not effective indoors	Low	Signal blockage indoors
LTE positioning reference signals	~100 m (20 MHz BW)	Low–Medium	Limited precision, wide BS spacing
Bluetooth/Wi-Fi fingerprinting	1–5 m (typical)	Medium–High	High deployment cost, limited universality
AI-based fingerprinting (RF/MLP)	Sub-meter to cm-level (reported)	Medium	Needs large, labelled training datasets
AI + massive MIMO channel mapping	~20 mm (reported, indoor)	Medium	Model robustness in highly varied environments

Table 3. Summary of key research directions for AI-enabled 6G.

Research direction	Description	Expected outcome
AI-driven network management	Applying AI to optimize network operations and resource allocation	Improved efficiency and more resilient networks
Integration with emerging technologies	Combining 6G IoT with VR/AR and autonomous systems	Enhanced user experience and new application areas
Sustainable IoT solutions	Developing environmentally friendly IoT technologies	Reduced environmental impact and sustainable growth
Advanced security mechanisms	Implementing strong security protocols for AI-based IoT systems	Greater trust and wider adoption
Human-centric IoT applications	Designing IoT systems around user needs and experience	Higher user satisfaction and improved usability

CONCLUSION

Read together with the first paper in this series, the picture that emerges is of a network that is being redesigned around continuous learning at every layer of the system. This paper has shown how machine learning, deep learning, reinforcement learning, and emerging quantum-assisted reinforcement learning each contribute distinct capabilities: pattern recognition in high-dimensional data, spatio-temporal traffic prediction, autonomous policy learning, and, potentially, an exponential speed-up in exploring huge decision spaces. Applied to CSI feedback, beam management, and wireless localization, these methods consistently outperform the statistical, model-based approaches that preceded them, although real-world deployment still has to reckon with training overhead, model generalization across environments, and the sheer computational and energy cost of running AI at the network scale.

The integration of AI and 6G still faces genuine obstacles in terms of scalability, security, privacy, ethics, and sustainability, and addressing them will require continued progress in big-data processing, real-time analytics, energy-efficient design, and high-performance computing, along with sustained collaboration among researchers, industry, and policymakers on standardization. If these challenges are met, AI-enabled 6G networks stand to deliver a genuinely new level of connectivity, efficiency, and innovation, and the two papers in this series together offer a structured starting point for researchers approaching this goal.

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