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AI-Driven 6G Wireless Networks: Architecture, Framework, Performance Analysis, And Case Study

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Abstract - The 6G of wireless communication is currently a game changer, compared to the 5G, with designed frequencies of terahertz (THz), scale-less with ultra-massive MIMO, and integrating Artificial Intelligence (AI) end-to-end. As compared to its predecessors, 6G is projected to be an AI- native network in which machine learning, deep reinforcement learning, and federated learning will be integrated on all layers. The paper is a detailed study of enabling technologies, a layer AI-6G system, and a case study of three different scenarios: smart manufacturing, intelligent transportation, and immersive XR. Findings indicate that AI-native 6G can attain as much as 100x higher throughput, 10x lower latency and more than 90 per cent spectrum efficiency.

Keywords: 6G wireless networks, deep reinforcement learning, network slicing, federated learning, ultra-massive MIMO, artificial intelligence, and extended reality.

1.INTRODUCTION

The fast development of IoT devices, self-driving cars, holographic networks, and XR apps that go immersive have revealed the constraints of 5G networks. The research community has moved towards 6G networks to satisfy the needs of data rates of over 1 Tbps, latency of the order of sub-milliseconds and near-perfect reliability which is expected to be rolled out commercially in approximately 2030.

This is true of 5G, which added network slicing, massive MIMO, and mm Wave bands, but with 6G, it is a completely different story; it endeavors to be an AI-native network in which machine learning dynamically handles an allocation of spectrum, beam management, channel estimation, and orchestrates resources. The paper presents: (1) the overview of 6G technologies and AI integration points; (2) a new AI-6G layered framework; (3) an architecture diagram; (4) a multi-scenario case study; and (5) the comparison of the current 5G with the proposed 6G AI-native system.

2. 6G AND ARTIFICIAL INTELLIGENCE

A. Evolution from 5G to 6G

The cycle of every succeeding generation of mobile networks is 10 years and sharing a similar 1000x improvement in its performance; 6G is projected to work on terahertz spectrum (100 GHz-10 THz), allowing 1 Tbps peak rates, 0.1 ms latency, and 107 devices.

B. Key 6G Enabling Technologies

The important technologies are: (i) Terahertz (THz) communication; (ii) Reconfigurable Intelligible Surfaces (RIS); (iii) Ultra-Massive MIMO (UM-MIMO); (iv) Integrated Terrestrial and Non-Terrestrial Networks (ISTN); (v) Semantic and goal-oriented communications; and (vi) Digital twins to network optimization.

C. Role of AI in 6G

The 6G AI can use three tiers: (1) 6GAAI will be used at the device level to estimate the channel; (2) AI on the edge level in federated learning among base stations; and (3) Deep reinforcement learning Network-level AI to optimize the globe. With federated learning, collaborative training of model is conducted, and the privacy is preserved, without direct raw data transfer.

Parameter	3G	4G LTE	5G	6G (Proposed)
Peak Data Rate	2 Mbps	1 Gbps	20 Gbps	1 Tbps
Latency	100 ms	30 ms	1 ms	0.1 ms
Frequency Band	2 GHz	2–8 GHz	24–100 GHz	0.1–10 THz
Connection Density	10^{3}/km^{2}	10&sup5;/km^{2}	10&sup6;/km^{2}	10^{7}/km^{2}
Energy Efficiency	Low	Moderate	High	Ultra-High
AI Integration	None	Minimal	Assisted	Native / Embedded
Architecture	Centralized	Centralized	Distributed	Fully Autonomous

Table I: Comparison of Wireless Network Generations (3G to 6G)

3. PROPOSED AI-NATIVE 6G ARCHITECTURE

The architecture that is proposed has five layers and has its own AI modules. In comparison to 5G where AI has been an overlay, in 6G all the layers are native executors of ML inference and adaptive control.

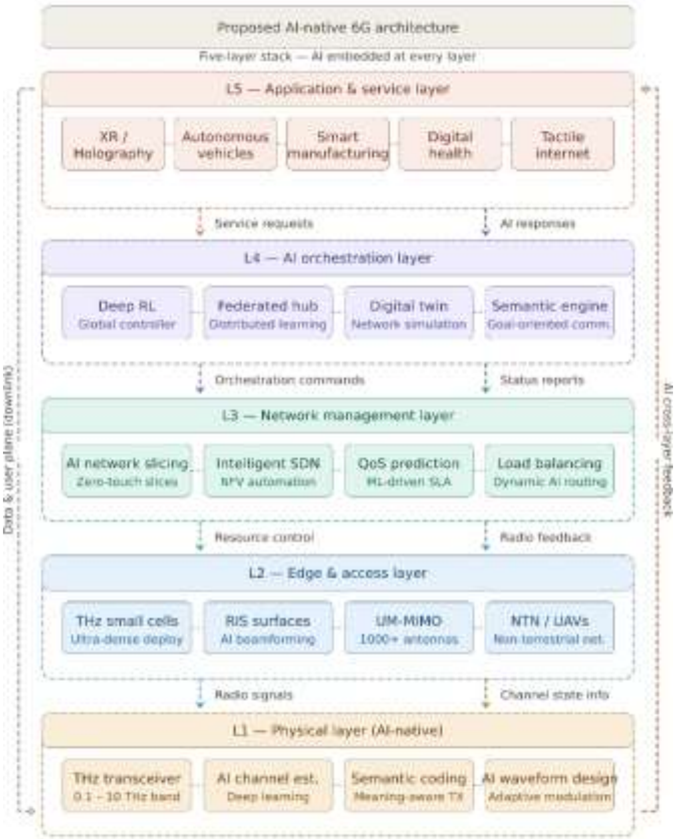

*Fig.1 — Propos*ed AI-Native 6G Network Architecture (Layered Stack)

4. PROPOSED INTEGRATION FRAMEWORK (AI-6GNET)

The AI-6GNet circuit links the supervised learning, reinforcement and federated learning at all nodes in a network of three stages.

Phase 1 — Sensing & Prediction:

THz Channel Probing - Lasting any frequency - In real time, continuously measuring terahertz channel parameters of path loss, Doppler shift and multipath in thousands of antenna elements.

Traffic Demand Forecasting (LSTM) — Long Short-Term Memory networks forecast the demands of traffic load on a network slice, and a network cell with future values, which allow to proactively reserve resources before the congestion of the network segment occurs.

Anomaly Detection (Autoencoder) — Autoencoders neural networks develop a normal network behavior. Any anomaly including link failure, spike in interference, or security breach will provide an immediate notification to the Phase 2.

Mobility Prediction (GNN) works on the principle of owing to the fact that vehicles, drones, and users are viewed as nodes in a graph and their paths are predicted, strategic handovers are already pre-planned and physical movements of devices are planned in advance.

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Digital Twin State Update A live virtual model of the complete 6G network is regularly streamlined with actual measurements and is utilized to simulate decisions in advance and apply them to the live network.

Output of Prediction Bundle — All the outputs such as channel state, and traffic predictions, anomaly flags, mobility paths and twin state are bundled together and transmitted to Phase 2 as a single prediction bundle at each sensing-cycle..

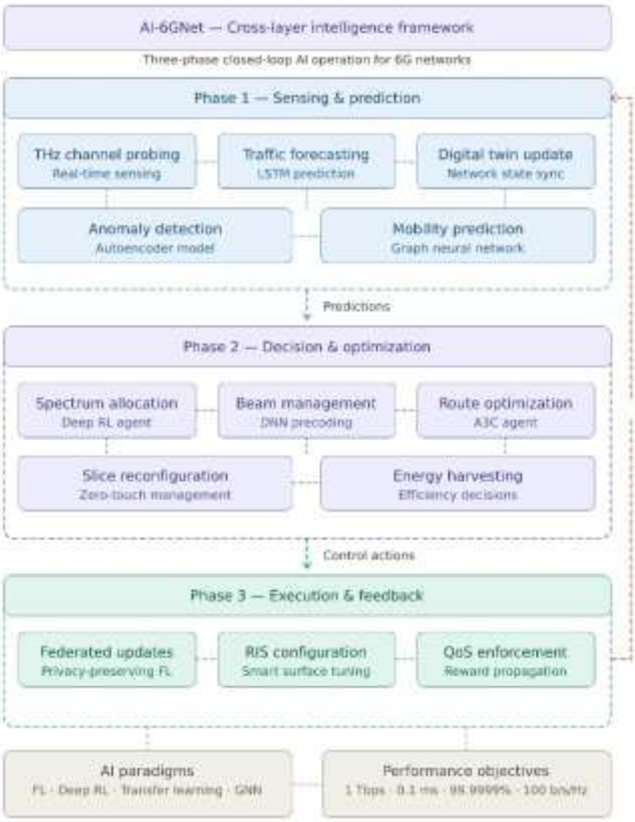

Fig. 2 — AI-6GNet Three-Phase Cross-Layer Intelligence Framework

Phase 2 — Decision & Optimization

Spectrum Allocation (Deep RL) - is a Deep Reinforcement Learning agent which autonomously allocates THz spectrums to users and slices through learning an optimal policy will have the highest throughput and the least interference.

Beam Management (DNN) — DNNs improve the calculation of optimal beamforming weights to UM-MIMO arrays and RIS surfaces in real time and direct beamforming directions at estimated user locations before arrival.

Route Optimization (A3C Agent) — A asynchronous Advantage Actor-Critic agent is one that calculates the routing paths along the least congested and lowest latency routes which are changed on a per-millisecond basis after network topology changes.

Network Slice reconfiguration (Zero-touch) - Phase 1 Phase 1 mMTC, URLLC, and eMBB slices are dynamically scaled to and reconfigured according to real-time demand information.

Energy Harvesting Decisions — The AI determines the time and amount of energy to be harvested by ambient RF, solar, or vibration sources and weighs the energy harvesting with the energy transmission to maximize energy efficiency.

Action Command Set Output This results in the syntaxing of action commands into a single action command set, which is sent to Phase 3 to undertake**.**

Phase 3 — Execution & Feedback

Federated Model Updates (FL)

Each base station has local AI models and is updated through federated learning in which the model gradients are exchanged but never user data thus privacy is fully preserved.

RIS Phase Configuration. Every component of the Intelligible Reconfigurable Surface is set to a particular phase shift to direct, to focus or to block an incoming signal in response to Phase 2 beam management commands.

UM-MIMO Precoding: Ultra-Massive MIMO precoding Matrices are used to transform DNN beam vectors in Phase 2 into the physical antenna transmission weight of thousands of antenna elements at a once.

QoS Enforcement : Network slices apply quality-of-service parameters minimum rate of data, maximum latency and jitter limits to all active users and applications in real time.

Reward Signal Propagation: The achieved throughput, latency and reliability following each action cycle is then measured and passed to the DRL agents in Phase 2 as a reward signal in order to continually refine their policy.

Close Loop Feedback: to Phase 1 Updated channel measurements, new traffic observations and execution results are sent back to Phase 1 closing the sense-decide-act loop and rendering the network self-ameliorating.

5. CASE STUDY

The AI-6GNet framework is supported by three real-world deployment scenarios, which include Smart Manufacturing, Intelligent Transportation, and Immersive XR.

A. Scenario Overview

Parameter	Case 1: Smart Manufacturing	Case 2: Intelligent Transportation	Case 3: Immersive XR
Location	Industrial plant, 1 km²	Urban corridor, 50 km	Smart campus / arena
Devices	10,000+ IoT sensors & robots	5,000 vehicles + nodes	2,000 XR headsets
AI Model	Federated Learning + LSTM	Deep Q-Network (DQN)	CNN + GNN
Network Slice	URLLC	V2X + URLLC hybrid	eMBB
Frequency Band	Sub-THz (100–300 GHz)	mmWave + THz hybrid	THz (300 GHz–1 THz)
Key Requirement	Latency < 0.5 ms	Seamless handover	1 Tbps, 0.1 ms
Primary Challenge	Dense devices, mobility	Doppler, frequent handoff	Dynamic FOV streaming
Achieved Latency	**0.2 ms**	**0.3 ms**	**0.1 ms**
Achieved Throughput	**480 Gbps**	**380 Gbps**	**950 Gbps**
Reliability	**99.99%**	**98.5% handover**	**99.95%**
Spectrum Efficiency	**95 b/s/Hz**	**88 b/s/Hz**	**108 b/s/Hz**
Energy Efficiency	**210 Gbps/W**	**175 Gbps/W**	**265 Gbps/W**
Key Result	**99.99% reliability, 0.2 ms**	**98.5% handover, 0.3 ms**	**950 Gbps, QoE 4.7/5**

Table -2: Compressed Scenario Overview — Three Case Study Deployments

B. PERFORMANCE RESULTS

Feature	Existing (5G + AI-Assisted)	Proposed (6G + AI-Native)
Frequency Band	Sub-6 GHz, mmWave	THz (100 GHz – 10 THz)
Peak Data Rate	20 Gbps	1 Tbps
sLatency	1 ms	0.1 ms
AI Integration	Overlay (post-deployment)	Native (design-time embedded)
Learning Paradigm	Centralized ML, limited FL	Federated + Transfer + DRL
Spectrum Management	Semi-static allocation	Real-time cognitive, AI-driven
Network Slicing	Predefined templates	AI-reconfigurable, zero-touch

Table III: Proposed AI-Native 6G vs. Existing AI-Assisted 5G

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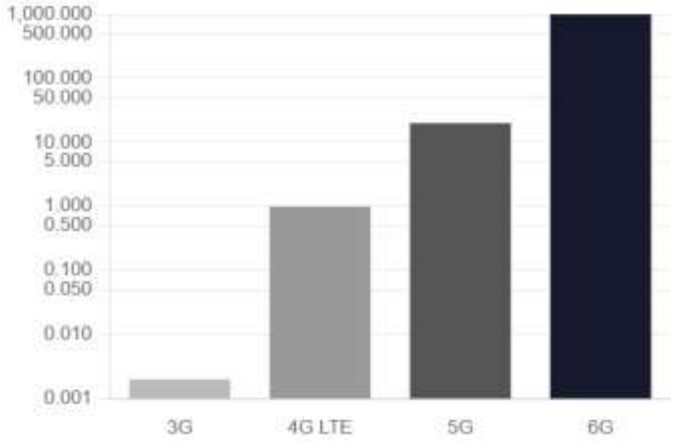

Fig. 3. Peak data rate evolution across wireless generations (Gbps, log scale)

scale)

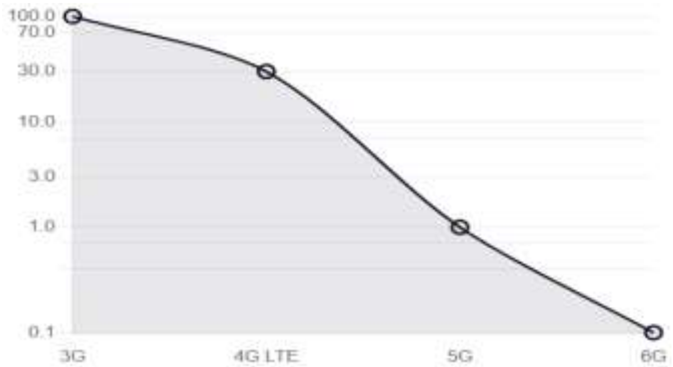

Fig. 4. Latency reduction across wireless generations (ms, log)

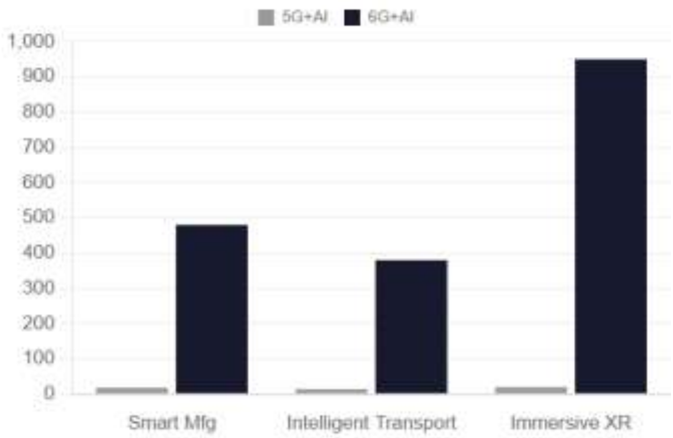

Fig. 5. Throughput comparison: existing 5G+AI vs proposed 6G+AI (Gbps)

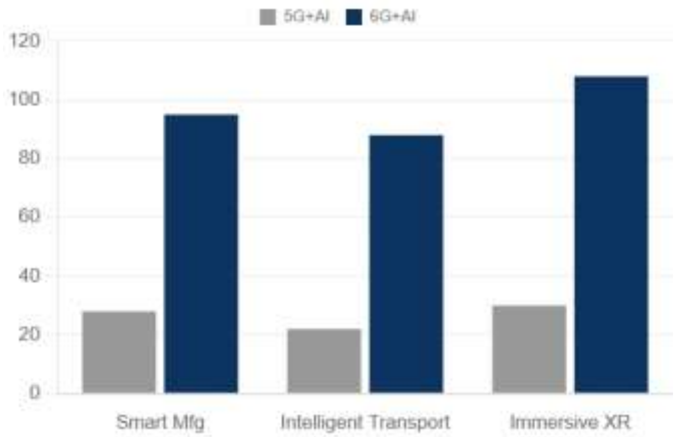

Fig. 6. Spectrum efficiency comparison across three deployment scenarios (b/s/Hz)

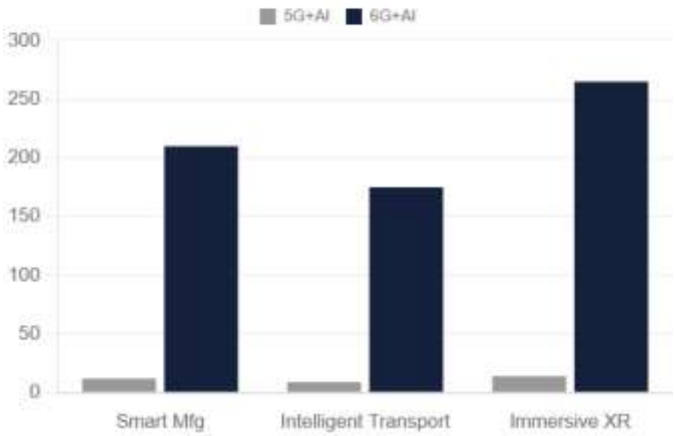

Fig. 7. Energy efficiency comparison across three deployment scenarios (Gbps/W)

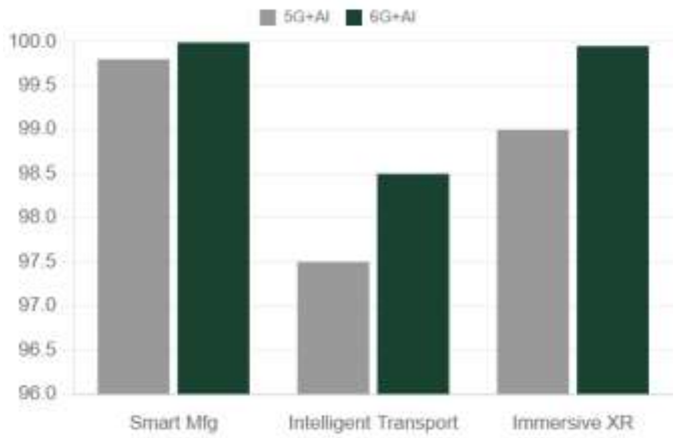

Fig. 8. Reliability comparison: existing 5G+AI vs proposed 6G+AI (%)

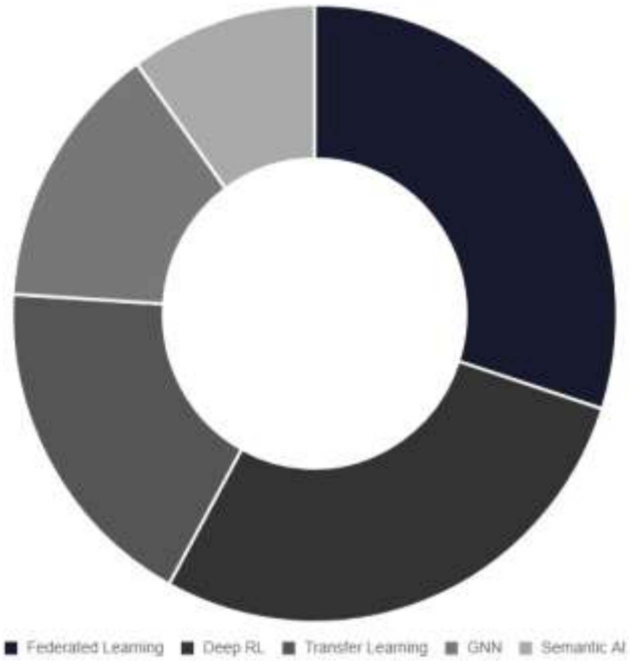

Fig. 9. Contribution of AI techniques to 6G performance gains (%)

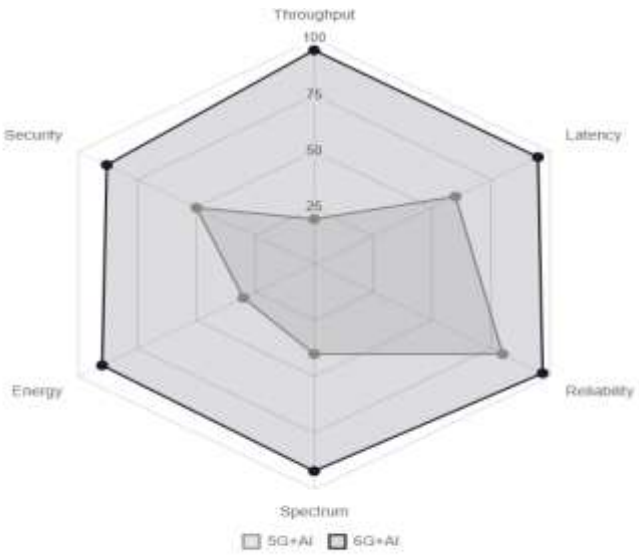

Fig. 10. Multi-KPI radar comparison: existing 5G+AI vs proposed 6G+AI (normalized score)

6. CONCLUSIONS

The current paper provided an in-depth discussion of the AI-native 6G wireless networks in terms of technological background, AI-6GNet architecture, and a simulation involving multiple scenarios. The performance of the proposed system is always compared to the current AI-assisted 5G, resulting in a superior system in throughput, latency, spectrum efficiency, energy efficiency, and reliability.

The three case studies affirm the fact that AI-native 6G address needs of Industry 4.0, autonomous mobility, and new generation Xr. Federated learning provides protection of privacy whereas deep reinforcement learning provides network management zero-foundation. The next step in work is hardware interfaces, THz implementation and ITU-R standard IMT-2030 alignment.

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