iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH
IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 13 Issue: XI Month of publication: November 2025

DOI: https://doi.org/10.22214/ijraset.2025.75641

Machine Learning for 6G Wireless Networks: Paradigms, Enablers, and the Pursuit of AI-Native Trustworthiness

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Abstract: The sixth generation (6G) of wireless communication systems is envisioned to be inherently AI-native, integrating intelligence into every network layer to support unprecedented capabilities, including terabit-per-second data rates, sub-millisecond latency, and pervasive sensing . This ambition re- quires managing extreme complexity introduced by revolutionary technologies such as Terahertz (THz) communication, Ultra- Massive MIMO (UM-MIMO), and Reconfigurable Intelligent Surfaces (RIS) . Machine Learning (ML) is recognized as the computational backbone for this transformation, enabling adaptive, self-optimizing, and context-aware wireless environments that fundamentally redefine how networks operate . This paper presents a systematic review, mapping ML across three progressive integration paradigms: AI for Network (AI4NET), Network for AI (NET4AI), and AI as a Service (AIaaS). We detail ML's pivotal role in enhancing the physical layer through deterministic Wireless Environment Control (WEC) and robust channel estimation using generative models . Furthermore, we elaborate on distributed intelligence architectures, such as Federated Learning (FL) and Split Learning (SL), which are essential for balancing high computational demands with data privacy and resource constraints in the emerging Computing Power Network (CPN) . Finally, we argue that the core viability of 6G depends on embedding trustworthiness into its architecture, emphasizing the mandatory roles of Explainable AI (XAI) for operational accountability and Distributed Ledger Technology (DLT) for immutable data provenance .
Index Terms: 6G, AI-Native, Machine Learning, AI4NET, NET4AI, AIaaS, Explainable AI (XAI), Federated Learning (FL), Intelligent Reflecting Surfaces (RIS), Digital Twin (DT).

I. INTRODUCTION

The evolution of wireless technologies has historically been driven by the need to support increasingly sophisticated applications and societal demands, enabling global mobility and massive device connectivity . Following the successful deployment of the fifth generation (5G) networks, which deliv- ered enhanced mobile broadband (eMBB) and Ultra-Reliable Low-Latency Communication (URLLC), the focus has deci- sively shifted toward the sixth generation (6G), anticipated for commercial launch around 2030 . The projected explosion in data volume and the demands of immersive applications like holographic communication, remote robotics, massive twinning (Digital Twins), and real-time human–AI interaction necessitate capabilities that far exceed the performance ceiling of existing 5G systems .

A. The Architectural Imperative of AI-Native Design

6G vision, particularly as framed by the European Hexa-X project, centers on creating a seamless cyber-physical continuum, tightly linking the human world, the physical world of objects and organisms, and the digital world of information and computing . This grand vision is anchored by core societal values that must be architecturally ingrained: Sustainability, Trustworthiness, and Inclusion . To real- ize these ambitions, 6G systems will leverage revolution- ary technologies, including Terahertz (THz) communication, Reconfigurable Intelligent Surfaces (RIS), Integrated Sensing and Communication (ISAC), and Ultra-Massive MIMO (UM- MIMO) . These advancements, however, introduce highly complex, dynamic, and non-linear optimization problems that are intractable for conventional, model-based mathematical solutions. Consequently, 6G must be inherently AI-native, embedding Machine Learning (ML) and Artificial Intelligence (AI) as core, intrinsic elements across all layers of the communication stack .

ML serves as the computational backbone, providing adaptive, self-optimizing, and context-aware solutions that enable the network to sense, learn, and optimize in real-time . ML is essential for modeling the non-linear behaviors of THz channels, optimizing RIS configurations, predicting mobility and traffic patterns, and autonomously orchestrating scarce resources with significantly higher efficiency and accuracy .

B. Unprecedented Key Performance Indicators (KPIs)

The performance targets for 6G are exceptionally stringent, especially for mission-critical Machine Type Communication (MTC) in Industrial IoT (IIoT) networks . The volumetric spectral and energy efficiency of 6G networks is expected to be 100 times greater than that of 5G . The requirement for ultra- high reliability, specifically up to $1-10^{-9}$ for the radio link, mandates the use of AI to transform the stochastic wireless channel into a predictable, deterministic environment . Table I details the necessary performance uplift across key MTC metrics, highlighting the challenges in achieving microsecond- level latency and centimeter-level accuracy .

TABLE I
COMPARISON OF SELECTED MACHINE TYPE COMMUNICATION (MTC) KPIS IN 5G AND 6G

KPI	5G target	6G target (IIoT/Enhanced)	ML Relevance in Bridging the Gap
Per radio link reliability	$1-10^{-5}$	$1-10^{-9}$	Proactive Resource Management (PRM), Deterministic Channel Control (RIS/WEC) .
Application level E2E latency	5 ms	< 1 ms	Real-time inference via Edge/Distributed ML (FL/SL), Predictive Analytics .
Spectral efficiency (downlink)	~ 25 bpcu	~ 40 bpcu	DL-aided Beamforming/CSI, Resource Optimization .
Connection density	1 device/m^2	up to 10 device/m^3	Scalable Orchestration, Traffic Pre- diction .
Positioning accuracy	30 cm	1 cm/5 mm	Integrated Sensing and Communica- tion (ISAC), Generative channel mod- els .
Jitter	$1\mu s$	$< 0.1\mu s$	Time Synchronization, Proactive Con- trol (WEC) .
Device lifetime	10 years	40 years	Green Technologies, Energy-efficient ML/Neuromorphic Computing .

II. FOUNDATIONAL PARADIGMS OF AI INTEGRATION

The strategic integration of AI into 6G is a structured evo- lution characterized by three distinct, progressive paradigms that reflect the deepening level of intelligence embedded into the network's function and service delivery model .

A. AI for Network (AI4NET)

AI4NET is the initial, pragmatic stage, focusing on employ- ing AI to augment and enhance existing network performance, efficiency, and user service experience . This approach is anal- ogous to applying an ”intelligent patch” to optimize specific, localized functions without fundamentally redesigning the core network architecture. Key AI4NET applications include :

1) Air Interface Enhancement: Utilizing Deep Learning (DL) models to optimize signal modulation/demodulation processes and perform highly accurate Channel State Information (CSI) feedback compression, making transmission more accurate and efficient

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue XI Nov 2025- Available at www.ijraset.com

2) Intelligent Resource Allocation: Employing sophisti- cated ML algorithms to analyze real-time network traffic patterns and user demands, thereby dynamically opti- mizing the allocation of bandwidth, power, and spectrum to reduce latency and improve utilization .
3) Network Operation and Maintenance (O&M) Im- provement: Deploying AI-powered systems for continu- ous monitoring and fault analysis, enabling autonomous and intellectualized management across network layers. This proactive approach shifts management from a re- active, manual mode to an intelligent, predictive one .

B. Network for AI (NET4AI)

NET4AI marks a pivotal architectural shift, mandating that the 6G network natively facilitates and buttresses AI operations

The network evolves into an integrated information platform that provides comprehensive support for AI model training, inference, security, and data storage . This requires the creation of a cohesive **Computing Power Network (CPN)** architecture

The network must natively manage new types of AI-specific traffic: **AI Signaling** (control messages for analysis) and **AI Data** (model parameters, training datasets) . NET4AI is the core concept of native intelligence, providing the robust infras- tructure necessary for achieving ubiquitous and trustworthy AI deployment.

C. AI as a Service (AIaaS)

AIaaS represents the final, transformative stage, where the 6G network innately provides scalable, distributed, and secur- able AI functions as core commercial services to end-users and vertical industries . This paradigm shifts the business model from a connectivity-centric provider to a service-centric en- abler of pervasive intelligence . AIaaS supports transformative applications such as immersive communication, holographic telepresence, and the control of intelligent industrial robots . A critical component is the establishment of a framework for *Quality of AI Service (QoAIS)*, which formally measures and standardizes the quality, reliability, performance, and efficiency of the specific AI functions exposed by the network, aligning technical delivery with service expectations .

III. ML TAXONOMY AND APPLICATIONS IN 6G

The demanding and heterogeneous requirements of 6G necessitate the deployment of a diverse spectrum of ML paradigms, each tailored to solve specific, complex problems across the communication stack .

A. Supervised Learning (SL)

SL models learn from labeled data to perform classification and regression tasks . This is invaluable in 6G for deterministic problem-solving:

- Traffic and Resource Prediction: SL, utilizing algo- rithms like Linear Regression and Logistic Regression, establishes relationships between network parameters to forecast future requirements, enabling proactive resource management and dynamic network slicing .
- Beam Management and CSI Feedback: Techniques such as Random Forest and Support Vector Machines

TABLE II
FUNCTIONAL OBJECTIVES AND KEY REQUIREMENTS OF AI INTEGRATION PARADIGMS IN 6G

Paradigm	Primary Objective	Enabling Technology / Architectural Sup- port	Impact on Network Layer/Model
AI4NET	Optimize network KPIs (efficiency, latency, energy) using extrinsic AI.	DNNs for CSI/Beamforming, RL for re- source optimization, ML for fault detection .	Optimization of PHY/MAC layer processes; network O&M intelligence enhancement.
NET4AI	Provide native computational, data, and se- curity infrastructure for distributed AI.	Distributed Computing (Edge/Cloud), AI signaling/data handling, FL/SL, CPN archi- tecture .	Fundamental architectural shift; support for large distributed models and ubiquitous in- telligence.

AIaaS	Commercial provision of measurable and customized intelligence as a core product.	QoAIS framework, Multi-dimensional resource provisioning, LLM integration, Intent-Based Networking (IBN) .	Cognitive networking, intent-based manage- ment, personalized service delivery.

(SVM) optimize beam selection and Channel State Information (CSI) feedback. An SVM-based method achieved comparable maximum uplink sum rates to sub- optimization techniques with significantly lower compu- tational complexity, which is crucial for massive MIMO systems .

- Security and Detection: SL is vital for real-time threat detection and security analytics by classifying network states or user behaviors, enhancing network resilience .

B. Unsupervised Learning (UL)

UL algorithms work with unlabeled data to discover hidden structures, features, and patterns for clustering and dimension- ality reduction . This is essential for managing the sheer scale and complexity of 6G data:

- Clustering and Dimensionality Reduction: Algorithms like K-Means Clustering and Principal Component Anal- ysis (PCA) are vital for tasks such as grouping secondary users in Terahertz (THz) Non-Orthogonal Multiple Ac- cess (NOMA) systems, or reducing the complexity of the massive volume of heterogeneous data generated in 6G networks .
- Anomaly Detection: UL models are effectively deployed for fault management and anomaly detection in highly complex 6G networks, identifying unusual network states without the need for explicit training on all potential failure modes .

C. Reinforcement Learning (RL) and Deep Learning (DL)

DL utilizes complex Artificial Neural Networks (ANNs) to process multi-layered data representations, serving as the core of modern AI . RL trains an agent to make sequential, optimal decisions in a dynamic environment .

- Deep Reinforcement Learning (DRL): By combining RL with Deep Neural Networks (DNNs), DRL addresses problems with vast, continuous state and action spaces, making it ideally suited for complex network control .
- Resource Orchestration: DRL algorithms like Deep Q- Network (DQN) and Deep Deterministic Policy Gradient (DDPG) dynamically allocate communication, comput- ing, and caching resources in heterogeneous architectures, such as Mobile Edge Computing (MEC) and Open Radio Access Networks (O-RAN) .
- Wireless Control: DRL is crucial for optimizing non- linear elements in the physical layer, notably Intelligent Reflecting Surfaces (IRS) phase shift control, power allocation in NOMA, and dynamic trajectory planning for UAVs and AUVs .
- Specific DL Models: Convolutional Neural Networks (CNNs) are highly effective for image and spectral data analysis, optimizing functions like signal detection in OFDM receivers

Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks handle sequential time-series data for accurate traffic and channel prediction, overcoming mem- ory loss inherent in handling long sequences .

D. Specialized Architectures

- Federated Learning (FL): FL is a distributed learning paradigm where models are trained locally on user de- vices, and only model updates are shared with a central server for aggregation. This is critical for 6G’s wide-scale edge deployment, ensuring user data privacy and security, overcoming communication overhead, and promoting dis- tributed intelligence .
- Graph Neural Networks (GNNs): GNNs are designed to process data structured as graphs, modeling complex network topologies, dependencies, and user relationships in a 6G mesh or cell-free architecture . They are key for intelligent traffic routing and resource allocation in highly scalable frameworks .
- Digital Twins (DT): DTs are virtual replicas of physical network components. ML models, particularly DRL, are trained within the DT environment to optimize network control strategies before applying them to the physical network, drastically reducing training costs and risks while improving performance and reliability .

IV. KEY TECHNOLOGICAL ENABLERS OF 6G

The journey toward 6G is driven by the maturation of several disruptive and complementary technologies that fun- damentally reshape the radio interface, network architecture, and security framework .

A. Radio Interface and Spectrum Innovations

1) Terahertz (THz) Communications: Exploiting THz frequencies, ranging from 100 GHz to 10 THz, is the most critical advancement in the radio interface. These ultra-wide swaths of unused spectrum offer enormous potential to enable data rates up to 1 Tbps . However, THz signals suffer from severe path loss and unique molecular absorption loss, making them highly vulnerable to blockages, necessitating reliance on Line-of-Sight (LoS) links for reliable transmission . ML is essential here for modeling non-linear channel behaviors and optimizing signal pre-distortion techniques to overcome hardware limitations at these high frequencies .

2) Intelligent Reflecting Surfaces (IRS/RIS): IRS, or RIS (Figure 1), are passive, software-controlled metasurfaces capable of intelligently directing and focusing electromagnetic waves . This technology is a paradigm shift, as it creates a virtual path where direct communication (LoS) is blocked, mitigating high path loss in THz communications . By control- ling the reflection phase shift, RIS converts the probabilistic wireless channel into a deterministic and software-controlled medium, significantly enhancing capacity and connectivity with low power consumption .

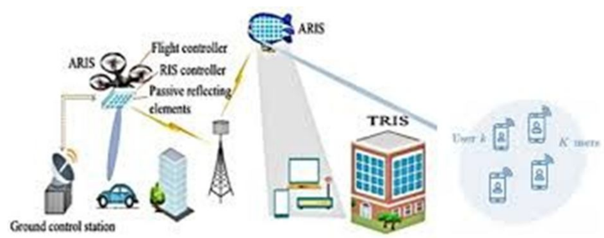

Fig. 1. : Hybrid Aerial and Terrestrial RIS-Aided Wireless Network.

This architecture integrates Aerial RIS (ARIS), deployed via UAVs or High Altitude Platforms, with Terrestrial RIS (TRIS) mounted on infrastructure. This configuration provides dynamic, three-dimensional coverage extension and enhanced communication reliability for K users, essential for the global coverage goals of 6G [**?**].

B. Cognitive and Integrated Functionalities

1) Integrated Sensing and Communication (ISAC): ISAC is a core capability of 6G, fully integrating wireless signal sensing and communication within a single system, often sharing the same resources . The entire communication net- work essentially functions as a sensor, enabling services like ultra-high accuracy localization (down to centimeter-level), simultaneous imaging and mapping, and gesture recognition . ISAC leverages wider bandwidth, higher frequency bands (up to THz), massive antenna arrays, and advanced AI algorithms to achieve super-resolution sensing capabilities .

2) Multi-Dimensional Architectures: 6G networks are conceived as highly distributed, multi-dimensional structures, providing true 3D coverage that integrates terrestrial, aerial (UAVs), and non-terrestrial (satellite) platforms . This hetero- geneous approach relies on the aggregation of technologies for access and backhaul, enabling pervasive edge computing and fundamental support for Digital Twins. The goal is to move computational and control functions closer to the user to support latency-sensitive applications like Augmented Reality (AR) and Virtual Reality (VR) .

V. ML FOR ENHANCED AIR INTERFACE AND PHYSICAL LAYER

The Physical Layer (PHY) in 6G must evolve into a flexible, data-driven entity capable of achieving ultra-high rate and reliability targets. This transformation is deeply reliant on ML.

A. Intelligent Reflecting Surfaces (RIS) Optimization and WEC

RIS is critical for realizing the *Wireless Environment Control (WEC)* functional block, mandated to transform the stochastic wireless channel into a highly deterministic one for ultra-high reliability ($1 - 10^{-9}$) . Optimizing the real- time phase shift configuration of thousands of passive RIS elements is a non-convex, high-dimensional problem . ML algorithms, particularly Deep Reinforcement Learning (DRL), are utilized to derive these optimal phase shifts by learning the complex, non-linear mapping between channel conditions and the optimal configuration . This autonomous control is essential for providing deterministic performance gains and mitigating environmental blockages .

B. CSI Feedback, Estimation, and Generative Robustness

The huge volume of Channel State Information (CSI) re- quired for efficient beamforming in Massive MIMO and THz systems causes prohibitively high feedback overhead . DL models, specifically *autoencoder architectures* (like CsiNet), compress this high-dimensional CSI data into highly compact feature representations, mitigating uplink overhead .

Furthermore, to address the *generalization gap* (poor performance in Out-of-Distribution or OOD scenarios), ad- vanced *generative models* are being deployed . Score-based diffusion models, for instance, are employed for RIS-MIMO channel estimation under unsupervised learning principles . These generative models demonstrate robust OOD perfor- mance and maintain high accuracy even when confronted with unexpected wireless conditions, signifying ML's crucial role in enhancing system resilience .

VI. AI-NATIVE RESOURCE AND NETWORK MANAGEMENT

ML is embedded within the core functional architecture of 6G to realize self-governing, autonomous operation, powered by specialized functional blocks that form cognitive control loops .

A. ML-Integrated Functional Architecture

The functional design of specialized 6G IIoT networks explicitly integrates the *ML and AI Algorithms* block as a key enabling technology servicing four crucial special- purpose functionalities: Wireless Environment Control (WEC), Traffic/Channel Prediction (T/CP), Proactive Resource Man- agement (PRM), and End-to-End Optimization (E2EO) . This architecture (Flowchart 1/Figure 2) realizes a closed-loop system of cognitive control, where Auxiliary Functions gather data, which is processed by the ML/AI Algorithms block, driving predictive models (T/CP) that, in turn, dictates the actions executed by *WEC* and *PRM*, leading to a Self- Evolving Network (SEN) .

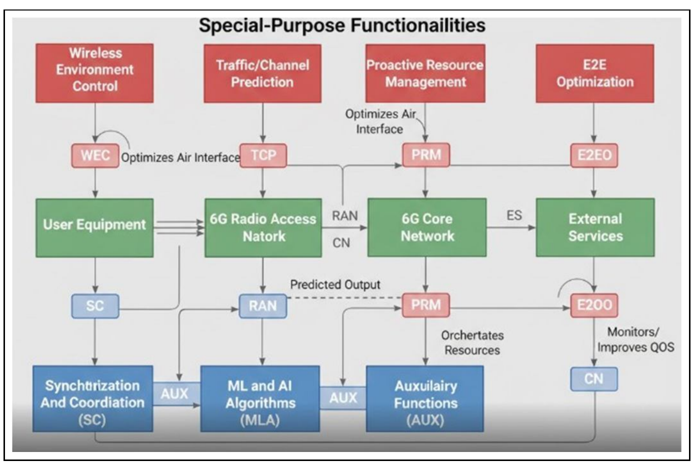

Fig. 2. ML-Oriented Functional Architecture for 6G Special IIoT Networks

B. Proactive Resource Management and Orchestration

PRM utilizes predictive intelligence to allocate resources ahead of time, ensuring scheduling precedes the demand curve, a critical requirement for achieving stringent URLLC and microsecond jitter targets . DRL techniques model network states and resource allocation as a Markov Decision Process (MDP), autonomously optimizing parameters like bandwidth, power, and slice allocation . This proactive approach extends to network slicing and Mobile Edge Computing (MEC) resource provisioning by forecasting end-user demand and dynamically matching it with available resources, leading to better Quality of Service (QoS) and efficiency . E2EO, similarly, monitors application-layer QoS using ML/AI on Big Data resources and iteratively adjusts configuration across the RAN and CN, managing the complex, multi-dimensional optimization problem of 6G .

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue XI Nov 2025- Available at www.ijraset.com

VII. ARCHITECTURES FOR DISTRIBUTED INTELLIGENCE (NET4AI)

The NET4AI paradigm is realized through architectures that support pervasive intelligence at the edge, addressing low latency, high connection density, and privacy .

A. *Federated Learning (FL) and Split Learning (SL)*

1) Federated Learning (FL): FL is the prevailing dis- tributed ML paradigm for privacy-preserving cooperative model training in 6G. By training models locally on device data and sharing only aggregated model parameter updates, FL eliminates the need to transmit sensitive raw data, thereby alleviating network congestion and maximizing bandwidth ef- ficiency . FL's applicability spans Horizontal FL (inter-source cooperation) and Vertical FL (feature collaboration within the same sample space), crucial for scalable and resilient network architectures
2) Split Learning (SL): SL addresses the limitations of resource-constrained devices that cannot support full FL training . SL segments the ML model, placing the initial, lighter layers on the client and the heavy computational layers on the powerful edge server . This mechanism enables deep model inference and training on battery-limited devices while preserving local data privacy, supporting a critical portion of the massive IoT ecosystem .

B. *Advanced AI Models and Computing Power Networks (CPN)*

The realization of pervasive edge intelligence mandates a cohesive *Computing Power Network (CPN) architecture, seamlessly spanning terminals, edge nodes, and centralized cloud resources . This CPN requires specialized **hardware acceleration* (GPUs, TPUs) , and for ultra-low energy and real-time latency, *Neuromorphic Computing* is emerging as a transformative enabler by integrating AI algorithms directly into the hardware .

1) Large Language Models (LLMs): LLMs are anticipated to be the cognitive foundation for realizing the self-operation and self-evolutionary loops of 6G networks . LLMs support *Intent-Based Networking (IBN)* by acting as the cognitive core, translating high-level human objectives (intent in natural language) into specific, executable configuration and resource management strategies . Successful deployment requires devel- oping specialized, low-parameter *on-device LLMs* tailored for 6G network operations, incorporating domain-specific knowledge to operate effectively on edge/terminal servers .
2) Quantum-Assisted Machine Learning (QML): Quantum Computing (QC) is identified as a radical long-term enabling technology for 6G . *Quantum-Assisted Machine Learning (QML)* exploits quantum mechanics to accelerate complex ML algorithms, crucial for solving high-dimensional, combi- natorial optimization problems endemic to 6G complexity . QC and Quantum Key Distribution (QKD) are also essential for establishing ultra-secure cryptographic foundations against future quantum attacks .

VIII. IMPERATIVE OF TRUSTWORTHINESS AND SECURITY

The commercial viability of 6G hinges on achieving archi- tectural **Trustworthiness** , a core value that must encompass security, reliability, and accountability across all layers.

A. *Distributed Ledger Technology (DLT) for Immutability*

The ubiquitous integration of AI models, which are suscepti- ble to subtle adversarial attacks, requires robust security . Dis- tributed Ledger Technology (DLT), including Blockchain, provides an essential component of this trust infrastructure by offering *immutable data provenance* and secure data sharing
. As shown in Figure **??** (Image 2), DLT is integrated with Distributed Learning (e.g., FL) to secure model aggregation and storage, mitigating distributed threats and ensuring model integrity across the Intelligent Control Layer .

B. *Explainable AI (XAI) for Accountability*

The "black-box" problem—the inability of complex DL models to provide transparent, auditable justifications for au- tonomous decisions—is a critical barrier to adoption in safety- critical 6G domains . **Explainable AI (XAI) is mandatory

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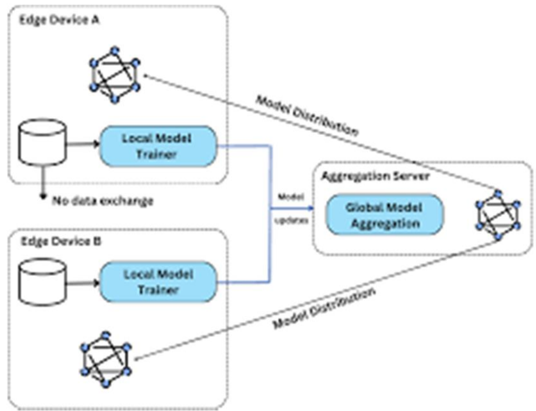

Fig. 3. Figure 5: The Federated Learning (FL) Distributed Training Paradigm. Edge devices train models locally using their private data and transmit only aggregated model updates (Model updates) to a central Aggregation Server, which performs Global Model Aggregation and redistribution (Model Distribution). This mechanism is critical for preserving data privacy and reducing communication overhead in 6G NET4AI architectures [**?**], [**?**].

for trustworthy AI governance in 6G . XAI frameworks, uti- lizing techniques like ensemble models (e.g., Extra Trees) and Shapley value interpretation, generate human-understandable justifications for AI-driven network decisions . This capability is essential for resolving the inherent trade-off between model accuracy and interpretability .

IX. AND IMPACTS OF 6G TECHNOLOGY

Wireless communication of the sixth generation (6G) is envisioned as an AI-native and sensing-enabled network that tightly integrates communication, computing, and intelligence within a unified architecture. One common conclusion drawn from current research is that 6G will not merely enhance con- nectivity but fundamentally transform global industries, human interactions, and digital ecosystems. With terabit-per-second data rates, sub-millisecond latency, the use of THz bands, intelligent reconfigurable surfaces, and deeply embedded AI, 6G will deliver applications far beyond the capabilities of 5G. One of the most prominent applications is immersive com- munication, ranging from holographic telepresence to multi- sensory XR and digital personal encounters. Future services such as 3D telepresence for remote meetings, virtual class- rooms, digital tourism, and remote collaboration require ex- tremely high bandwidth and ultra-low latency. Enabled by integrated sensing and communication (ISAC), 6G networks will use radio signals simultaneously for data transmission and environmental sensing, allowing precise movement capture and seamless interaction.

Another impactful domain is the development of large-scale digital twins—real-time virtual replicas of physical systems such as factories, vehicles, cities, or even human bodies. With its reliability and near-instant responsiveness, 6G will enable real-time monitoring, simulation, and predictive control. Such "massive twinning" will transform manufacturing, urban plan- ning, resource management, healthcare, and industrial automa- tion. Millions of interconnected digital twins will collaborate simultaneously, driving new levels of operational efficiency and autonomy.

Healthcare will also undergo a major transformation. The precision and dependability of 6G will enable remote robotic surgeries, continuous health monitoring, and AI-driven diag- nostics. Advanced applications such as telesurgery and haptic medicine demand near-zero latency and ultra-high reliabil- ity—requirements unmet by 5G. Wireless sensing will allow non-contact monitoring of vital signs such as heart rate, respiration, and movement, enhancing patient comfort and enabling early emergency detection.

Transportation and mobility will benefit immensely from 6G through autonomous driving, unmanned aerial vehicles (UAVs), and urban air mobility systems. These applications re- quire centimeter-level positioning accuracy, cooperative com- munication, and real-time decision-making. Intelligent sur- faces, ISAC, and ubiquitous AI will support these systems. Furthermore, UAVs connected via 6G will strengthen connec- tivity in remote areas and aid in disaster recovery, logistics, agriculture, and surveillance.

Beyond technical advancements, 6G will create a unified global mesh of terrestrial, aerial, maritime, and satellite net- works. This will improve connectivity for rural areas, ships, re- mote communities, and disaster-prone regions. Unlike previous generations, 6G aims to provide seamless service even at high mobility—on fast trains, aircraft, and across the globe. These capabilities will uplift sectors such as agriculture, banking, retail, manufacturing, remote work, and global logistics.

Ultimately, 6G represents more than faster communica- tion—it is a vision for a resilient, intelligent, and human- centric digital ecosystem. It will reshape communication, work, education, transportation, and sustainability while fos- tering a more connected and empowered global society.

X. FUTURE RESEARCH DIRECTIONS FOR 6G TECHNOLOGY

As the global vision for sixth-generation networks evolves, numerous research directions emerge to address existing chal- lenges and unlock the full potential of 6G. Future research must integrate advancements in wireless communication, arti- ficial intelligence, computing architectures, sustainability, and security to enable a robust and human-centric 6G ecosystem. A primary research area is advanced THz communication and hardware design. Although the THz spectrum promises unprecedented bandwidth, implementation remains limited due to propagation losses, atmospheric absorption, and immature hardware. Research is needed on low-cost THz materials, compact antennas, high-power amplifiers, and reconfigurable RF architectures. Accurate THz channel models, real-world propagation studies, and mobility-robust beam tracking must also be developed to achieve reliable THz communication.

Another key direction is energy-efficient 6G architecture design. Given dense base station deployment, AI-driven op- erations, and ISAC integration, reducing network energy consumption is essential. Research should focus on green transceiver design, low-power base stations, energy harvesting techniques, and intelligent sleep scheduling. Integrating renew- able energy sources with communication infrastructure and developing energy-aware optimization algorithms will further strengthen sustainability goals.

Developing AI-native networks is central to 6G evolution. AI in 6G will be embedded into the communication fabric itself. Key areas include federated learning, distributed intelli- gence, and real-time autonomous decision-making at the net- work edge. Research must advance lightweight, explainable, and trustworthy AI models that function under strict latency, reliability, and privacy constraints. Standardized metrics for Quality of AI Service (QoAIS) are essential for ensuring transparency and safety in mission-critical applications.

Integrated Sensing and Communication (ISAC) forms an- other major research frontier. ISAC aims to merge sensing and communication to support high-precision localization, environmental mapping, gesture recognition, and autonomous navigation. Future challenges include interference manage- ment between sensing and communication, joint resource allocation, and optimized waveform design. High-resolution ISAC solutions will empower digital twins, robotics, smart cities, and intelligent transportation.

Future 6G networks are expected to function as a global "network of networks," integrating terrestrial, aerial, maritime, and satellite communication. Research is required on unified protocols, intelligent routing, and adaptive handover mech- anisms to guarantee seamless connectivity across heteroge- neous platforms. This includes advancements in non-terrestrial networks (NTNs), optical wireless communication, software- defined satellite systems, and high-altitude platforms. Security, privacy, and trust management constitute another critical direction. Deep AI integration and pervasive sensing increase vulnerability to adversarial attacks, model poisoning, and data breaches. Quantum-safe cryptography, secure feder- ated learning frameworks, blockchain-based trust systems, and continuous authentication must be developed to ensure secure and resilient networks. Finally, socio-economic and regulatory research is vital for equitable 6G deployment. Future work must explore cost- efficient deployment strategies, inclusive spectrum policies, ethical AI governance, and global digital inclusion. Closing the connectivity gap and ensuring fair access to 6G will be essential long-term goals.

XI. CONCLUSION

The integration of Machine Learning is the decisive factor transforming the sixth-generation (6G) communication system from a mere technological upgrade into an autonomous, cog- nitive ecosystem . This structural shift is necessitated by the extreme complexity and dynamism introduced by fundamen- tal enablers such as Terahertz (THz) communication, Ultra- Massive MIMO (UM-MIMO), and Reconfigurable Intelligent Surfaces (RIS), problems that classical model-based solutions are incapable of managing efficiently . The realization of per- vasive intelligence is structured by the systematic progression through three core paradigms: from using AI as an external enhancement tool (AI4NET), to redesigning the infrastructure for native AI support (NET4AI), and culminating in the commercialization of measurable intelligence as a core product (AIaaS) .

Achieving the unprecedented 6G Key Performance Indi-cators (KPIs)—particularly ultra-high reliability ($1 - 10^{-9}$), ultra-low latency (< 1 ms), and microsecond-level jitter (< 0.1µs)—relies entirely on ML-driven technologies . AI is essential for transforming the traditionally stochastic physi- cal layer by enabling deterministic control of the wireless environment through RIS (Wireless Environment Control or WEC), thereby mitigating blockages and ensuring predictable channel conditions (Figure 1).

Furthermore, ML ensures system robustness by deploying advanced generative models for channel estimation that maintain high accuracy even when exposed to unpredictable Out-of-Distribution (OOD) scenarios. Within the core network, ML algorithms, primarily Deep Reinforcement Learning (DRL), power specialized function- alities like Proactive Resource Management (PRM) and End- to-End Optimization (E2EO) (Figure 2), ensuring scheduling precedes the demand curve and addressing the complex, multi- dimensional optimization required for joint communication and computing resource allocation .

The architectural foundation of 6G intelligence (NET4AI) is built on distributed ML architectures, driven by the need to integrate computation closer to the edge . Federated Learning (FL) and Split Learning (SL) are indispensable for balancing high computational demands with communication efficiency, resource constraints, and data privacy across the Comput- ing Power Network (CPN) architecture . Looking forward, Large Language Models (LLMs) are anticipated to be the cognitive core, enabling *Intent-Based Networking (IBN)* by translating high-level human objectives into executable network strategies . However, successfully deploying this cognitive layer requires developing specialized, low-parameter *on-device LLMs* to manage computational complexity at the terminal and edge servers . Complementary technologies like Quantum-Assisted Machine Learning (QML) hold radical potential for accelerating the training of vast AI models and solving computationally hard, high-dimensional optimization problems with a quadratic speedup . The core long-term viability and commercial adoption of AIaaS is conditional on establishing architectural Trustwor- thiness . This mandatory requirement is multi-layered: it integrates technical reliability via robust, adaptive ML mod- els, and safeguards security and privacy through Distributed Ledger Technology (DLT) . DLT (e.g., Blockchain) provides essential features like *immutable data provenance* and se- cure, decentralized model storage, mitigating advanced threats such as malicious aggregation injection attacks in distributed learning environments (Figure 3) . Critically, Explainable AI (XAI) is mandatory for governance, solving the ”black-box” problem by providing transparent, auditable justifications for autonomous decisions . XAI ensures that operational efficiency is balanced with human accountability, thereby translating technical reliability into societal trust (Figure 4) . Future research must prioritize the standardization of the *Quality of AI Service (QoAIS) framework to measure the commercial delivery of intelligence. Furthermore, accelerat- ing the development of secure, domain-specific **on-device LLMs* for autonomous orchestration and refining XAI tech- niques for real-time applicability in safety-critical domains are essential steps to ensure that 6G’s network autonomy is consistently transparent, auditable, and inherently trustworthy . The continued synergy between ML and physical/architectural design will ultimately determine the success of 6G in realizing a sustainable, hyper-connected, and fully intelligent cyber- physical continuum.

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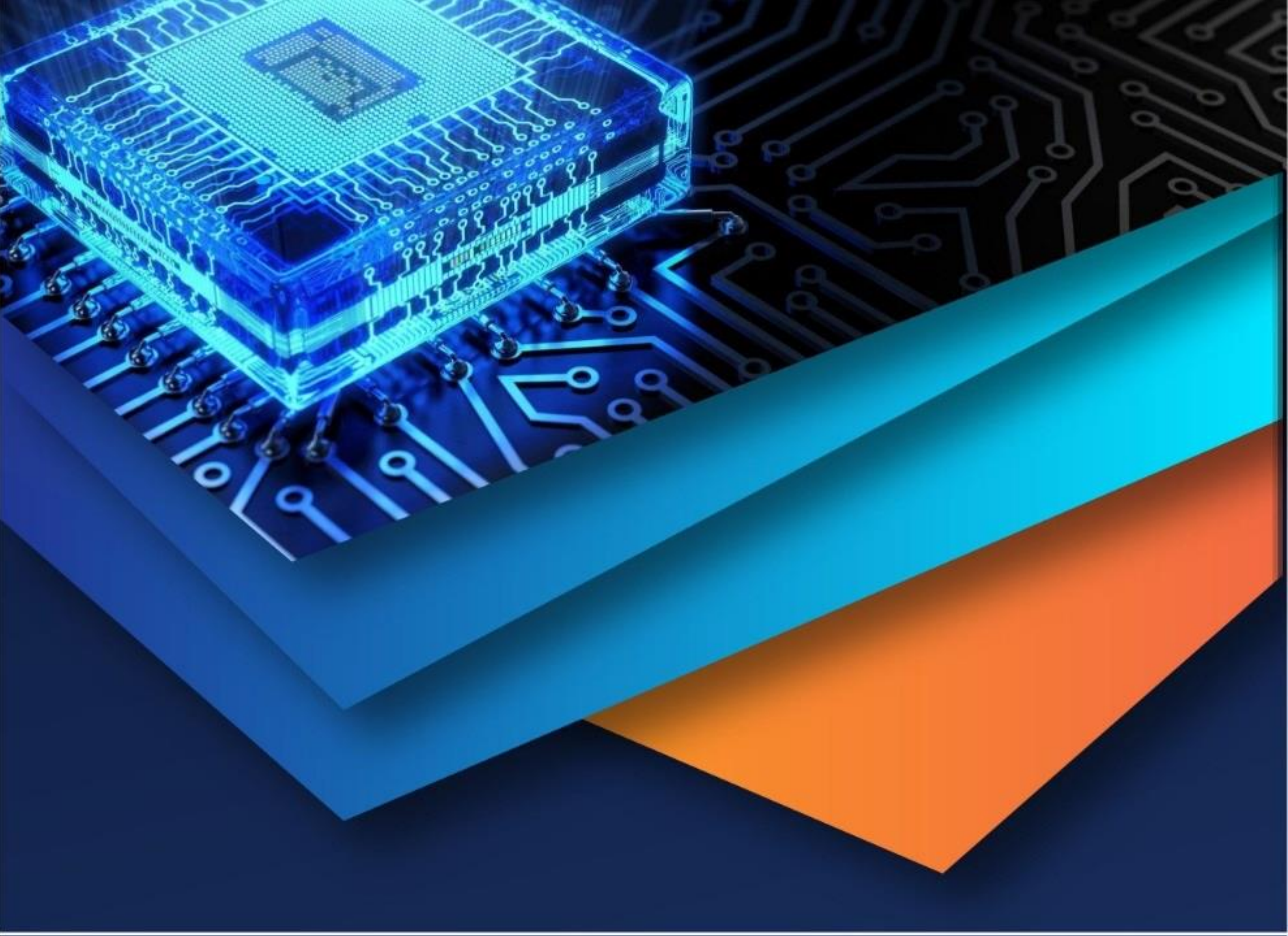

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