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Artificial Intelligence-Driven Control and Optimization in 6G Communication Networks: A Comprehensive Review

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Abstract
The rapid evolution toward sixth-generation (6G) communication networks is driving a fundamental shift from conventional model-driven systems to intelligence-driven architectures, where artificial intelligence (AI) plays a central role in network control and optimization. However, despite significant progress, existing research remains fragmented, with most AI-based solutions focusing on isolated network functions rather than addressing system-level integration and deployment challenges. This paper presents a system-level critical review of AI-driven control and optimization in communication networks, with particular emphasis on 6G environments. The study adopts a systematic literature review combined with a critical synthesis approach to analyze the capabilities, limitations, and architectural implications of machine learning, deep learning, and reinforcement learning techniques. The analysis reveals that while AI approaches offer substantial improvements in performance and adaptability, they face key challenges related to scalability, computational complexity, data availability, integration with existing architectures, and lack of explain ability and reliability guarantees. Furthermore, a significant gap is identified between algorithmic advancements and real-world deployment feasibility. To address these limitations, the paper highlights the need for integrated and hybrid AI frameworks, as well as architecture-aware design strategies that support scalable, trustworthy, and autonomous network operation. Overall, this work provides a structured synthesis of current research, a comparative analysis of AI paradigms, and a set of future research directions toward AI-native 6G communication systems, contributing to bridging the gap between theoretical innovation and practical deployment.

Keywords: *Artificial Intelligence; 6G Communication Networks; Network Control; Resource Optimization; Machine Learning; Deep Learning; Reinforcement Learning; Autonomous Networks; AI-Native Architecture*

1. Introduction:

The transition from fifth-generation (5G) to sixth-generation (6G) communication systems is increasingly recognized as a fundamental transformation rather than a conventional generational upgrade. Unlike previous wireless evolutions driven primarily by throughput and latency improvements, 6G is envisioned as an intelligent, service-oriented, and autonomously managed network ecosystem, supporting emerging applications such as immersive communication, digital twins, and distributed artificial intelligence across terrestrial and non-terrestrial environments (Saad et al., 2020; ITU-R, 2023). This paradigm shift places network control and optimization at the core of system design, rather than treating them as secondary operational functions.

However, this transformation introduces a critical challenge: the growing mismatch between network complexity and the limited adaptability of traditional control and optimization mechanisms. Modern and beyond-5G networks operate under highly dynamic conditions characterized by heterogeneous infrastructures, fluctuating traffic patterns, strict quality-of-service requirements, and distributed computing constraints. Conventional approaches based on static policies, rule-based decision-making, and model-driven optimization often fail to provide the required level of responsiveness and scalability in such environments (Sun et al., 2019; Mao et al., 2018).

Artificial intelligence (AI) has therefore emerged as a key enabler for addressing these limitations. A wide range of techniques—including machine learning, deep learning, and reinforcement learning—are being applied to support resource allocation, traffic prediction, interference management, mobility control, and energy efficiency. Within this context, recent studies distinguish between AI for communication, where learning enhances network performance, and communication for AI, where networks facilitate distributed intelligence and edge-based inference (Zhou et al., 2019; Mahmood, T. A., 2026). This dual perspective reflects the evolving role of communication systems as both consumers and enablers of intelligent services.

Despite the rapid growth of AI-driven solutions, the current body of research remains fragmented and largely problem-specific. Most studies focus on optimizing individual network functions in isolation, without adequately addressing how these solutions can be integrated into coherent, scalable, and interoperable system-level architectures. Furthermore, many approaches demonstrate promising performance under idealized simulation conditions, while overlooking practical constraints such as computational overhead, data availability, latency requirements, and trustworthiness (Dhulkefl et al., 2025; Wang et al., 2020). As a result, a significant gap persists between algorithmic advancements and real-world deployment feasibility.

In addition, existing surveys often adopt either a broad perspective on AI in 6G or a narrow focus on specific techniques, without clearly distinguishing between control, optimization, and autonomous network management. While these concepts are alidate, trust, and debug AI-driven actions, particularly in scenarios requiring high reliability and accountability.

closely related, they represent different layers of system intelligence: control governs adaptive decision-making, optimization focuses on performance improvement under constraints, and autonomy extends these capabilities toward self-management and lifecycle governance. The lack of a unified analytical framework that integrates these dimensions highlights a critical gap in the literature.

To address this gap, this paper presents a system-level critical review of AI-driven control and optimization in 6G communication networks. The study aims to analyze how different AI paradigms contribute to network intelligence, evaluate their strengths and limitations, and assess their suitability for large-scale deployment. In particular, the review focuses on identifying key challenges related to scalability, computational complexity, data constraints, interoperability, and trust, while examining their implications for future network architectures.

The main contributions of this work are threefold. First, it provides a structured synthesis of AI techniques applied to control and optimization in next-generation communication networks. Second, it develops a comparative analysis that highlights the trade-offs, limitations, and system-level implications of these approaches. Third, it identifies critical research gaps and outlines future directions toward AI-native, scalable, and trustworthy 6G network architectures.

2. Literature Review

2.1 From Conventional Networks to AI-Native Architectures

The evolution of communication networks toward 6G represents a fundamental transition from model-driven architectures to intelligence-driven systems, where artificial intelligence (AI) is embedded as a core operational component rather than an auxiliary optimization tool. In earlier generations, network control and optimization relied primarily on deterministic models and rule-based mechanisms, assuming relatively stable environments and predictable system dynamics (Sun et al., 2019). However, such assumptions no longer hold in emerging 6G scenarios characterized by heterogeneous infrastructures, dynamic traffic patterns, and distributed computing environments (Saad et al., 2020).

This shift has led to the emergence of the concept of AI-native networking, in which learning mechanisms are integrated across multiple layers of the network, including control, management, and service orchestration. Unlike traditional approaches where AI is applied to isolated tasks such as traffic prediction or anomaly detection, AI-native systems treat intelligence as a decision-making substrate that continuously adapts network behavior under uncertainty (Zhou et al., 2019; Letaief et al., 2019).

Despite its conceptual appeal, the transition toward AI-native architectures remains incomplete and fragmented. Existing studies often focus on integrating AI into specific network functions without addressing system-level coordination, interoperability, and architectural coherence. This results in a proliferation of disjointed solutions, where local optimizations do not necessarily translate into global performance improvements (Wang et al., 2020; Dang et al., 2020).

Furthermore, current implementations frequently assume idealized conditions, such as perfect data availability and unlimited computational resources, which limits their applicability in real-world deployments. As a result, a critical gap persists between the theoretical vision of AI-native networks and their practical realization, highlighting the need for unified frameworks that integrate control, optimization, and intelligence within a coherent architectural paradigm.

This study adopts a systematic literature review (SLR) combined with a critical synthesis approach to investigate AI-driven control and optimization in 6G communication networks. The SLR framework ensures transparency, reproducibility, and structured evidence collection, while the critical synthesis enables deeper examination of methodological assumptions, limitations, and system-level implications (Kitchenham & Charters, 2007; Page et al., 2021).

This combined approach is particularly suitable for 6G research, where rapid innovation often exceeds empirical validation and architectural standardization (Saad et al., 2020).

2.2 Machine Learning for Network Intelligence

Machine learning (ML) has emerged as a foundational enabler of network intelligence, primarily due to its ability to extract patterns from large-scale network data and support predictive decision-making. In communication networks, supervised learning techniques are widely used for tasks such as traffic prediction, user behavior modeling, and fault detection, while unsupervised methods facilitate clustering, anomaly detection, and pattern discovery in complex network environments (Mao et al., 2018; Sun et al., 2019).

The integration of ML into network operations reflects a broader transition from model-driven optimization to data-driven intelligence, where decisions are increasingly based on learned representations rather than predefined analytical models. This shift enables networks to adapt to dynamic conditions, particularly in environments characterized by non-linearity and high variability, as expected in 6G systems (Saad et al., 2020; Zhou et al., 2019).

Despite these advantages, the effectiveness of ML-based approaches remains constrained by several critical limitations. First, many ML models rely heavily on historical data distributions, which limits their ability to generalize under non-stationary conditions. In highly dynamic network environments, where traffic patterns and user behavior evolve rapidly, models trained on past data may exhibit degraded performance when exposed to unseen scenarios (Dulac-Arnold et al., 2021).

Second, a significant portion of existing studies evaluates ML techniques under simplified simulation settings, often assuming idealized conditions such as accurate channel state information and stable network configurations. While these assumptions facilitate controlled experimentation, they reduce the reliability of reported performance gains when transitioning to real-world deployments (Wang et al., 2020).

Third, the limited interpretability of ML models presents a major barrier to their integration into mission-critical network control systems. Black-box decision-making processes hinder transparency, making it difficult for network operators to

Furthermore, the literature reveals a persistent focus on function-specific optimization, where ML models are designed to address isolated tasks rather than contributing to a unified system-level intelligence framework. This fragmentation limits the overall impact of ML, as improvements in individual components do not necessarily translate into global network performance gains.

Consequently, while ML provides a strong foundation for enabling network intelligence, its practical effectiveness depends on addressing challenges related to generalization, robustness, interpretability, and system-level integration. These limitations highlight the need for more holistic approaches that move beyond isolated learning tasks toward coordinated and architecture-aware intelligence in future 6G networks.

2.3 Deep Learning: High Capability, High Cost

Deep learning (DL) has significantly advanced the capabilities of intelligent communication systems by enabling the modeling of high-dimensional and nonlinear relationships inherent in wireless environments. Unlike traditional machine learning methods, DL architectures—such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs)—have demonstrated strong performance in complex tasks including channel estimation, signal detection, modulation recognition, and spectrum sensing (O'Shea & Hoydis, 2017; Ye et al., 2018).

The effectiveness of DL in communication networks stems from its ability to learn hierarchical feature representations directly from raw data, reducing the need for handcrafted models and domain-specific assumptions. This is particularly beneficial in 6G environments, where network conditions are highly dynamic and difficult to capture using analytical models (Zhang et al., 2019; Saad et al., 2020).

However, these performance gains come at a significant cost. DL models are inherently computationally intensive, requiring large-scale training datasets, high processing power, and substantial energy consumption. This creates a fundamental tension between model accuracy and deployment feasibility, particularly in edge computing scenarios where computational resources are limited (Mahmood et al., 2026; Kairouz et al., 2021).

Moreover, the scalability of DL-based solutions remains a critical concern. Many studies report high accuracy under controlled experimental conditions but fail to demonstrate robustness when deployed in heterogeneous and distributed network architectures. In practice, variations in network topology, user behavior, and environmental conditions can significantly affect model performance, limiting the generalizability of trained models (Dulac-Arnold et al., 2021; Wang et al., 2020).

Another key limitation is the centralization bias of many DL approaches. Training deep models often relies on centralized data collection, which introduces challenges related to latency, communication overhead, and data privacy. While distributed learning paradigms such as federated learning have been proposed to address these issues, they introduce additional complexity in terms of model synchronization and convergence (McMahan et al., 2017; Kairouz et al., 2021).

From a system-level perspective, the integration of DL into network control raises important architectural questions. Specifically, it remains unclear whether DL models should be deployed in centralized cloud environments, distributed edge nodes, or hybrid configurations. Each approach involves trade-offs between latency, scalability, and resource efficiency, which are often insufficiently addressed in existing literature (Dang et al., 2020; Letaief et al., 2019).

Consequently, while deep learning represents a powerful enabler of intelligent network functionality, its practical adoption in 6G systems requires careful consideration of computational constraints, scalability limitations, and architectural integration challenges. These issues highlight a broader research gap in designing resource-efficient and deployment-aware DL frameworks for next-generation communication networks.

2.4 Reinforcement Learning for Autonomous Control

Reinforcement learning (RL) has become one of the most promising paradigms for autonomous network control, particularly in environments characterized by uncertainty, partial observability, and sequential decision-making. Unlike supervised learning, which depends on labeled datasets, RL enables agents to learn control policies through interaction with the environment, making it especially suitable for dynamic tasks such as resource allocation, handover management, adaptive routing, and power control in wireless systems (Sutton & Barto, 2018; Mao et al., 2018).

The main attraction of RL in communication networks lies in its ability to optimize long-term system behavior rather than isolated short-term decisions. This is particularly relevant in 6G scenarios, where control decisions must continuously adapt to changing traffic demands, mobility patterns, and heterogeneous service requirements. In this sense, RL offers a natural framework for moving from static optimization toward closed-loop and self-adaptive control (Nasir & Guo, 2023; Saad et al., 2020).

However, despite its conceptual strength, RL faces substantial barriers to practical deployment. A major challenge is the need for extensive exploration, which in real operational networks may lead to unsafe or suboptimal actions during learning. While trial-and-error exploration is acceptable in simulation, it becomes problematic in real-time communication systems where poor decisions can directly affect service quality, reliability, or network stability (Dulac-Arnold et al., 2021).

In addition, RL methods often suffer from slow convergence and instability, especially in large-scale and non-stationary environments. Their performance is highly sensitive to reward design, state representation, and exploration strategies, all of which become increasingly complex in 6G systems. This raises an important concern: although RL is frequently promoted as a pathway to fully autonomous networks, its learning dynamics remain difficult to control and validate in practice (Mao et al., 2018; Zhang et al., 2021).

To address scalability and coordination challenges, recent research has increasingly focused on deep reinforcement learning (DRL) and multi-agent reinforcement learning (MARL). DRL extends RL to high-dimensional state spaces through deep neural networks, while MARL enables multiple distributed agents to coordinate actions across network entities. These developments are particularly relevant for interference management, distributed control, and edge-based decision-making in dense 6G environments (Busoniu et al., 2008; Zhang et al., 2021).

Yet these advances also introduce additional complexity. DRL amplifies issues related to computational overhead and interpretability, while MARL suffers from coordination difficulties, non-stationarity, and communication overhead among agents. As the number of agents grows, ensuring convergence and consistent behavior becomes increasingly difficult, limiting large-scale deployment feasibility (Kairouz et al., 2021; Wang et al., 2020).

Consequently, RL should not be viewed as a complete solution to autonomous network control, but rather as a powerful yet constrained framework whose practical value depends on safety mechanisms, hybrid integration, and architecture-aware deployment. This suggests that the future of RL in 6G lies less in standalone autonomy and more in its integration with model-based control, constrained learning, and system-level validation frameworks.

2.5 Toward Integrated AI Frameworks for Control and Optimization

A recurring limitation in the current literature is that AI techniques for communication networks are often developed as isolated solutions targeting specific tasks, such as traffic prediction, interference mitigation, or resource allocation, rather than as components of a unified control and optimization architecture. While this task-specific focus has produced important algorithmic advances, it has also resulted in a fragmented research landscape in which local improvements do not necessarily translate into system-level intelligence or end-to-end operational efficiency (Sun et al., 2019; Wang et al., 2020).

This fragmentation is particularly problematic in 6G environments, where network functions are increasingly interdependent and must operate across multiple layers, domains, and infrastructures. Control decisions in one component may directly affect optimization outcomes in another, making it insufficient to treat prediction, scheduling, routing, and orchestration as independent problems. As a result, recent research has begun to emphasize the need for integrated AI frameworks capable of coordinating sensing, learning, decision-making, and actuation within a coherent system architecture (Saad et al., 2020; Dang et al., 2020).

Several emerging paradigms reflect this shift. AI-native architectures seek to embed intelligence across the control, management, and service layers of the network, enabling end-to-end adaptability rather than isolated optimization. Similarly, digital twin-based frameworks provide virtual representations of network states that can support predictive control and risk-aware decision-making, while intent-driven networking introduces higher-level abstractions through which operators define objectives and AI systems derive the corresponding control actions (Kreutz et al., 2015; Nguyen et al., 2021).

Despite their conceptual promise, these frameworks remain largely vision-driven rather than deployment-ready. A key challenge lies in integrating heterogeneous AI models across different functional layers while preserving interoperability, stability, and real-time responsiveness. In practice, current studies rarely provide clear mechanisms for coordinating multiple learning modules or resolving conflicts between local and global objectives. This reveals a persistent gap between architectural ambition and implementation maturity (Kairouz et al., 2021; Dulac-Arnold et al., 2021).

Another challenge concerns the lack of standardized interfaces and evaluation frameworks for AI-enabled network architectures. Without common design principles and interoperable control mechanisms, integrated intelligence risks becoming another layer of fragmentation rather than a solution to it. This issue is especially important for 6G, where AI is expected not only to optimize network functions but also to shape the architecture itself (ITU-R, 2023; Letaief et al., 2019).

Consequently, the future of AI-driven communication systems depends not only on better algorithms, but on the development of architecture-aware, interoperable, and system-level frameworks that integrate control and optimization within a unified intelligence stack. This transition from algorithm-centric research to framework-centric design represents one of the most important directions for realizing practical AI-native 6G networks.

3. Review Methodology

3.1 Methodological Design

This study adopts a systematic literature review (SLR) combined with a critical synthesis approach to examine AI-driven control and optimization in 6G communication networks. While the SLR framework ensures structured identification, selection, and evaluation of relevant studies, the critical synthesis enables deeper analysis of methodological assumptions, limitations, and system-level implications.

This combined methodology is particularly suitable for the present study, given the fragmented and multi-disciplinary nature of AI-enabled networking research, where algorithmic advances often lack integration into coherent architectural frameworks (Kitchenham & Charters, 2007; Page et al., 2021).

3.2 Literature Search Strategy

A structured multi-stage search strategy was employed to capture relevant studies across the intersection of artificial intelligence and next-generation communication networks. The search focused on publications from 2020 to 2024, representing the most active phase of AI-driven 6G research, while selectively incorporating foundational works to support conceptual grounding (Saad et al., 2020; Sun et al., 2019).

To ensure domain specificity, the search relied on problem-oriented keywords rather than generic queries. These included:

- AI-driven network control
- intelligent resource optimization
- reinforcement learning for wireless systems
- autonomous network management

This targeted approach ensures alignment with the core scope of the review, namely control, optimization, and network intelligence, and reduces the inclusion of conceptually irrelevant studies.

3.3 Data Sources

The literature was collected from high-impact academic databases, including IEEE Xplore, ScienceDirect, SpringerLink, and Wiley Online Library, which collectively represent the primary publication venues in wireless communications and AI-enabled networking.

To ensure alignment with emerging architectural visions, relevant standardization reports such as IMT-2030 (6G framework) were also included (ITU-R, 2023; Letaief et al., 2019).

3.4 Inclusion and Exclusion Criteria

To ensure analytical consistency and relevance, explicit selection criteria were applied. Inclusion criteria:

- Peer-reviewed journal or top-tier conference publications
- Studies addressing AI techniques in communication networks
- Research focusing on control, optimization, or autonomous management
- Publications from 2020 onward
- Works providing algorithmic, architectural, or system-level insights

Exclusion criteria:

- Non-peer-reviewed or informal publications
- Studies unrelated to AI-driven network functionality
- Works lacking methodological clarity or validation
- Redundant studies with minimal contribution

This selection strategy prioritizes analytical relevance over volume, ensuring that included studies contribute directly to the research objectives.

3.5 Study Selection Process

The study selection followed a structured screening process aligned with PRISMA guidelines (Page et al., 2021):

1. Initial retrieval using targeted keyword queries
2. Title and abstract screening
3. Full-text evaluation based on relevance and methodological rigor
4. Final selection based on contribution to AI-driven control and optimization

The process included iterative refinement to distinguish between overlapping research domains, particularly optimization-focused methods, control frameworks, and autonomous network architectures, which are often conflated in existing literature.

3.6 Data Extraction and Analysis

A structured data extraction framework was applied to each selected study, capturing key attributes such as:

- AI techniques (ML, DL, RL, federated learning)
- Application domains (resource allocation, traffic prediction, interference management)
- Network context (5G, beyond-5G, 6G)
- Evaluation approaches and performance metrics
- Reported limitations

The extracted data were analyzed using a comparative and thematic synthesis approach, enabling the identification of research trends, classification of techniques, and systematic evaluation of methodological gaps (Zhou et al., 2019; Kairouz et al., 2021).

3.7 Analytical Perspective

To support system-level evaluation, the analysis is guided by three key dimensions:

- Conceptual coherence: the degree of integration of AI within network control architectures
- Operational realism: consideration of scalability, latency, and deployment constraints
- Architectural alignment: consistency with AI-native 6G visions

These dimensions enable a structured assessment of the gap between algorithmic performance and practical deployment feasibility, which remains a central challenge in AI-driven communication networks (Dulac-Arnold et al., 2021; Wang et al., 2020).

4. Comparative Analysis of AI Approaches for Network Control and Optimization

4.1 Comparative Perspective on AI Paradigms

A critical examination of the literature reveals that AI-driven approaches in communication networks can be broadly categorized into machine learning (ML), deep learning (DL), and reinforcement learning (RL), each reflecting distinct assumptions about network behavior, decision-making processes, and optimization objectives. While this classification is commonly adopted, existing studies often present these paradigms in isolation, overlooking their fundamental trade-offs and system-level implications (Mao et al., 2018; Saad et al., 2020).

ML-based approaches primarily focus on prediction and pattern extraction, making them well-suited for tasks such as traffic estimation and anomaly detection. However, their reliance on historical data limits adaptability in dynamic environments. In contrast, DL-based methods provide superior performance in high-dimensional problems but introduce significant computational and energy overhead. RL-based approaches, on the other hand, enable adaptive and sequential decision-making, positioning them as key enablers of autonomous control, albeit with challenges related to convergence, stability, and safety (Dulac-Arnold et al., 2021; Zhang et al., 2021).

4.2 Fundamental Trade-Offs

A deeper analysis highlights that no single AI paradigm consistently outperforms others across all network scenarios. Instead, each approach involves inherent trade-offs that must be carefully considered in system design:

- Accuracy vs. Efficiency:
  DL models achieve high accuracy but require substantial computational resources, whereas ML models offer lower complexity at the cost of reduced expressive power.
- Adaptability vs. Stability:
  RL enables continuous adaptation but often suffers from instability and unpredictable convergence, particularly in non-stationary environments.
- Centralization vs. Distribution:
  DL approaches are typically centralized, while RL and federated learning support distributed intelligence, introducing coordination challenges and communication overhead (Kairouz et al., 2021; Wang et al., 2020).
- Performance vs. Interpretability:
  More complex models generally provide better performance but reduce transparency, complicating their integration into mission-critical systems.

  These trade-offs are frequently underexplored in existing studies, which tend to report performance gains without analyzing their broader system implications.

4.3 System-Level Limitations in Current Research

Beyond algorithmic performance, a key limitation across the literature is the fragmentation of AI solutions. Most studies optimize specific network functions independently, without considering cross-layer interactions or end-to-end system behavior. This leads to:

- Disjointed optimization objectives
- Lack of coordination between network components
- Limited scalability in large-scale deployments
- Inconsistent performance across heterogeneous environments

Such fragmentation undermines the potential of AI to deliver holistic network intelligence, particularly in 6G systems where tight integration between control, optimization, and management is required (Dang et al., 2020; Letaief et al., 2019).

4.4 Toward Hybrid and Integrated Approaches

Given the limitations of individual paradigms, recent research increasingly advocates for hybrid approaches that combine the strengths of multiple AI techniques. For example, ML models can be used for prediction, while RL handles decision-making, and DL provides feature extraction capabilities.

These hybrid frameworks aim to balance accuracy, adaptability, and computational efficiency, enabling more robust and scalable solutions. However, they also introduce new challenges related to system complexity, integration, and coordination between different learning modules (Zhou et al., 2019; Kairouz et al., 2021).

From a system-level perspective, the effectiveness of hybrid approaches depends on their ability to operate within coherent architectural frameworks, rather than as loosely coupled components. This reinforces the need for AI-native designs that integrate multiple learning paradigms into unified control and optimization pipelines.

4.5 Comparative Summary of AI Approaches

To provide a structured and system-level comparison of artificial intelligence paradigms in communication networks, Table 1 summarizes the key characteristics, strengths, limitations, and application domains of machine learning (ML), deep learning (DL), reinforcement learning (RL), and hybrid approaches. This comparative view enables a clearer understanding of the trade-offs associated with each technique and their suitability for different network control and optimization tasks.

Table 1. Comparative Analysis of AI Approaches for Network Control and Optimization

Best Use Cases	Limitations	Strengths	Approach
Traffic prediction, anomaly detection	Limited adaptability in dynamic environments, reliance on historical data	Low computational complexity, fast inference, effective for pattern recognition	ML
Signal processing, feature extraction	High computational and energy cost, low interpretability	High accuracy, strong capability in handling complex and high-dimensional data	DL
Resource allocation, network control	Slow convergence, instability, safety concerns in real-world deployment	Adaptive decision-making, supports long-term optimization and autonomous control	RL
System-level optimization and orchestration	Increased system complexity, integration and coordination challenges	Combines strengths of multiple approaches, improved flexibility and performance	Hybrid

As shown in Table 1, no single AI paradigm consistently satisfies all requirements of next-generation communication networks. Deep learning offers superior performance in complex tasks but suffers from significant computational overhead, making it challenging for real-time and edge deployments. In contrast, machine learning provides efficient and lightweight solutions but lacks robustness in highly dynamic environments. Reinforcement learning enables adaptive and autonomous decision-making, yet its practical applicability is constrained by convergence instability and safety concerns.

Importantly, the table highlights that the effectiveness of each approach is context-dependent, varying according to network conditions, system constraints, and application requirements. This reinforces a key insight emerging from the literature: AI techniques should not be evaluated in isolation, but rather in terms of their system-level implications and interactions.

Consequently, recent research increasingly advocates for hybrid and integrated approaches that combine predictive, learning, and control capabilities within a unified framework. Such approaches aim to balance performance, scalability, and adaptability, while addressing the limitations of individual paradigms. However, their success depends on the development of coherent architectural designs and coordination mechanisms, which remain open challenges in the realization of AI-native 6G networks.

5. Challenges in AI-Driven Network Control and Optimization

5.1 Scalability and System Complexity

One of the most critical challenges in AI-driven communication networks is scalability. While many studies demonstrate strong performance in controlled or small-scale environments, their effectiveness often degrades significantly when applied to large-scale networks involving massive numbers of devices, heterogeneous infrastructures, and distributed control entities (Saad et al., 2020; Dang et al., 2020).

This issue is particularly pronounced in distributed and multi-agent systems, where the complexity of coordination, communication, and policy learning increases rapidly with network size. As the number of interacting agents grows, ensuring consistent and stable behavior becomes increasingly difficult, often leading to performance degradation or instability.

5.2 Computational Complexity and Real-Time Constraints

AI-driven control and optimization introduce significant computational overhead, especially in deep learning and reinforcement learning models. Training and inference processes can be resource-intensive, making them difficult to deploy in real-time environments where ultra-low latency is required (Dulac-Arnold et al., 2021; Kairouz et al., 2021).

This creates a fundamental trade-off between model accuracy and responsiveness, particularly in edge computing scenarios where computational resources are constrained. Furthermore, continuous learning requirements—necessary for adapting to dynamic network conditions—can further increase system complexity and delay decision-making processes.

5.3 Data Availability, Quality, and Privacy

The effectiveness of AI models depends heavily on the availability of high-quality data, which presents a major challenge in communication networks. Data collection is often constrained by privacy regulations, security concerns, and proprietary ownership, limiting access to large-scale datasets (Kairouz et al., 2021).

Additionally, real-world data may be noisy, incomplete, or biased, which can negatively impact model performance and reliability. Centralized data collection also raises concerns regarding privacy and data protection, particularly in applications involving sensitive information such as healthcare and autonomous systems.

While approaches such as federated learning aim to address these issues, they introduce additional challenges related to communication overhead, synchronization, and convergence.

5.4 Integration with Existing Network Architectures

Another significant challenge lies in integrating AI-driven mechanisms into existing communication infrastructures. Current networks are built on layered architectures with well-defined protocols, making it difficult to incorporate AI-based decision-making without redesigning control loops and system interfaces (Wang et al., 2020; Kreutz et al., 2015).

Most existing studies focus on standalone AI models without addressing how they can be embedded into real-world systems. This creates a gap between algorithm development and practical deployment, limiting the applicability of proposed solutions.

5.5 Explainability and Trust

The lack of explainability in AI models, particularly deep learning systems, represents a major barrier to their adoption in communication networks. Black-box decision-making processes make it difficult to understand how decisions are made, reducing trust and hindering debugging and validation processes.

In mission-critical applications, where incorrect decisions can lead to service disruption or security vulnerabilities, the absence of transparency becomes a serious concern. This highlights the need for explainable AI (XAI) techniques that balance performance with interpretability.

5.6 Stability and Reliability of Learning-Based Control

Unlike classical control systems, AI-based approaches often lack formal guarantees for stability and reliability. This raises critical questions regarding system behavior under unexpected conditions, distribution shifts, or adversarial scenarios (Mao et al., 2018; Dulac-Arnold et al., 2021).

Most existing studies focus on average performance rather than worst-case scenarios, leaving potential failure modes insufficiently explored. As a result, there is a need for hybrid frameworks that combine learning-based methods with formal verification and robustness analysis.

5.7 Critical Synthesis: The Gap Between Vision and Reality

A key insight emerging from the literature is the growing gap between the vision of AI-native 6G networks and the current state of research. While AI is widely presented as a transformative solution, practical implementation remains constrained by scalability limitations, computational overhead, data challenges, integration complexity, and lack of theoretical guarantees (Saad et al., 2020; Letaief et al., 2019).

This suggests that the transition toward intelligent and autonomous networks is not merely a technical evolution, but a system-level transformation requiring advances in architecture, theory, and governance.

6. Future Research Directions

6.1 Toward AI-Native Communication Networks

A fundamental direction for future research lies in the transition toward AI-native communication networks, where intelligence is embedded as a core architectural principle rather than an external optimization layer. Current systems largely integrate AI as an add-on component, limiting its impact on network design and operation. In contrast, future 6G networks are expected to incorporate learning mechanisms directly into the control plane, data plane, and management layers, enabling end-to-end adaptability and intelligent orchestration (Saad et al., 2020; ITU-R, 2023).

Achieving this vision requires rethinking network architectures to support learning-driven protocols, adaptive control loops, and semantic communication paradigms, where decisions are based not only on data transmission but also on task-oriented objectives.

6.2 Autonomous and Self-Managed Networks

The realization of fully autonomous networks represents another key research frontier. While current systems exhibit partial automation, achieving true autonomy requires continuous learning, robust decision-making under uncertainty, and safe exploration mechanisms for reinforcement learning.

Future research should focus on developing closed-loop control systems that integrate sensing, learning, and actuation in real time, enabling networks to self-configure, self-optimize, and self-heal without human intervention. However, autonomy must be carefully balanced with human oversight and governance, particularly in safety-critical applications (Mao et al., 2018).

6.3 Hybrid and Multi-Paradigm AI Systems

Given the limitations of individual AI techniques, future research is expected to move toward hybrid AI frameworks that combine machine learning, deep learning, and reinforcement learning within unified architectures.

Such approaches can leverage:

- ML for prediction
- DL for representation learning
- RL for decision-making

However, designing these systems requires addressing challenges related to model coordination, interoperability, and system complexity, ensuring that integrated solutions remain scalable and efficient (Kairouz et al., 2021; Zhou et al., 2019).

6.4 Scalable and Distributed Intelligence

As communication networks continue to grow in scale and complexity, future research must focus on distributed and scalable AI frameworks. Centralized approaches are unlikely to meet the latency and resource constraints of 6G systems, particularly in edge and ultra-dense environments.

Emerging paradigms such as federated learning and edge intelligence offer promising directions, enabling decentralized learning while preserving data privacy. However, these approaches introduce new challenges related to communication overhead, synchronization, and convergence, which require further investigation (Kairouz et al., 2021).

6.5 Trustworthy and Explainable AI

Ensuring trust, transparency, and accountability will be critical for the widespread adoption of AI-driven communication networks. Future research should focus on developing explainable AI (XAI) techniques that provide insights into model behavior without compromising performance.

In addition, there is a need for frameworks that incorporate robustness, safety guarantees, and formal verification, particularly in mission-critical applications where system failures can have severe consequences.

6.6 Bridging the Gap Between Theory and Practice

Perhaps the most important research direction is bridging the gap between algorithmic innovation and real-world deployment. While many studies report promising results under simulation conditions, practical implementation remains limited by computational constraints, data availability, and system integration challenges (Dulac-Arnold et al., 2021; Wang et al., 2020).

Future work should therefore emphasize:

- Real-world experimentation and testbeds
- Deployment-aware model design
- Standardized evaluation frameworks

This shift from performance-centric to deployment-oriented research is essential for realizing the full potential of AI-driven 6G networks.

7. **Conclusion**

This paper has presented a system-level critical review of artificial intelligence-driven control and optimization in communication networks, with a particular focus on emerging 6G systems. Unlike traditional surveys that primarily catalogue existing techniques, this study has emphasized the conceptual, architectural, and operational dimensions of integrating AI into next-generation communication infrastructures.

The analysis demonstrates that while AI techniques—including machine learning, deep learning, and reinforcement learning—offer significant potential for enhancing network performance, their current application remains fragmented, scenario-specific, and often disconnected from system-level integration requirements. In particular, the review highlights a persistent gap between algorithmic advancements and practical deployment, where many proposed solutions are validated under idealized conditions but lack scalability, robustness, and interoperability in real-world environments.

Furthermore, this work has identified several critical challenges, including scalability limitations, computational complexity, data constraints, integration difficulties, lack of explainability, and absence of theoretical guarantees. These issues collectively indicate that the transition toward intelligent and autonomous 6G networks is not merely a matter of adopting advanced algorithms, but requires a holistic rethinking of network control, optimization, and architectural design.

A key insight emerging from this study is that no single AI paradigm is sufficient to address the diverse and often conflicting requirements of next-generation communication systems. Instead, future networks will likely rely on hybrid and integrated approaches that combine data-driven intelligence with model-based control, enabling a balance between adaptability, reliability, and efficiency.

From a broader perspective, this review contributes by providing:

- A structured and critical synthesis of AI techniques for network control and optimization

- A comparative analysis highlighting trade-offs and system-level implications
- A unified perspective on the integration of control, optimization, and autonomous network management
- Identification of key research gaps and future directions toward AI-native 6G systems

Looking forward, the evolution toward AI-native communication networks will depend on the ability to bridge the gap between theoretical innovation and practical deployment, moving toward scalable, trustworthy, and architecture-aware solutions. In this context, this work provides a foundation for future research aimed at realizing intelligent, autonomous, and sustainable communication networks aligned with the vision of IMT-2030.

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