Iğdır Üniversitesi Fen Bilimleri Enstitüsü Dergisi, 16(1), 14-30, 2026
Journal of the Institute of Science and Technology, 16(1), 14-30, 2026
ISSN: 2146-0574, eISSN: 2536-4618
Computer Engineering **DOI: 10.21597/jist.1676718**
Research Article
Geliş tarihi / *Received*: 15.04.2025 **Kabul tarihi / *Accepted*: 03.07.2025**

To Cite: Bilen, T. (2026). Knowledge-Defined Networking: A Superior Paradigm for Autonomous 6G Systems. *Journal of the Institute of Science and Technology*, 16(1), 14-30.

Knowledge-Defined Networking: A Superior Paradigm for Autonomous 6G Systems

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Highlights:
- Network Management
- Autonomous Systems
- 6G

Keywords:
- 6G
- KDN
- Small Cell
- Autonomous Systems

ABSTRACT:

The emergence of 6G networks introduces a new level of complexity by requiring robust and adaptive solutions for network management. Although Artificial Intelligence (AI) and Machine Learning (ML) approaches can support dynamic network conditions, their dependence on large datasets, lack of transparency, and high computational demands limit their effectiveness in real-world applications. Accordingly, this paper presents knowledge-defined networking (KDN) as a superior approach that combines domain-specific knowledge with AI/ML capabilities to enhance network management performance. The proposed KDN architecture consists of four modular planes—Data, Control, Knowledge, and Management—that interact seamlessly to improve decision-making and management. Through a comparative analysis, this study highlights the benefits of KDN in routing management, including higher packet delivery ratios (up to 21% improvement), reduced latency (up to 32% lower), lower energy consumption (up to 27% savings), and improved adaptability (up to 36% enhancement) in changing network conditions. Empirical results from a simulated 6G environment show that KDN consistently outperforms other AI/ML approaches. These results support KDN as a crucial framework to overcome the limitations of AI/ML for intelligent and reliable network management.

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INTRODUCTION

The introduction of 6G networks brings transformative improvements to wireless communication. 6G promises ultra-high data rates, low latency, and massive device connectivity, enabling a wide range of intelligent services (Na et al., 2024). Compared to previous generations, it offers substantial advancements in spectrum efficiency, energy consumption, and the integration of artificial intelligence (AI) and machine learning (ML) into network management. These technological breakthroughs are expected to power next-generation applications such as immersive augmented and virtual reality, real-time remote healthcare, and fully autonomous transportation systems. By extending the capabilities of existing infrastructures, 6G is positioned to drive innovation and unlock new possibilities across various sectors (Zong et al., 2019).

One of the foundational elements of 6G architecture is the deployment of ultra-dense small cells. These cells are distributed throughout urban and rural areas to enhance coverage and increase network capacity. Unlike traditional macro cell-based networks, small cells enable localized high-throughput communication, ensuring reliable service even in environments with high user density (Tinh et al., 2022). As a result, small cell deployment plays a vital role in satisfying the strict latency and bandwidth demands of 6G applications.

However, the deployment of ultra-dense small-cell networks introduces several technical and practical challenges. Key issues include managing interference between closely located cells, enabling efficient handover mechanisms, and maintaining consistent quality of service across overlapping coverage zones, as illustrated in Figure 1. The close proximity of cells inherently increases the risk of interference, while frequent handovers demand sophisticated coordination to preserve session continuity. In addition, the large-scale rollout of small cells involves considerable infrastructure investment and logistical complexity, including challenges related to site acquisition, power provisioning, and backhaul connectivity.

Figure 1. The challenges for the 6G small cell deployment and AI/ML integration

To address these challenges, artificial intelligence and machine learning techniques have been widely explored in the literature (Tshakwanda et al., 2024). These methods can improve network performance by dynamically allocating resources, minimizing interference, and optimizing handover operations. AI algorithms are capable of analyzing large volumes of data to support more efficient and adaptive network control (Yi et al., 2025). Machine learning models, in particular, can forecast traffic patterns and adjust network parameters in real-time to maintain service quality. Furthermore, AI-based solutions can enhance fault detection by identifying network anomalies and initiating automated corrective actions. As illustrated in Figure 1, such capabilities make AI and ML valuable tools for enhancing efficiency and reliability in ultra-dense small-cell environments.

Despite their advantages, AI and ML approaches face notable limitations in practical deployments, as also summarized in Figure 1. The computational complexity of advanced algorithms often results in substantial processing and energy requirements. In addition, these models heavily depend on the availability of large, high-quality datasets for training. In real-world conditions, however, such datasets may be incomplete, outdated, or unavailable, potentially leading to degraded performance. Another concern involves algorithmic bias caused by imbalanced training data or unanticipated network scenarios, which can lead to unfair or ineffective decision-making. Moreover, integrating AI/ML solutions into existing network infrastructure typically involves significant technical and operational effort, increasing the deployment complexity and time.

Knowledge-Defined Networking (KDN) has emerged as a promising alternative to address these limitations (Bilen T., 2025). By unifying artificial intelligence, software-defined networking (SDN), and machine learning within a cohesive architecture, KDN facilitates intelligent, adaptive, and context-aware network management. It is designed to collect network data, learn from historical and real-time patterns, and make informed decisions to optimize performance. Unlike standalone AI/ML systems, KDN enhances learning efficiency by embedding decision logic within a modular, feedback-driven control framework. In addition, the incorporation of SDN enables KDN to flexibly configure and manage resources in response to dynamic network states. As such, KDN provides a scalable and practical solution for managing the complexity of ultra-dense small-cell networks.

In the literature, various works have utilized KDN for different aims. (Souza et al., 2022) proposes a fault-tolerant framework for Virtual Network Function scheduling in data centers by leveraging KDN and Long Short-Term Memory for multi-step forecasting and resource optimization. It aims to address challenges like affinity rules, failure management, and efficient resource utilization in Network Functions Virtualization. The methodology integrates deep learning for predictions, affinity-based resource allocation, and automated rescheduling to enhance reliability and performance in large-scale environments. (Yang et al., 2025) introduces a KDN-based adaptive framework for optimizing computation offloading and resource allocation in large-scale dynamic networks. The goal is to enhance long-term user satisfaction by addressing resource allocation challenges through a perception module and deep reinforcement learning (DRL)-based strategy. The methodology involves the environmental resource change perception module for real-time resource assessment and the AL-CORA algorithm for adaptive, multi-objective optimization using Markov Decision Processes. (Zeman et al., 2023) proposes a reinforcement learning-based framework for KDN to optimize 6G network architectures. The focus is to utilize Software-Defined Networking, P4-programmable devices, and in-band network telemetry to achieve real-time feedback and dynamic policy adjustments. The methodology integrates reinforcement learning principles into network design by considering the entire network as a learning entity. (Zhang et al., 2025) presents a novel Knowledge-defined Edge Computing architecture that integrates KDN into edge computing for intelligent task offloading and resource allocation in large-scale dynamic networks.

It aims to minimize delay and energy consumption by optimizing resource requirements, controller deployment, and task offloading decisions. The methodology includes algorithms to achieve efficient resource utilization and adaptive controller placement.

A self-driving network architecture combining KDN, SDN, and P4-based In-band Network Telemetry to enable closed-loop network management is proposed in (Hyun & Hong, 2017). It aims to reduce operational costs and improve performance by leveraging packet-level telemetry, centralized SDN control, and AI-driven decision-making. The methodology integrates metadata collection, machine learning for policy generation, and intent-driven network reconfiguration to create automated management processes. (Zhang et al., 2023) proposes a KDN-oriented multi-domain SDN routing framework that integrates a graph neural network-based Double Deep Q-network algorithm for intelligent routing. The aim is to enhance network performance by reducing delay jitter and packet loss rates. The methodology involves modelling SDN network topology as graph data, using reinforcement learning for intelligent routing decisions, and deploying a three-layer multi-controller architecture to optimize inter-domain routing.

An AI-assisted KDN framework for cross-layer orchestration in IP-over-elastic Optical Networks is proposed in (Zhu et al., 2018). It aims to enhance network performance and cost-effectiveness by integrating deep learning for proactive traffic analysis and prediction. The methodology incorporates a deep learning module for traffic forecasting, a control plane for real-time cross-layer orchestration, and adaptive routing based on predicted network dynamics.

Table 1. Overview of recent KDN-based studies

Study	Main Objective	Approach / Methodology	Scope and Key Contribution
Souza et al., 2022	To provide fault-tolerant scheduling of virtual network functions in data centers	Integration of Long Short-Term Memory-based prediction with knowledge-defined networking for multi-step forecasting and resource rescheduling	Enhances reliability and resource utilization in network function virtualization environments
Yang et al., 2025	To optimize computational offloading and resource allocation in large-scale dynamic networks	A knowledge-defined networking architecture supported by a perception module and deep reinforcement learning strategy	Improves long-term user satisfaction by adapting to dynamic environmental conditions
Zeman et al., 2023	To enable adaptive policy learning in future network architectures	A knowledge-defined networking framework that combines reinforcement learning, software-defined networking, P4 programmable devices, and in-band network telemetry	Provides real-time feedback and network-wide learning for intelligent policy adaptation
Zhang et al., 2025	To perform intelligent task offloading and energy-efficient resource scheduling at the edge of the network	Deployment of a knowledge-defined edge computing architecture with dynamic controller placement and optimization algorithms	Minimizes delay and energy consumption in edge computing environments
Hyun and Hong, 2017	To design a self-driving network with closed-loop control	Combination of software-defined networking, artificial intelligence, and packet-level telemetry in a unified architecture	Enables automated decision-making and intent-based network reconfiguration
Zhang et al., 2023	To improve inter-domain routing in software-defined multi-domain networks	A graph-based approach that uses a double deep Q-network within a knowledge-defined networking model	Reduces packet loss and jitter by intelligently learning from network topology data
Zhu et al., 2018	To coordinate optical layer and internet protocol layer for efficient data transport	Integration of deep learning-based traffic prediction with knowledge-defined cross-layer orchestration	Achieves cost-effective and adaptive routing in elastic optical networks
Sánchez et al., 2024	To analyze emerging security concerns in next-generation networks	A comprehensive review of 5G and 6G security requirements with focus on trust, policy, and isolation	Highlights the role of knowledge-based control in future secure network architectures
Akbar et al., 2024	To summarize global challenges in 6G architecture and intelligence integration	Systematic survey of key enablers including artificial intelligence, automation, and dynamic orchestration	Supports the need for knowledge-driven frameworks to manage 6G complexity

In addition to prior KDN-based approaches, recent comprehensive surveys and system-level analyses provide broader context and validation for our architecture. For instance, (Scalise et al. 2024) present a systematic review of security challenges in 5G/6G environments, highlighting how knowledge-defined mechanisms are crucial to addressing emerging trust and isolation requirements. Furthermore, global 6G surveys (e.g., Akbar et al., 2024) emphasize challenges in AI-integration, security, and adaptive architectures, further validating our choice to meld domain knowledge and AI for robust 6G routing. A summary of key knowledge-defined networking studies and their contributions is provided in Table 1.

Unlike the above works, the proposed model features a unified four-plane architecture: Data Plane, Control Plane, Knowledge Plane, and Management Plane. This design integrates real-time feedback loops across all layers to optimize 6G network management dynamically. Unlike conventional systems, which often depend on separate layer orchestration or limited predictive capabilities, this model facilitates direct communication between the Data and Knowledge planes. This enables immediate insight generation and actionable intelligence. The proposed model also introduces a Knowledge Generation Module within the Knowledge Plane. This module transforms raw AI/ML outputs into structured knowledge that aligns with operational needs. It effectively bridges the gap between analytics and practical implementation. By utilizing this closed-loop, knowledge-driven framework, the proposed model surpasses traditional approaches. Accordingly, it achieves greater adaptability and transparency in decision-making, specifically tailored to the unique demands of 6G networks.

This paper proposes a modular and feedback-driven knowledge-defined networking (KDN) architecture tailored for the autonomous management of 6G networks. Unlike traditional artificial intelligence and machine learning approaches, which often rely on static models and extensive offline training, the proposed system integrates real-time domain knowledge with AI outputs in a transparent and adaptable manner. KDN enhances system-level intelligence by enabling bidirectional coordination across all functional planes (Data, Control, Knowledge, and Management) thus improving the ability to react to fast-changing network conditions. It offers improved flexibility by supporting real-time policy adaptation, enhanced scalability through modular design, and greater security via knowledge-enforced control mechanisms. Through its global view of network states and contextual decision-making capabilities, KDN addresses the performance and manageability gaps often observed in ultra-dense and dynamic 6G infrastructures. Furthermore, KDN is inherently compatible with emerging 6G requirements such as network slicing, autonomous service delivery, and integration with digital twins, making it a future-proof and practical solution for next-generation wireless systems. The main contributions of this paper are summarized as follows:

- We propose a modular and layered KDN architecture that enables direct and continuous data flow from the data plane to the knowledge plane, significantly improving real-time adaptability and responsiveness.
- We emphasize the architectural role of KDN in enabling autonomous system behavior, by introducing a closed-loop feedback mechanism that supports intelligent, context-aware decision-making across diverse network conditions.
- We conduct a detailed comparative analysis of KDN and conventional AI/ML approaches, demonstrating the superiority of KDN in dynamic 6G environments with respect to key performance metrics including Packet Delivery Ratio (PDR), latency, energy efficiency, and adaptability.

The rest of the paper is organized as follows: We first give the proposed model under the Materials and Methods Section. Then, we explain the simulation environment and details under the Results and Discussion Section. Finally, we finalize the paper in Conclusion Section.

MATERIALS AND METHODS

The Proposed Model

The proposed KDN-based 6G Management Model consists of four main functional planes: the Data Plane, Control Plane, Knowledge Plane, and Management Plane, as shown in Fig. 2. These planes work within a closed-loop feedback system. This setup allows for continuous network optimization through real-time monitoring, smart decision-making, and adaptive policy adjustments. Each plane has a specific role, but they are all closely connected. This connection ensures that the system is responsive and coherent. The modular and layered design improves scalability and flexibility. It also allows decisions to be adjusted dynamically based on changing network conditions, service demands, and performance goals.

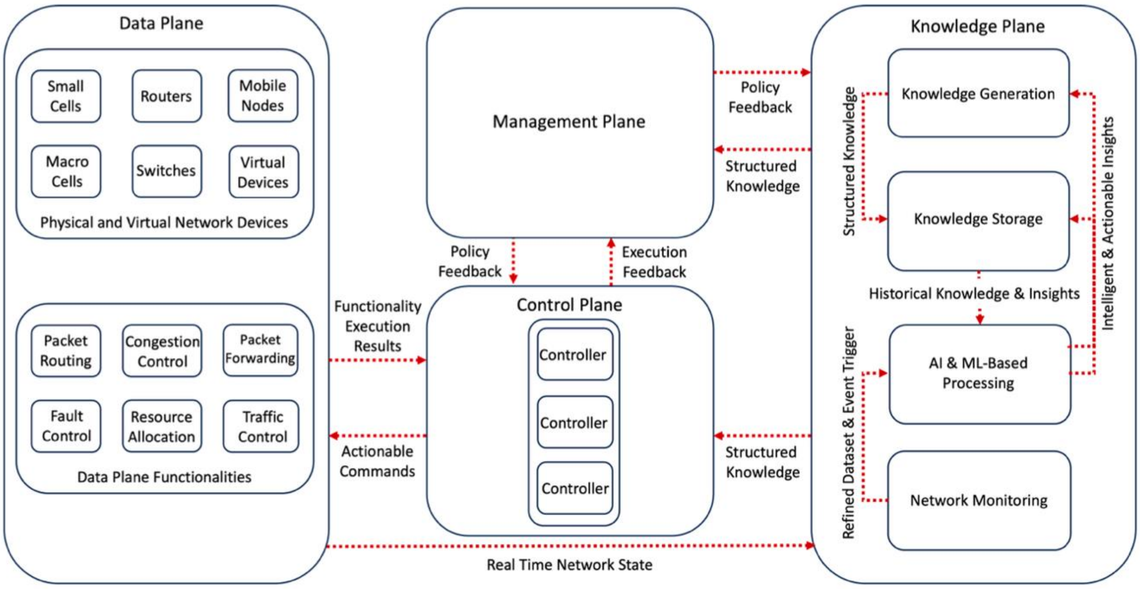


Figure 2. The proposed model

Data plane

The Data Plane includes the physical and virtual infrastructure of the 6G network. This consists of switches, routers, small cells, and base stations that form the foundation of ultra-dense, high-throughput communication environments. In 6G networks, the Data Plane must support massive device connectivity, sub-millisecond latency requirements, and energy-aware forwarding. Its main job is to handle traffic in real time, forward packets, and execute routing decisions under dynamic and often volatile conditions. As shown in Figure 2, this layer continuously collects important network metrics such as traffic volume, latency, error rates, signal quality, and energy consumption. These raw data streams are sent directly to the Knowledge Plane for immediate analysis, creating a low-latency feedback loop between real-time operations and intelligent control. Simultaneously, the Data Plane receives execution commands from the Control Plane. These commands may include routing path assignments, QoS prioritizations, and load balancing strategies for 6G. This bidirectional interaction enables the Data Plane not only to enforce decisions but also to provide granular feedback that helps refine policies, ensuring continuous optimization under 6G-grade demands.

Control plane

The Control Plane, as summarized in Table 2, follows SDN (Software Defined Networking) principles and acts as a programmable link between the Data Plane and the Knowledge/Management planes. It includes a centralized controller and APIs for two-way communication. The controller takes structured decisions from the Knowledge Plane and turns them into specific instructions for the Data Plane. Southbound interfaces manage low-level commands (like OpenFlow), while northbound APIs connect with high-level orchestration logic and strategic policies. As shown in Figure 2, the Control Plane also sends operational outcomes, such as throughput performance and execution logs, back to the Management Plane for ongoing strategy evaluation. By connecting abstract policies with executable commands, the Control Plane is essential for maintaining flexibility in the architecture.

Knowledge plane

The Knowledge Plane, as summarized in Table 2, serves as the analytical and cognitive core of the proposed KDN-based 6G management architecture. It plays a central role in enabling transparent, context-aware, and adaptive decision-making by synthesizing real-time network data, historical knowledge, and AI/ML-generated insights. Its primary goal is to convert raw, fragmented information into structured, actionable knowledge aligned with operational goals. To achieve this, the knowledge plane is composed of four tightly integrated components: the Knowledge Generation Module**,** Knowledge Storage Module**,** Network Monitoring Module, and AI & ML-Based Processing Module. Each serves a distinct function but operates in coordination to close the loop between data sensing and policy execution. The details of these components could be explained as follows:

- **Knowledge generation module:** This module is responsible for transforming AI/ML outputs into structured, domain-specific knowledge that can be effectively utilized within network operations. While the AI/ML-based module excels at extracting patterns, correlations, and predictions from large-scale data, these outputs often lack contextual structure. The Knowledge Generation Module bridges this gap by formalizing such outputs into interpretable formats such as statistical summaries, rule-based representations, policy graphs, decision trees, or topological mappings. These forms of structured knowledge are tailored to reflect the network's performance objectives, security constraints, and service-level policies. By organizing learned insights in a format usable by downstream components, this module ensures that machine intelligence becomes operationally deployable. It enables the KDN system to autonomously adapt to both immediate network conditions and long-term trends. Therefore, it enhances the robustness and responsiveness of control decisions.
- **Knowledge storage module:** This module functions as a structured and extensible repository that maintains both static and dynamic knowledge elements essential for network management. It stores predefined policies, architectural blueprints (e.g., network topology), QoS thresholds, and SLAs, alongside time-varying data such as real-time traffic metrics, congestion maps, anomaly logs, and decision histories. Architecturally, the module is designed as a hierarchical and heterogeneous storage system capable of handling relational, time-series, and graph-structured data. It supports scalable mechanisms such as distributed storage clusters, intelligent caching strategies, and compression-based optimization for efficiency. A crucial function of this module is its bi-directional integration with the AI/ML and Knowledge Generation modules. It not only provides historical context to aid training and inference but also receives tagged insights to support interpretability and traceability. By maintaining consistency through validation layers and conflict resolution rules, this module enables rapid access to validated knowledge, which is essential for tasks such as fault prediction, proactive resource allocation, and policy refinement.
- **Network monitoring module:** The monitoring module acts as a continuous sensing layer that ensures situational awareness within the network. It gathers fine-grained telemetry data from the Data Plane, including traffic volumes, latency distributions, link utilization, error patterns, and environmental

context (e.g., mobility levels or device churn). Advanced data sampling techniques and low-overhead telemetry protocols (e.g., In-band Network Telemetry or INT) are employed to capture the dynamics of the network without degrading performance. This module not only serves as the entry point for raw data but also performs lightweight preprocessing (such as noise filtering, time windowing, and basic statistical analysis) to reduce the load on the AI/ML layer. In event-driven scenarios, it can trigger alerts or threshold-crossing signals that initiate dynamic policy evaluations. Thus, the monitoring module forms a vital link between the operational status of the network and its intelligent control systems, enabling real-time responsiveness and closed-loop adaptation.

- **AI&ML-Based processing module:** This module is tasked with transforming raw and preprocessed network data into actionable insights through a variety of AI and ML techniques. It ingests input from three sources: (i) the Data Plane, providing real-time operational metrics; (ii) the Knowledge Storage Module, offering historical context and domain rules; and (iii) the Management Plane, which feeds back the effectiveness of previously implemented strategies. Depending on the application, the module may employ supervised learning (e.g., traffic classification), unsupervised learning (e.g., anomaly detection), or reinforcement learning (e.g., routing and resource allocation). It may also support federated or transfer learning approaches in cross-domain scenarios. The output of this module is passed to the Knowledge Generation Module for formalization and system-wide use. This layer enables the KDN architecture to remain proactive, scalable, and adaptive in highly dynamic environments.

Together, these four modules endow the Knowledge Plane with the ability to convert raw data into reliable, context-aware, and transparent decisions. The resulting structured knowledge is transmitted to the Control Plane, where it is translated into executable actions that are then enforced in the Data Plane. This layered coordination enables intelligent automation and situational adaptation in the face of evolving 6G network conditions.

Management plane

The Management Plane, as summarized in Table 2, represents the strategic and supervisory layer of the KDN-based 6G architecture. Unlike the operational and real-time orientation of the Data, Control, and Knowledge planes, the Management Plane focuses on long-term network objectives, high-level policy definitions, and system-wide orchestration. It serves as the primary decision authority for defining service-level goals, managing global consistency, and ensuring that automated operations remain aligned with overall performance expectations. This layer continuously ingests structured feedback from both the Knowledge Plane such as learned behavior patterns, evolving optimization strategies, and historical performance insights. Also, it receives the feedbacks from the Control Plane including policy compliance status, error logs, and action outcomes. By synthesizing these multi-source inputs, the Management Plane is capable of assessing whether current policies are achieving their intended outcomes or whether adaptation is required. Based on this assessment, it can proactively revise, re-prioritize, or entirely redeploy network-wide strategies.

Furthermore, the Management Plane plays a vital role in lifecycle orchestration, such as provisioning new slices, decommissioning outdated resources, and coordinating inter-domain collaboration in multi-operator 6G environments. Its strategic oversight ensures that the intelligent, automated processes governed by the other planes continuously reflect the evolving business, regulatory, and performance landscapes. In addition to its autonomous role, the Management Plane also serves as the principal interface for human-in-the-loop interaction. Network administrators and operators can intervene through this plane to conduct root-cause analysis, override automated decisions in critical situations (e.g., hardware failures, emergency re-routing), or inject new service intents.

Table 2. Summary of KDN plane roles

Plane	Role and Functionality
Data Plane	- Handles data plane functionalities. - Collects raw metrics and sends them to the knowledge plane. - Sends functionality execution results as operational feedback to the control plane. - Executes instructions from the Control Plane
Control Plane	- Translates insights from the Knowledge and Management Planes into actionable commands. - Implements operational strategies derived from the Knowledge Plane. - Provides feedback about functionalities to the Knowledge Plane for refining strategies.
Knowledge Plane	- Serves as the analytical core of knowledge defined networks. - Processes raw data, generates insights using artificial intelligence & machine learning, and maintains structured knowledge to the control and management planes.
Management Plane	- Oversees high-level policy creation and long-term strategic planning. - Combines the analytical capabilities of the Knowledge Plane with the operational actions of the Control Plane. - Validates operational success and refines policies based on execution results.

RESULTS AND DISCUSSION

Simulation Setup

The simulations were conducted using the NS-3 (Network Simulator 3) platform (version 3.38), which offers high flexibility and precision for modeling ultra-dense and dynamic 6G network topologies. NS-3 supports packet-level simulation, advanced mobility patterns, and customizable wireless channel models, making it particularly suitable for evaluating architectures like KDN that rely on real-time decision mechanisms. Python (version 3.10) was employed for auxiliary tasks, including the generation of dynamic traffic profiles under varying network loads and the parsing and visualization of trace outputs exported from NS-3.

To ensure statistical robustness, each simulation scenario was repeated 30 times with randomized seeds. The experiments were grouped into two main categories: (i) Varying user densities, ranging from sparse to highly dense deployments, and (ii) Network dynamism levels, defined via a composite metric that includes user mobility speed, traffic burst frequency, and topology reconfiguration rate. Dynamism levels were scaled from 1 (quasi-static) to 10 (highly volatile) to simulate the challenging operational contexts of 6G. For instance, a dynamism level of 1 corresponds to a quasi-static scenario with stable traffic and fixed topology, whereas level 10 represents an environment with high-speed users, unpredictable traffic bursts, and frequent topology reconfigurations. Accordingly, this scale models the intensity of real-time variability in the network.

The simulated network topology follows a mesh-based architecture consisting of interconnected switches, routers, and small cells, with variable inter-node distances to reflect both urban macrocell and smallcell deployment patterns. Backhaul links were assumed to have a constant capacity of 1 Gbps. Wireless transmission employed a 64-QAM modulation scheme over a 20 MHz bandwidth and a 3.5 GHz carrier frequency, with default transmission and reception powers of 2W and 0.5W, respectively. The antenna gain was set to 5 dBi, and the node mobility was modeled using the Random Waypoint model. The maximum coverage radius of a small cell was 100 meters. Table 3 summarizes the key simulation parameters used across all experiments.

Table 3. Simulation parameters

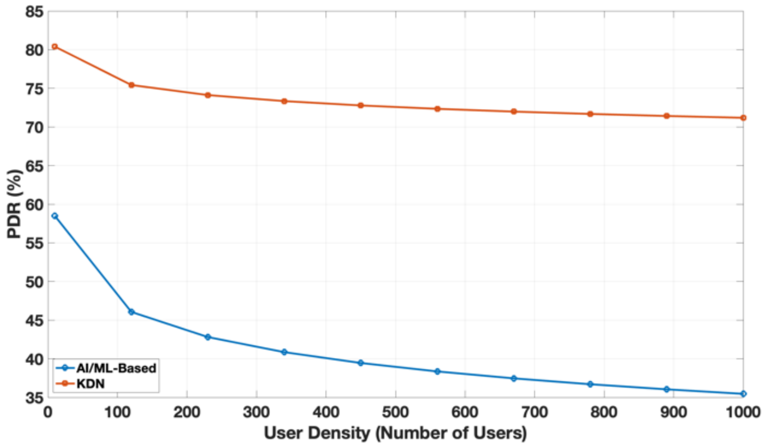
Parameter	Value / Description
Simulation Tool	NS-3 (version 3.38)
Programming Language	Python 3.10 (traffic generation & log parsing)
Simulation Time	120 seconds per run
Number of Nodes	150 (variable topology: small cells, routers, UEs)
Topology Type	Grid and Random Mesh (for density variability)
Mobility Model	Random Waypoint (5–15 m/s range)
Mobility Variation	3 levels (low, medium, high)
Traffic Types	CBR (UDP) + Bursty (Pareto-based TCP)
Traffic Mix Ratios	100:0, 75:25, 50:50, 25:75, 0:100 (CBR:Bursty)
Bandwidth	20 MHz
Carrier Frequency	3.5 GHz
Modulation Scheme	64-QAM
Transmission Power	2 Watts
Reception Power	0.5 Watts
Antenna Gain	5 dBi
Noise Floor	–100 dBm
Coverage Radius (per cell)	100 meters
Path Loss Model	Log-Distance + Shadowing
Backhaul Capacity	1 Gbps
Queue Type	DropTail (per-interface FIFO)

Traffic generation was designed to reflect heterogeneous application behaviors. Both TCP and UDP flows were utilized, incorporating a mix of Constant Bit Rate (CBR) streams and Pareto-distributed bursty traffic to represent video streaming, background file transfer, and control plane signaling. This mixture aims to emulate real-world traffic dynamics within dense network deployments. Also, in these simulations, two routing paradigms were evaluated:

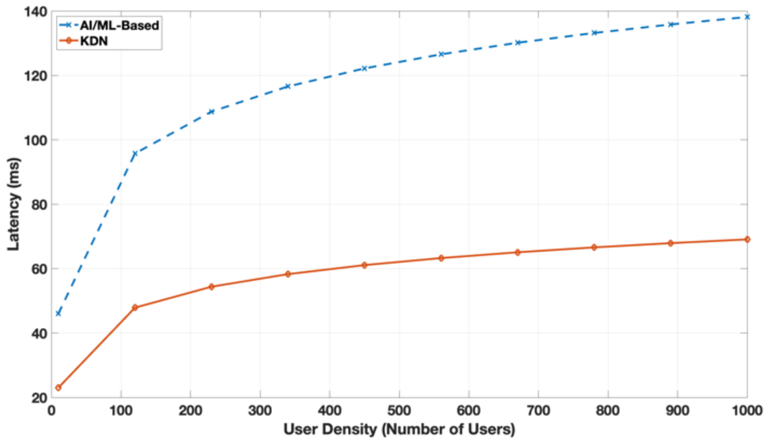
- The AI/ML-based routing utilized a Q-learning agent. The agent selected routes based on network states defined by link load and delay. The Q-table was updated using temporal difference learning with a learning rate of 0.1 and a discount factor of 0.9. An ε-greedy policy with $\varepsilon = 0.2$ controlled exploration. These hyperparameters were tuned in preliminary experiments to achieve optimal trade-offs between Packet Delivery Ratio (PDR) and latency. Training was conducted offline on representative network snapshots, and once convergence was achieved (~250 episodes), the learned policy was applied during evaluation runs.
- The KDN-based routing, in contrast, did not rely on offline training. Instead, it leveraged a real-time knowledge plane that continuously collected telemetry, processed state abstractions, and issued routing policies based on current network feedback. This design allowed for adaptive policy updates in response to traffic and topology changes without the need for retraining, thus offering more responsiveness under dynamic conditions.

Simulation results

Based on the above explained simulation environment, we evaluate the proposed approach's performance according to packet delivery ratio (PDR), latency, energy, and adaptability with increasing user density and network dynamism. In scenarios with increasing user density, AI/ML-based approach begins to performance deterioration as network congestion rises. More specifically, as shown in Figure 3a, PDR declines sharply as the number of users increases beyond a threshold. The AI/ML-based approach cannot dynamically incorporate real-time network fluctuations since it is depended on pre-trained models. For this reason, it results in higher packet loss. On the other hand, as shown in Figure 3a, KDN demonstrates superior PDR even at high user densities. Here, the knowledge plane's generation module is combined with the control plane's real-time execution. This allows proactive routing decisions that enable minimal PDR degradation. Similarly, the computational overhead of AI/ML-based systems becomes a bottleneck with increasing user density. Accordingly, as shown in Figure 3b, latency grows non-linearly due to the time required for handling large-scale datasets for routing optimization. However, KDN-based approach keeps average latency low even under heavy network loads, as shown in Figure 3b. At that point, KDN avoids the high computational complexity associated with AI/ML algorithms by directly applying domain-specific knowledge.



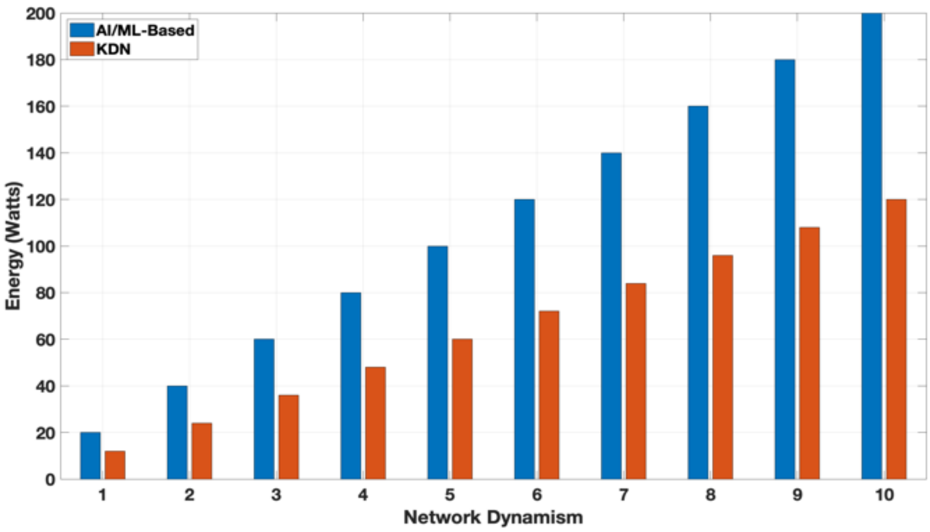
(a)



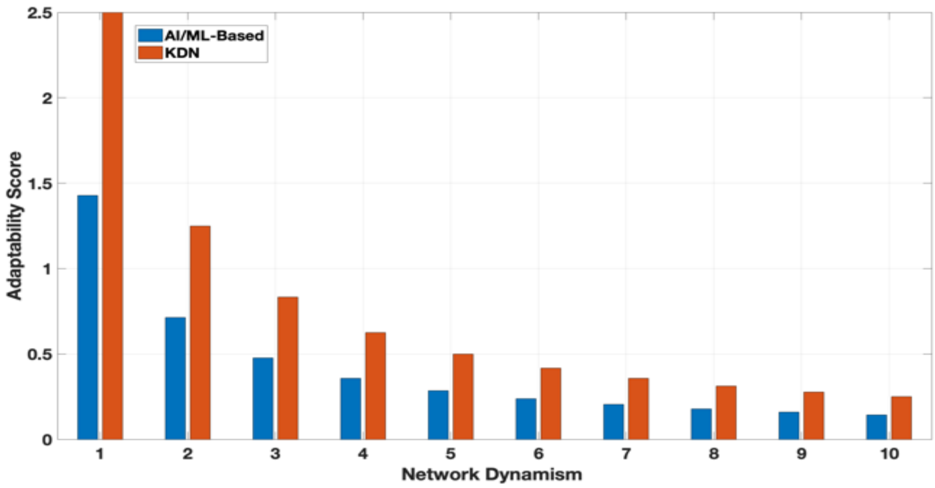
(b)

Figure 3. PDR (a) and latency (b) Analysis according to user density number

Additionally, AI/ML-based systems encounter substantial limitations in highly dynamic network environments, where traffic conditions and topology may change rapidly and unpredictably. In such scenarios, maintaining optimal performance requires frequent updates or retraining of the learning models to reflect the new system state. This process is computationally intensive and significantly increases energy consumption, as illustrated in Figure 4a. More specifically, adapting to sudden fluctuations in traffic volume or user mobility patterns requires substantial processing resources. This results in higher latency and reduced system responsiveness, as shown in both Figure 4a and Figure 4b. In contrast, the proposed KDN architecture addresses these challenges through its real-time knowledge plane, which continuously assimilates network metrics without the need for offline retraining. By leveraging a feedback-driven control mechanism between the data, control, and knowledge planes, the system can update routing policies and resource allocations on-the-fly. This design enables low-latency adaptation to dynamic conditions while significantly reducing computational overhead. As a result, the KDN-based system maintains higher adaptability and improved energy efficiency under dynamic traffic patterns and topological changes, as demonstrated in Figures 4a and Figure 4b.



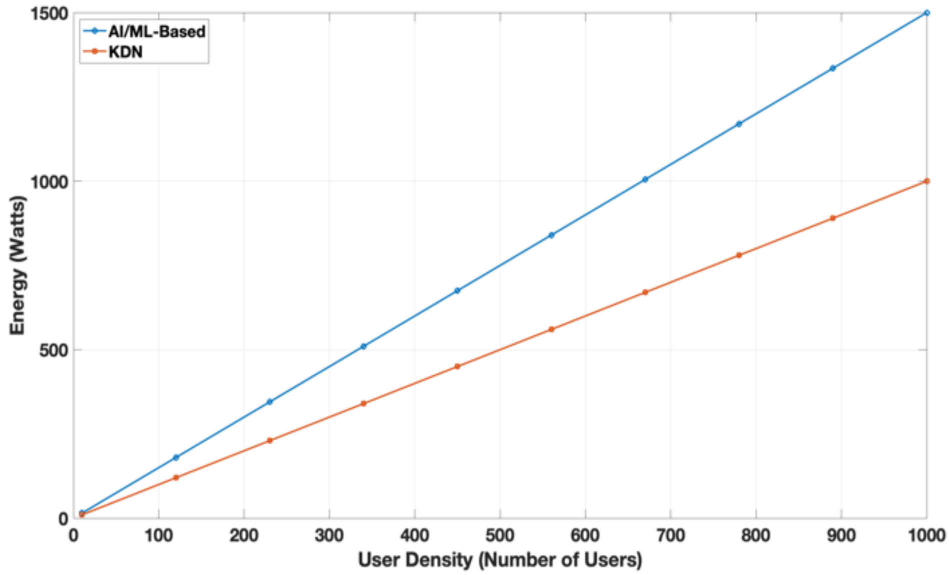
(a)



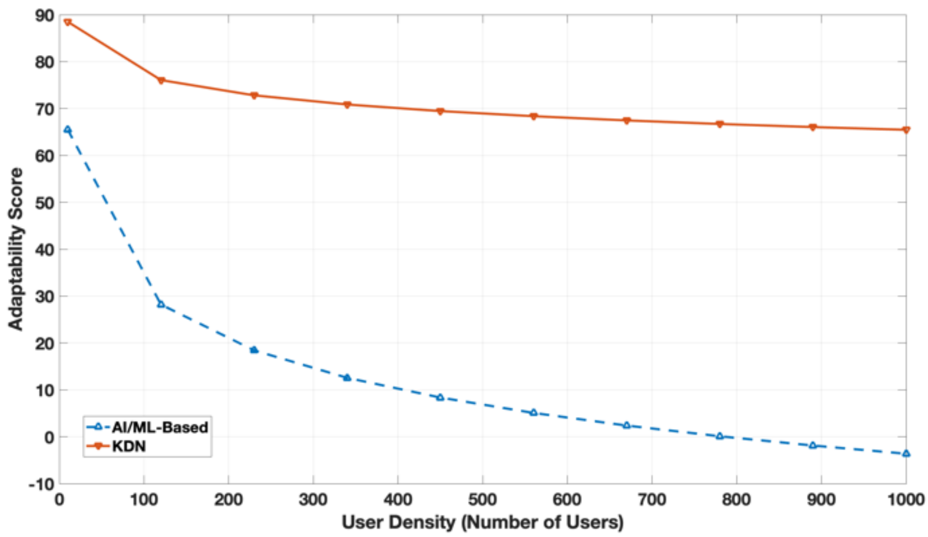
(b)

Figure 4. Energy (a) and adaptability (b) analysis according to network dynamism

AI/ML-based approaches exhibit significantly higher energy consumption as user density increases, as illustrated in Figure 5a. This is primarily due to their limited ability to adapt to unanticipated traffic loads without undergoing substantial retraining or manual reconfiguration. The iterative computations required for model adjustment introduce considerable processing overhead, leading to increased power usage and latency. In contrast, the KDN architecture minimizes energy consumption by replacing resource-intensive learning cycles with knowledge-driven decision processes. By relying on predefined rules and continuously updated real-time metrics, the KDN system avoids the repetitive optimization loops that characterize conventional AI/ML models, resulting in lower computational cost, as shown in Figure 5a. Moreover, AI/ML models must frequently retrain to remain effective as user density scales or new traffic patterns emerge, which constrains their ability to respond swiftly to environmental changes. As depicted in Figure 5b, this leads to reduced adaptability under high-density conditions. The KDN system, on the other hand, continuously incorporates incoming information from the data plane into its knowledge structures. This enables it to dynamically adjust routing and resource decisions in response to evolving network conditions. Consequently, KDN maintains high adaptability scores even under peak user loads, as shown in Figure 5b.



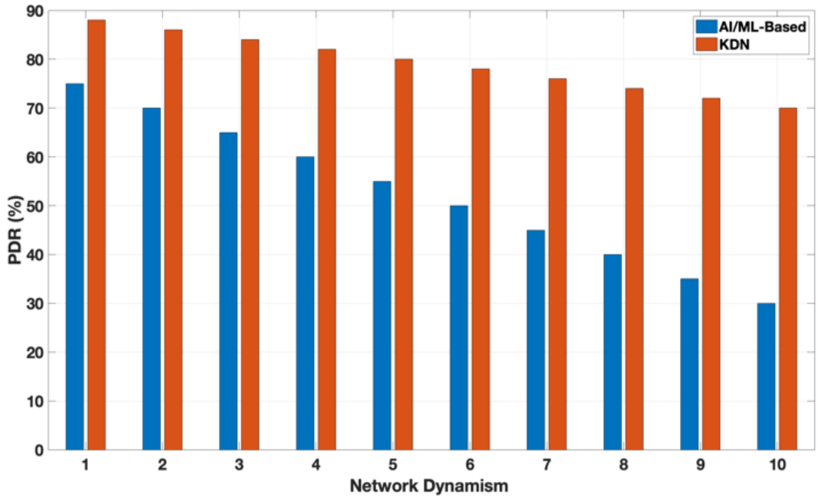
(a)



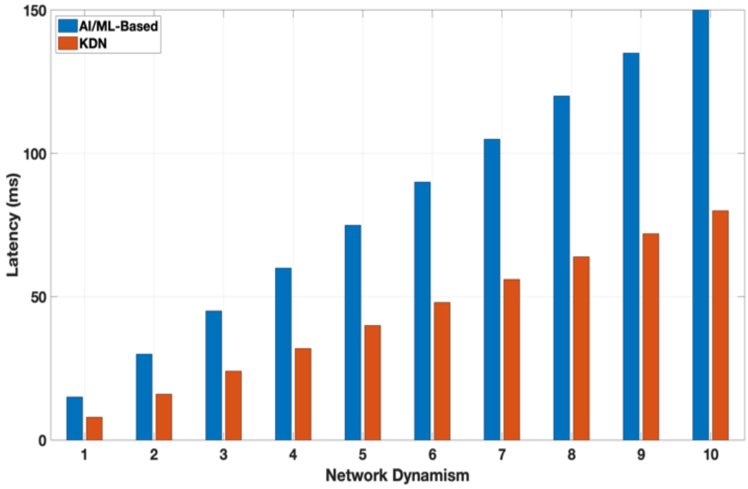
(b)

Figure 5. Energy (a) and adaptability (b) analysis according to user density number

Dynamic network conditions pose a significant challenge for conventional AI/ML systems, which often rely on static models and fixed training datasets. As shown in Figure 6a, the performance of AI/ML models deteriorates under increasing dynamism levels. Their reliance on non-adaptive training data results in reduced packet delivery ratio (PDR), and sudden shifts in traffic patterns frequently lead to suboptimal routing decisions. While retraining can improve performance, this process introduces additional latency during routing, further degrading responsiveness in time-sensitive environments. In contrast, the proposed KDN architecture maintains high routing efficiency across dynamic conditions. This is achieved through adaptive feedback loops and continuous real-time updates to the knowledge plane, allowing the system to revise policies on-the-fly without the need for full model retraining. As illustrated in Figure 6a and Figure 6b, this design enables KDN to consistently deliver higher PDR and lower latency, even in rapidly fluctuating environments. The inherent adaptability of the KDN model stems from its ability to translate live network measurements into actionable insights in real-time, ensuring robust performance across a wide range of dynamism levels. These features are particularly critical in 6G scenarios, where service continuity and ultra-low latency are essential. Therefore, KDN's lightweight, feedback-aware decision cycle offers a scalable alternative that better aligns with the distributed and fast-changing nature of 6G infrastructure.

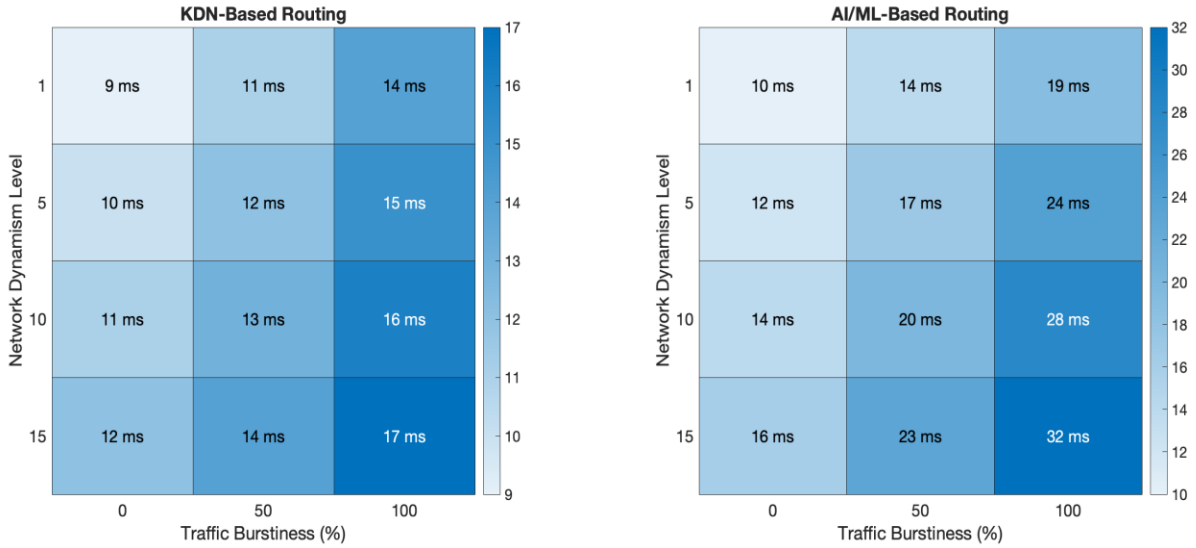


(a)



(b)

Figure 6. PDR (a) and latency (b) analysis according to network dynamism



(a) (b)

Figure 7. Average latency heatmaps for (a) KDN and (b) AI/ML approaches under varying traffic burstiness levels.

Figure 7 illustrates the average latency of the proposed KDN model and the AI/ML-based approach under different traffic burstiness levels. As traffic becomes increasingly bursty (transitioning from constant bit rate (CBR) flows to highly variable traffic patterns), the AI/ML model exhibits a rapid increase in latency due to its limited ability to adapt without retraining. In contrast, the KDN-based system maintains significantly lower latency values across all burstiness levels, thanks to its real-time feedback mechanisms and predefined knowledge-based decision logic. This heatmap comparison highlights KDN's ability to efficiently manage heterogeneous traffic conditions. Specifically, KDN ensures consistent performance even in the presence of abrupt traffic surges typical of 6G application scenarios.

To further support the comparative evaluation in terms of energy and latency, we conducted additional measurements focusing on computational overhead, memory usage, and convergence time. For each routing decision, the AI/ML-based model (implemented using tabular Q-learning) required an average of 3.1 milliseconds and consumed approximately 8.5 MB of memory to store the Q-tables and policy structures. In contrast, the proposed KDN model, which relies on rule-based logic and real-time feedback integration, achieved routing decisions with an average latency of 1.8 milliseconds and required only 5.2 MB of memory, primarily for maintaining runtime state and knowledge structures. Moreover, the AI/ML model required approximately 250 simulation steps to reach a stable policy under typical network conditions. During this training phase, performance fluctuated due to exploration and policy refinement. On the other hand, the KDN model operated in an adaptive manner from the beginning, leveraging domain knowledge to guide decisions without requiring a distinct training phase. This difference highlights KDN's advantage in reducing setup time and maintaining stability under dynamic conditions.

Overall, the results show that the proposed KDN-based model achieves significant performance improvements across multiple network conditions. These findings confirm the effectiveness of a knowledge-driven, feedback-integrated architecture in managing future 6G infrastructures. More specifically, the architecture's ability to continuously incorporate real-time metrics and transform them into actionable decisions via the knowledge plane. As network density and variability increase, the proposed model maintains high levels of reliability and efficiency, highlighting its potential as a practical foundation for next-generation autonomous network management.

Discussion & Future work

Despite its advantages, the proposed KDN architecture may encounter certain limitations when applied to large-scale and highly heterogeneous network environments. As the network size increases, the processing demands on the knowledge plane (particularly for collecting, abstracting, and synthesizing real-time data) can grow substantially. This may lead to latency in decision generation or bottlenecks in high-traffic scenarios, especially when multiple feedback loops are activated simultaneously.

To address this, further architectural refinements will be necessary. For example, hierarchical knowledge abstraction could be used to distribute processing tasks across different layers or domains, thereby reducing the burden on the central knowledge module. Alternatively, decentralized or federated knowledge plane models may allow for local learning and decision-making while maintaining global coordination. These directions represent promising future enhancements for scaling KDN to nationwide or cross-domain 6G infrastructures.

Additionally, we plan to integrate real-time Digital Twin frameworks into the architecture to support predictive management and continuous synchronization between physical and virtual network states. The proposed KDN model will also be extended to support end-to-end 6G network slicing, with dynamic orchestration and SLA (Service Level Agreement)-aware resource control. Finally, to evaluate its robustness and applicability under real-world conditions, we aim to deploy the framework in a physical testbed environment to validate its performance in terms of scalability, fault-tolerance, and cross-domain adaptability.

CONCLUSION

In this study, we demonstrated the advantages of KDN over conventional AI/ML-based approaches for managing next-generation 6G networks. The proposed architecture integrates structured domain knowledge with AI/ML capabilities within a modular, feedback-driven framework. This integration enables real-time adaptability, transparent decision-making, and efficient control across multiple network layers. Through extensive simulations, KDN consistently outperformed AI/ML baselines in key performance metrics. Specifically, it achieved up to 21% improvement in packet delivery ratio, 32% reduction in end-to-end latency, 27% lower energy consumption, and 36% higher adaptability in response to changing network conditions. These results underscore the practical benefits of embedding a knowledge generation and interpretation layer into network control systems, effectively closing the gap between data-driven intelligence and operational decision-making. Therefore, by overcoming several key limitations of AI/ML, the proposed KDN framework positions itself as a transformative solution for intelligent, autonomous, and scalable 6G network management. It not only enhances performance under current demands but also offers the architectural flexibility required to accommodate future technologies such as digital twins, network slicing, and real-time orchestration.

Conflict of Interest Statement

The article author declare that there is no conflict of interest.

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