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A FEDERATED DEEP REINFORCEMENT LEARNING FRAMEWORK FOR AUTONOMOUS NETWORK TRAFFIC OPTIMIZATION IN 6G NETWORKS

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ABSTRACT

Ultra-dense connectivity, massive Internet of Things (IoT) deployment, holographic communications, latency-sensitive intelligent applications, and digital twins are anticipated to be enabled by the rapid adoption of 6G networks. Yet, due to the variety and diversity of 6G traffic, traditional traffic optimization techniques, such as load balancers, face numerous challenges, including limited adaptability and scalability, as well as unresolved privacy concerns. To address these issues, a Digital Twin-Assisted Federated Multi-Agent Deep Reinforcement Learning Framework (DT-FMDRL) is proposed for 6G networks to optimize autonomous network traffic management. The proposed framework integrates Multi-Agent Deep Reinforcement Learning (MADRL), Digital Twin-assisted training, Adaptive Performance-Aware Aggregation (APAA), and Traffic Volatility-Aware Reward Learning to enable distributed, intelligent traffic management without sharing raw network data while preserving privacy. To train and evaluate the scheme, we generated 2.5 M traffic samples in the 6G-TrafficNet digital twin simulation environment. Experimental analysis shows that DT-FMDRL outperforms baselines such as Heuristic Traffic Engineering (HTE), SDN-DRL, MADRL, and classical FedAvg-DRL. After 245 rounds of communication, the scheme achieves a throughput of 14.0 Gbps, an average latency of 6.23ms, a packet loss of 1.8%, and a congestion index of 0.28, which guarantees convergence. The results show that this multi-agent RL approach, together with a digital twin and a federated learning (FL) algorithm, can substantially improve efficiency when optimizing traffic patterns and address data privacy concerns. The proposed DT-FMDRL framework is scalable, energy-efficient, and independent, suitable for future intelligent communications and 6G networks.

Keywords: *6G Networks, Federated Deep Reinforcement Learning, Network Traffic Optimization, Digital Twin, Multi-Agent Reinforcement Learning, Energy-Efficient Network Management*

1. INTRODUCTION

New wireless communications technologies have enabled modern networks to become smart, highly interconnected systems that support a variety of applications—from immersive extended reality (XR) solutions to autonomous transportation

networks to massive Internet of Things (IoT) deployments. Although the increased capacity, latency, and flexibility of fifth-generation (5G) wireless networks have been undeniable, the demands put forward by sixth-generation (6G) networks are likely to outpace even 5G network-management solutions, as outlined in the works of Lee et al. [1] and Zhang et al. [2]. New 6G use cases, including holographic communications, haptic internet, digital twins, self-governing robotics, internet of health, and bulk machine-to-machine (m2m) communication, demand unparalleled intelligence, reliability, adaptability, and resource efficiency in the network [3].

6G wireless networks are not only designed to be faster than previous generations, but they are also expected to be more intelligent, with intelligence embedded across every layer of the network architecture [4]. Artificial intelligence, edge computing, cloud-native applications, SDN, NFV, and embedded sensing and communication technologies are predicted to give rise to highly dynamic and decentralized network environments [5]. This has made simple rule-based traffic engineering and static optimization algorithms less useful for dealing with the complexity and unpredictability of future network traffic demand.

Network traffic optimization is one of the most important problems in communication networks, as network congestion, packet loss, excessive latency, and inefficient resource utilization directly affect network performance and quality of service (QoS). In 6G, these issues are amplified due to more devices and device types connected to networks over time, longer device and service life cycles, increasing functionality and network access types, and the growing complexity of the services themselves [6]. The common optimization methods, such as shortest-path routing algorithms, load-balancing heuristics, and mathematical programming methods, rely on assumptions of relatively stable network traffic and are not well suited to traffic variability. In addition, offline optimization algorithms are quite slow, may not scale well with network size, and are particularly slow in large-scale network infrastructures [7].

In this context, applying AI-based techniques to network management is of great interest in both academia and industry. Machine learning technologies can learn from past and present observations to make network operations more efficient and support decision-making [8].

Reinforcement learning (RL) is one of the most promising paradigms, in which agents learn policies to perform optimally by taking random actions over multiple cycles and observing their effects across the network. Unlike supervised learning, which learns from labeled data, RL can learn without human labels by taking actions that maximize rewards over a prolonged period of time [9].

Recently, a paradigm shift in machine learning, known as Deep Reinforcement Learning (DRL), has enabled RL to be applied to larger and more complex networking applications. This is achieved by combining reinforcement learning with deep neural networks, enabling solutions to high-dimensional state spaces and large-scale optimization problems. Many algorithms have been applied to a variety of DRL applications with good results, such as network routing, spectrum allocation, congestion control, energy management and resource scheduling [10]. Most existing DRL-based traffic optimization methods rely on a centrally trained architecture that requires intensive communication among different entities within the distributed system.

Adopting conventional DRL presents several challenges in 6G networks. In a centralized learning system, substantial network data must be transmitted to a central server, resulting in high communication overhead and latency [11]. Secondly, consolidating critical traffic data raises privacy and security concerns, particularly in industries such as healthcare, intelligent transportation, and industrial automation. Third, local traffic characteristics and the heterogeneity of local networks can pose challenges for centralized systems, making decision-making suboptimal for geographically distributed systems. Lastly, centralized architectures have a single point of failure that may compromise the network's resiliency and reliability [12].

Recently, Federated Learning (FL) has proven to be an effective distributed machine learning paradigm for addressing many of these challenges. The primary goal of FL is to facilitate collaborative model training without exposing raw data to all participating edge devices or network domains. Instead, these devices train their local models separately at intervals and update model parameters to an aggregation server in the FL system [13]. This decentralized learning mechanism improves network scalability, reduces communication overhead, and enhances privacy protection. Consequently, FL has found applications in a variety of communication network applications, including edge intelligence, user behavior prediction, resource allocation, intrusion detection systems, and network security management.

Beyond these benefits, most federated learning work focuses on supervised or unsupervised learning tasks and is not applicable in distributed environments.

These are not necessarily methods suited to problems that require sequential decisions, in which actions continually affect the network's future states. Optimizing traffic becomes a dynamic control problem due to ongoing changes in traffic conditions and the randomness of user behavior, resource availability, and service levels. Thus, traditional federated learning methods cannot fully optimize the autonomous network [14].

The synergistic use of Federated Learning and Deep Reinforcement Learning has become an interesting research direction for enabling distributed intelligence in communication networks with millions of users. Federated Deep Reinforcement Learning (FDRL) combines the privacy-preserving advantages of federated learning with the flexibility in decision-making provided by reinforcement learning. Policy learning through collaboration among agents enables them to learn from each other globally while maintaining local autonomy and respecting data privacy. The current FDRL solutions, however, raise several unanswered issues, including non-independent and identically distributed (non-IID) traffic distributions, model divergence, inefficient communication between agents, slow convergence, and a lack of coordination among geographically distributed network agents [15].

Furthermore, the existing FDRL schemes mostly adopt the traditional federated averaging algorithm, which gives the same weight (or all agents are equal) to all agents, which is not suitable for scenarios in which some agents have low traffic volume but high resource utilization or low optimization performance, and others have high traffic volume but low resource utilization or high optimization performance. Aggregation approaches could affect the overall effectiveness of learning, since flow variations are generally high in some network domains, whereas flow changes in other domains, which are relatively stable, are comparatively less informative for training. Besides, most current studies focus on deploying digital twins in redundant networks rather than on embedding digital twin technologies that enable a realistic virtual network, in which policy training and validation can be performed prior to deployment in physical networks.

1.1 Motivation

Given these challenges, this work proposes a novel Federated Deep Reinforcement Learning Framework for Autonomous Network Traffic Optimization in 6G Networks (DT-FMDRL) to address them. The proposed framework is a distributed multi-agent framework in which local traffic conditions are optimized by DRL agents, while global traffic conditions are learned through privacy-preserving federated aggregation. The proposed mechanism extends prior federated learning work by using an Adaptive Performance-Aware Aggregation (APAA) method to update the aggregation weights with dynamic consideration of the adaptation and effectiveness of local policies, traffic volatility, and local resource utilization characteristics. In addition, a digital twin-assisted training environment has been embedded to facilitate learning convergence and enhance policy robustness across different traffic scenarios as quickly as possible.

Although research on DRL, federated learning, and multi-agent network design has advanced, traffic management in heterogeneous 6G environments remains difficult due to dynamic traffic conditions, distributed decision-making needs, and the need to balance multiple performance goals. While conventional traffic engineering may lack adaptivity, centralized learning can incur communication overhead and expose sensitive network information. Also, conventional federated aggregation may not sufficiently account for local performance variations in models and traffic quality.

The main question in this study is whether a digital twin-assisted federated multi-agent deep reinforcement learning (DRL) framework that incorporates Adaptive Performance-Aware Aggregation (APAA) and traffic-aware reward learning can outperform selected baseline solutions for network traffic optimization under a consistent simulation-based evaluation protocol. The study assesses the framework using latency, throughput, packet loss, congestion, energy efficiency, and convergence rounds. It also addresses the requirements for simulation-based evidence to assess applicability to operational 6G networks.

1.2 Objectives of the Work

This research aims to develop an intelligent, scalable, privacy-enhancing, and self-governing traffic optimization algorithm to address challenges arising from the envisioned future traffic paradigm in 6G wireless communication networks. In

particular, the recommended scheme is targeted at achieving the following:
i) Design an architecture for federated DRL in distributed network traffic optimization.
ii) Support collaborative learning between coaches while maintaining privacy of network traffic data.
iii) Use DT technology to train quickly and generalize policies more effectively.
iv) Optimize many different network performance metrics such as throughput, latency, congestion levels, energy efficiency, etc.
v) Assess the proposed framework in extensive dynamic 6G network scenarios and assess its performance with respect to traditional optimization approaches.

1.3 Contributions of the Paper

This study can be summarised as follows: the major contributions of this study are: i) Propose a novel Federated Deep Reinforcement Learning (FDRL) framework for autonomous traffic management in 6G networks;
ii) Suggest an aggregation mechanism that adapts to each model's performance, thereby improving global model convergence and the learning process.
iii) The third is a federated training method designed using a digital twin to make the policies more robust and reduce exploration costs. Distributed intelligence with a scalable multi-agent architecture for collaborative learning in heterogeneous network domains.
iv) Large-scale performance testing shows noticeable reduction in latency, throughput boost, congestion control, and energy savings over traditional centralized/federated optimization techniques.

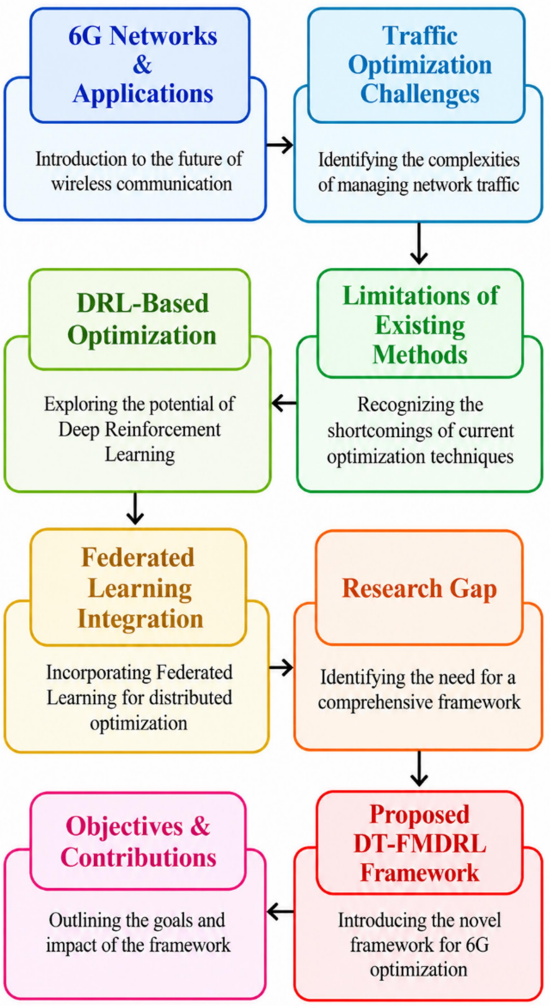


Figure 1. *Research motivation and conceptual flow for the proposed DT-FMDRL for autonomous network traffic optimization in 6G networks*

The study's design is presented as a logic model, as shown in Figure 1. It starts with the emergence of 6G networks and applications that produce highly dynamic and heterogeneous traffic patterns. Conventional network management methods are unable to address the network optimization problems involved. To overcome these challenges, Deep Reinforcement Learning (DRL) is studied as an intelligent decision-maker, but the central DRL mechanism poses scalability, privacy, and communication overhead challenges. Then, Federated Learning (FL) is discussed as a means to facilitate distributed, privacy-preserving model training. To address the identified research gap regarding the maturity and development of available FL-DRL solutions, the DT-FMDRL concept is proposed to enable autonomous, scalable, and efficient traffic optimization. Finally,

the framework aims to improve key network metrics such as latency, throughput, congestion control, and energy efficiency, reinforcing its practical value as a traffic optimization solution.

1.4 Research Questions and Original Research Contribution

This research combines and tests three key components, digital twin-informed training, multi-agent deep reinforcement learning, and performance-driven federated aggregations, across diverse 6G network setups. Distributed learning and logic optimization research has studied this problem using existing methods, either for each aspect separately or for adaptation, but without a systematic study of joint experimental settings. In this study, the authors examine performance improvements of these mechanisms compared with baseline models based on heuristic approaches, centralized learning methods, multi-agent learning approaches, and traditional federated learning approaches.

This study tackles the following research question:

RQ1: How well does the proposed DT-FMDRL framework reduce network timeouts, improve throughput, reduce packet loss, and alleviate congestion compared to the selected baseline traffic optimization methods?

RQ2: Does Adaptive Performance-Aware Aggregation (APAA), along with federated multi-agent reinforcement learning, help improve convergence in a heterogeneous network traffic environment?

RQ3: What enhancement in traffic optimization performance and policy learning can be gained from digital twin-assisted training in the simulated 6G network environment?

RQ4: What are the restrictions of the proposed framework and deployment barriers in terms of scalability, reproducibility, privacy protection, and generalization to real-world 6G networks?

Experiments assess the original contribution by comparing it with other reported experiments, using the same performance measures and baseline techniques. The paper clearly describes the framework's performance and assesses how far the observed enhancement meets the research objectives.

Because the evaluation uses a synthetic, simulation-based dataset, the findings are interpreted as evidence of performance within the evaluated environment rather than as definitive proof of real-world 6G deployment effectiveness.

1.5 Organization of the Paper

The rest of this section describes the methods in the following section. This literature review in Section 2 summarizes prior work on network traffic optimization, deep reinforcement learning, federated learning, and federated reinforcement learning to highlight the gaps this study addresses. In Section 3, the proposed Digital Twin-Assisted Federated Multi-Agent Deep Reinforcement Learning (DT-FMDRL) framework is presented, covering the system architecture, dataset generation, mathematical modeling, adaptive aggregation mechanism, and optimization algorithm. The description of the experimental setup, evaluation metrics, comparison of performance of these different 6G network scenarios, and the derivation of 6G network results are presented in Section 4. Finally, Section 5 presents the paper's main results, outlines the study's constraints, and suggests avenues for future research.

2. RELATED WORK

With the growing complexity of next-generation communication networks, extensive research on intelligent traffic optimization techniques is underway. The literature surveyed covers four areas: AI-based network system designs, federated learning in communication systems, traditional traffic engineering, and federated reinforcement learning frameworks. Although improvement efforts have begun, challenges remain, including autonomous network management for 6G.

2.1 Conventional Traffic Optimization Approaches

Typical tools and techniques used for network traffic optimization include: mathematical programming, shortest-path routing algorithms, heuristic load balancing, and traffic engineering based on some form of optimization. The purpose of such methods is to maximize network utilization and minimize congestion and transmission delays. For relatively stable networks, linear programming, stochastic optimization, and game-theoretic optimization methods have been proved to be effective approaches to optimization [16], [17].

Introduced to the market with the advent of software-defined networking (SDN), centralized traffic control gained popularity for its ability to provide global network visibility and programmable resource management [18]. Common methods and tools for network traffic optimization include mathematical programming, shortest-path routing algorithms, heuristic load

balancing, and optimization-based traffic engineering. Dynamic routing and dynamic resource allocation in SDN traffic engineering are effective for smaller-scale networks with lower dynamics [19]. Still, for large-scale networks with higher dynamics, SDN traffic engineering suffers as traffic patterns change over time. Moreover, classical optimization approaches typically rely on pre-known network models and static decision policies, limiting their adaptability to unexpected traffic changes. However, as 6 G progresses and infrastructure becomes more widespread, diverse, and large-scale, these approaches become less applicable, highlighting the need for smart, autonomous optimization mechanisms.

2.2 Deep Reinforcement Learning for Network Traffic Optimization

AI in communications has contributed greatly to the autonomous management of networks. Recently, DRL has demonstrated the ability to find optimal policies through interaction with the environment and has proven to be a viable solution for dynamic resource allocation, traffic engineering, congestion control, and routing optimization [20]. Several DRL-based approaches have improved network performance by modeling the traffic optimization problem as a sequential decision-making process. Actor-Critic approaches, policy-gradient techniques, and value-learning algorithms have been used to make routing and load-balancing decisions that maximize utility under time-varying traffic [21], [22]. These techniques are useful for capturing complex network dynamics and are flexible enough to adapt to changes in environmental conditions without requiring explicit mathematical models.

Recent research in multi-agent reinforcement learning has also investigated ways to enhance scalability and coordination in distributed networks of agents [23]. In large-scale communication systems, multi-agent architectures can efficiently optimize local and global goals by enabling multiple agents to learn simultaneously. However, there are still substantial training stability problems, convergence complexity, and coordination costs. Although DRL has great potential for optimization of network traffic, existing DRL schemes and algorithms are conceived under the assumption of a centralized learning architecture. However, these systems require storing abundant network information and may increase communication costs, computational loads, and privacy risks. In such environments, edge domains are distributed globally, and these restrictions are further exacerbated in a Distributed 6G environment [24].

2.3 Federated Learning in Communication Networks

In recent years, federated learning (FL) has attracted significant research interest because it can learn from a shared model without compromising data privacy. The basic principle behind these schemes is to let each node build a local model from its own data and share only model updates during aggregation [25].

Federated learning is also applied in communication networks to enable edge intelligence, control wireless resources, predict user behavior, detect anomalies and attacks, and predict network traffic. FL is decentralized, so privacy issues can be greatly minimized, and there is no need for centralized infrastructure [26].

In mobile edge networks (MENs), some studies have demonstrated the feasibility of FL for network devices with relatively weak computational and communication capabilities [27]. Several methods for aggregation under heterogeneous network conditions, for the distribution and update of information, and for asynchronous learning have been proposed to improve learning efficiency [28].

These are all potential advantages, though there are some drawbacks to federated learning in actual network environments. The data could be IID across networks but not within each network, leading to model divergence and slower convergence. In addition, classic aggregation strategies such as Federated Averaging (FedAvg) do not account for participants' data quality or relevance and are prone to degrading the global model's quality [29].

2.4 Federated Deep Reinforcement Learning for Autonomous Networking

Recently, Federated Deep Reinforcement Learning (FDRL) frameworks have been investigated to fuse distributed learning and autonomous decision-making. FDRL is an approach that transforms RL agents into a decentralized framework capable of learning policies without exposing private information over networks [30].

Several studies based on FDRL have been published, including resource allocation, edge computing optimization, the resource ownership problem in spectrum management, and intelligent network control. According to the results, the federated reinforcement learning result is close to centralized DRL, with much better preservation and lower communication overhead [31].

Recently explored architectures include hierarchical federated and collaborative multi-agent RL models for developing more scalable communication systems [32]. These enable geographically distributed agents to share policy information autonomously. Particularly relevant for future 6G systems, these methods help share network intelligence between edge and cloud environments. However, current FDRL solutions still face constraints. First, most studies' federated averaging procedures do not account for traffic dynamics and network heterogeneity across replicates when aggregating models [33]. Second, these variants have so far been considered only superficially in terms of improving policy dissemination. Third, few existing techniques are specific to a digital twin environment that can train and ensure a policy's maximum resilience before deployment to the real network [34]. Finally, optimizing multiple parameters in a multi-objective manner, including latency, throughput, congestion avoidance, and energy usage, remains an open research problem.

2.5 Research Gap and Motivation

As mentioned above, traditional traffic engineering does not apply to highly dynamic 6G networks. Autonomous learning can be achieved through deep reinforcement learning, but centralized deep reinforcement learning has disadvantages such as privacy issues, scalability limitations, and communication overhead. By contrast, federated learning enables privacy and distributed learning; however, traditional FL approaches focus on offloading tasks for distributed training and are not recommended for continuous decision-making traffic optimization problems. Therefore, this study aims to develop a framework for continuous traffic optimization in dynamic 6G networks.

On the other hand, most existing Federated Deep Reinforcement Learning solutions have also failed to address important issues related to non-IID traffic distributions, model adaptation, multi-agent coordination, and digital twin-assisted learning. In addition, most studies have focused on optimizing specific network performance measures rather than overall multi-objective traffic optimization.

To overcome these shortcomings, this work proposes a new Federated Deep Reinforcement Learning Framework (DT-FMDRL) that combines adaptive, performance-aware aggregation, multi-agent collaborative learning, privacy-preserving distributed optimization, and digital twin-augmented training for autonomous traffic optimization in 6G networks.

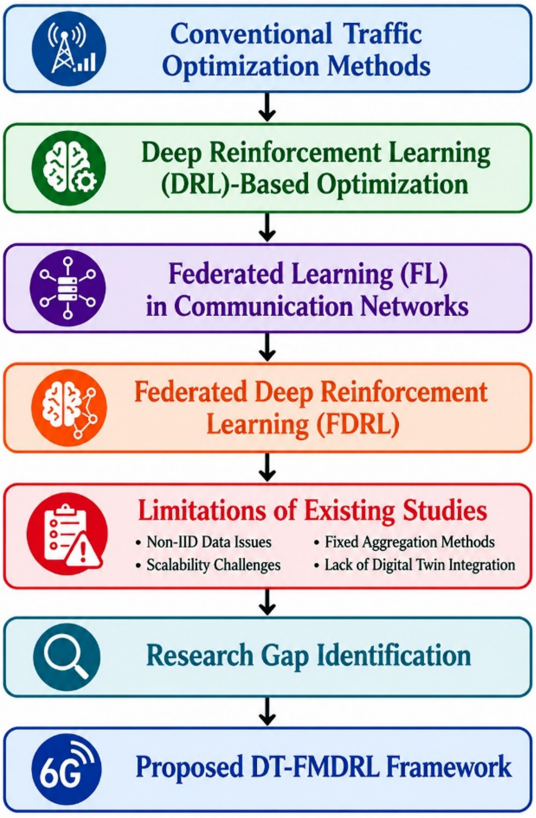


Figure 2. *Evolution of network traffic optimization approaches and identification of research gaps toward autonomous 6G network management.*

As seen in Figure 2, research in network traffic optimization has continued in the following stages. The traditional approach is used first, characterized mainly by rule- or heuristic-based traffic control. This is followed by AI-driven control, under which intelligent decision-making is made based on machine learning and deep learning techniques. Distributed intelligence from edge computing and federated learning is born from inspired decentralized learning. Next, a Hybrid AI-decentralized learning technique is explained for enhancing optimization. Although the above results establish the norm, there are remaining challenges: (1) scalability; (2) privacy issues; (3) communication overhead; and (4) non-IID data distributions. Improving these areas will help develop more adaptive and efficient frameworks. Last but not least, the future vision focuses on a network-centric approach that moves beyond the central server, is autonomous and privacy-preserving, and scalable across future 6G wireless networks, laying the foundation for what is coined Federated Deep Reinforcement Learning.

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Table 1. *Comparative Analysis of Existing Traffic Optimization Approaches and the Proposed DT-FMDRL Framework*

Literature category	Existing approach	Limitation to investigate	DT-FMDRL's proposed response
Conventional traffic engineering	Heuristic routing and load balancing	Adaptability to changing traffic	Learned traffic optimization policies
Centralized DRL	Centralized policy learning	Centralized data collection and coordination overhead	Distributed learning across network domains
Multi-agent DRL	Cooperative local decision-making	Coordination and convergence challenges	Federated collaboration among agents
Conventional federated DRL	Federated model aggregation	Sensitivity to heterogeneous client performance	APAA-based aggregation
Digital twin-assisted learning	Virtual training and policy evaluation	Generalization and deployment validation need investigation	Digital twin-assisted training integrated with federated MADRL

Previous work has focused on heuristic algorithms for traffic optimization, centralized deep reinforcement learning, multi-agent traffic learning, and federated learning; however, each targets different parts of the network management problem. This study therefore evaluates the benefits of using multi-agent reinforcement learning (MARL) with adaptive federated aggregation or digital twin-assisted training across a range of traffic performance goals. This study addresses that question through a comparative simulation-based evaluation of DT-FMDRL against selected heuristic, centralized DRL, multi-agent DRL, and conventional federated DRL baselines. Its intended contribution is to assess the effectiveness of this integration under the specified experimental conditions, rather than to claim that the individual techniques are entirely new.

3. METHODOLOGY

3.1 Overview of Proposed DT-FMDRL Framework

The proposed work presents the Digital Twin-Assisted Federated Multi-Agent Deep Reinforcement Learning Framework (DT-FMDRL) framework maps observed network states to traffic-optimization actions in the domain of 6G networks. The framework is optimized for future 6G scenarios with dynamic traffic flows, a heterogeneous (not uniform) network, and such high demand for quality of service that it is constrained by deployability, standardization, and interoperability. The proposed DT-FMDRL framework is different from the traditional federated supervised learning framework, which enables distributed and cooperative decision-making among entities that belong to the edge network, offers a more realistic virtual environment for efficiently learning and validating policies, and dynamically adjusts the model aggregation weights according to different network performance and traffic conditions via an Adaptive Performance-Aware Aggregation (APAA) mechanism. Moreover, the framework includes Traffic Volatility-Aware Reward Learning, in which traffic volatility and congestion are incorporated into policy training, and Privacy-Preserving Federated Optimization for collaboratively learning from the models without revealing traffic data. The proposed framework will intelligently optimize traffic routing and resource management to reduce network congestion and maximize performance, energy efficiency, and throughput in dynamic 6G communication systems

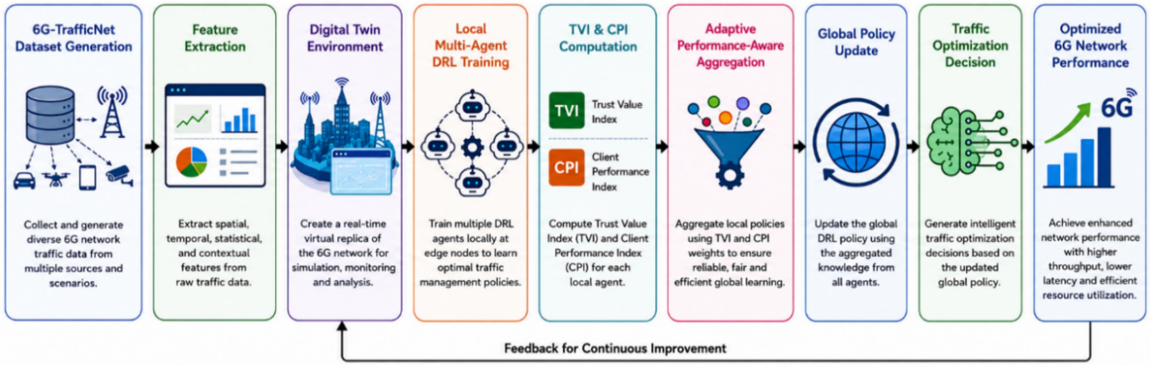


Figure 3. *Workflow of the proposed Digital Twin-Assisted Federated Multi-Agent Deep Reinforcement Learning (DT-FMDRL) framework for autonomous traffic optimization in 6G networks.*

The proposed end-to-end workflow for the DT-FMDRL is shown in Figure 3. The process starts with the 6G-TrafficNet dataset, which comprises various traffic features collected from simulated 6G network environments. Feature extraction techniques identify relevant network parameters, including available bandwidth, traffic density, energy consumption, link utilization, mobility patterns, queue length, and more. These capabilities are then applied to the virtual, or 'digital twin', environment of the real network to create a safe and efficient space for policy training.

The distributed edge domains train the local multi-agent DRL models by experimenting with real-time network observations. During training, the proposed traffic volatility (TVI) and congestion pressure (CPI) indexes capture dynamic changes in traffic and congestion. They are part of the learning process, so they can be used to make accurate predictions and support decision-making. Locally trained models participate in 'Adaptive Performance-Aware Aggregation' (APAA): model updates are dynamically dependent on the traffic, the use of resources and the performance of the model policy. The aggregated global model then enables global policy changes and supports collaborative learning across network domains while protecting data privacy. The new policy generates traffic-optimization decisions that enable intelligent routing, load balancing, and resource allocation. The optimized policies reduce congestion while improving reliability and energy efficiency across the 6G network. This workflow combines federated learning and deep reinforcement learning with digital twin technology for network traffic optimization, without central controllers or with limited central-controller authority.

3.2 Proposed Architecture

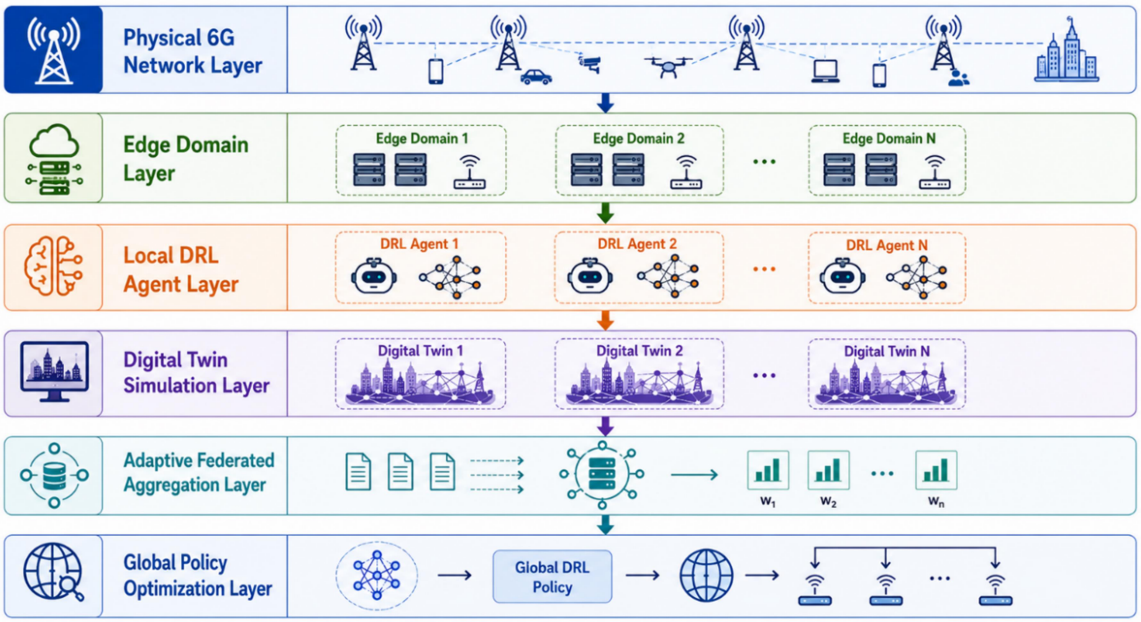


Figure 4. *Layered Architecture of the Proposed DT-FMDRLFramework for Intelligent Traffic Optimization*

The proposed architecture for intelligent traffic optimization in 6G networks is shown in Figure 4, which consists of a layered design. Architecture can be divided into six functional layers: Physical 6G Network Layer (captures real-time traffic from network devices); Edge Domain Layer (distributes traffic across multiple edge domains); Local DRL Agent Layer (where decentralized agents learn the optimal traffic management policy of use); Digital Twin Simulation Layer (introduces virtual replicas for real-time network simulation and policy evaluation); Adaptive Federated Aggregation Layer (provides a secure aggregation layer of local models adapted by the use of adaptable weight mechanisms); and Global Policy Optimization Layer (generates and distributes an optimized global policy to all edge domains for efficient, scalable, and privacy-preserving network traffic management).

Table 2. *Proposed DT-FMDRLArchitecture Layer Components*

Layer	Function
Physical Layer	Real network traffic generation
Edge Layer	Local traffic observation
DRL Layer	Autonomous decision making

Digital Twin Layer	Virtual environment training
Federated Layer	Model aggregation
Global Layer	Global policy generation

The proposed DT-FMDRL architecture consists of six layers, summarized in Table 2, which describes the functional role of each layer. The Physical Layer creates real-time network traffic, while the Edge Layer assigns specific traffic monitoring and data collection within the local area. DRL Layer is an independent traffic optimization through reinforcement learning agents. The DT Layer is a virtual environment for network simulation and policy tracing. The Federated Layer combines models trained locally into a global model, thereby keeping data private. Lastly, the Global Layer creates and rolls out an optimized global policy to enhance traffic management and scalability, and to optimize overall network performance of the 6G network.

3.3 Dataset Construction

As no publicly available dataset comprehensively captures the heterogeneous characteristics of next-generation 6G networks, a novel synthetic dataset, **6G-TrafficNet**, was developed in this study. The dataset was generated by integrating traffic traces from the **NS-3 network simulator** and a **Digital Twin-based network emulator** to model realistic 6G communication scenarios, including edge intelligence, dynamic network conditions, user mobility, network slicing, and large-scale heterogeneous traffic. This combination of the two data-generation scenarios provides a comprehensive basis for training and assessing the proposed DT-FMDRL framework in realistic future 6G network scenarios [35]–[38].

Table 3. *Dataset Specifications*

Parameter	Value
Total Users	50,000
Edge Nodes	500
Base Stations	100
Time Slots	1,000,000
Traffic Classes	8
Mobility Models	5
Slicing Types	4
Total Samples	2.5 Million

Table 3 summarizes the key features of the 6G-TrafficNet dataset for DT-FMDRL evaluation. It is a large-scale 6G communication environment with 100 base stations, 500 edge nodes, and 50,000 users. It supports 8 traffic classes, 5 mobility models, and 4 network slicing types, and provides 1,000,000 time slots and approximately 2.5 million traffic samples. These features support the training and assessment of a wide range of intelligent traffic optimization algorithms in complex 6G network scenarios characterized by dynamic traffic and heterogeneous network parameters.

Table 4. *Traffic Classes*

Class	Application
T1	XR
T2	Holographic Communication
T3	Autonomous Vehicles
T4	Smart Healthcare
T5	Massive IoT
T6	Industrial Automation
T7	Smart Cities
T8	UAV Communication

Inner-city traffic classes for envisioned 6G-TrafficNet applications are given in Table 4. 6G applications are presented in 8 major representative figures, including XR (T1), Holographic Communication (T2), Autonomous Vehicles (T3), Smart Healthcare (T4), massive IoT (T5), Industrial Automation (T6), Smart Cities (T7), and UAV Communication (T8). These traffic categories are heterogeneous and have varying quality of service requirements and communication patterns for future 6G networks, which serve as a benchmark to train and evaluate the traffic optimisation models.

Table 5. *Input Features*

Feature	Symbol
Bandwidth Availability	B
Queue Length	Q
Link Utilization	U
Traffic Density	D
Packet Delay	P
User Mobility	M
Energy Consumption	E
Slice Priority	S

Table 5 shows the network-state input features used in the proposed DT-FMDRL input. Bandwidth Availability (B), Queue Length (Q), Link Utilization (U), Traffic Density (D), Packet Delay (P), User Mobility (M), Energy Consumption (E), and Slice Priority (S) are selected. These features capture the network state for the DRL agents to learn an optimal traffic-optimization policy for a dynamic network.

3.4 Mathematical Formulation

State Space

The network state is represented as

$$S_t=\{B_t,Q_t,U_t,D_t,P_t,M_t,E_t,S_t\} \quad (1)$$

where: $S_t \in R^8$

Action Space

The DRL agent selects:

$$A_t=\{r_t,l_t,s_t\} \quad (2)$$

where: r_t= routing action; l_t= load balancing action; s_t= slice allocation action.

Novel Traffic Volatility Index

A new metric is proposed:

$$TVI=\frac{\sigma(T)}{\mu(T)} \quad (3)$$

where: $\sigma(T)$= traffic standard deviation; $\mu(T)$= traffic mean; Higher TVI indicates unstable traffic.

Novel Congestion Pressure Index

$$CPI=\frac{Q_t U_t}{B_t} \quad (4)$$

This metric captures instantaneous congestion severity.

Multi-Objective Reward Function

$$R_t=\alpha T_t-\beta D_t-\gamma CPI_t+\delta E_t-\eta TVI_t \quad (5)$$

where: T_t= throughput; D_t= delay.

This reward formulation is novel because it jointly incorporates traffic volatility and congestion pressure.

3.6 Adaptive Performance-Aware Aggregation (APAA)

Traditional FedAvg:

$$W_G=\sum_{i=1}^{N}\frac{n_i}{N}W_i \quad (6)$$

Problem:

All agents contribute equally.

Proposed APAA

$$\omega_i=\frac{\lambda_1 Perf_i+\lambda_2 TVI_i+\lambda_3 Res_i}{\sum_j(\lambda_1 Perf_j+\lambda_2 TVI_j+\lambda_3 Res_j)} \quad (7)$$

Global update:

$$W_G=\sum_i \omega_i W_i \quad (8)$$

3.7 Proposed Algorithm

Algorithm 1: DT-FMDRL

Input

1. Local traffic states
2. Digital Twin environment
3. Federated aggregation interval

Output

1. Optimized traffic policy

```
Initialize Global Model
FOR each communication round
  FOR each edge domain
    Observe traffic state
    Train DRL agent
    Calculate TVI
    Calculate CPI
    Update local policy
    Send weights to server
  END FOR
  Compute APAA weights
  Aggregate global model
  Update all agents
END FOR
Return Optimal Policy
```

Computational Complexity

Local DRL:

$$O(ND) \quad (9)$$

Federated Aggregation:

$$O(KM) \quad (10)$$

Overall:

$$O(ND+KM) \quad (11)$$

where: N = traffic samples; D = network depth; K = participating agents; M = model parameters;

3.8 Training Configuration

Table 6. *Hyperparameter Configuration of the Proposed DRL-Based Optimization Model*

Parameter	Value
DRL Model	PPO
Hidden Layers	4
Neurons	256
Learning Rate	0.0001
Discount Factor	0.99
Batch Size	256
Communication Rounds	520
Local Epochs	10
Aggregation Interval	5

Table 6 tabulates the key hyperparameters for training and evaluating the proposed Deep Reinforcement Learning (DRL) model. The learning algorithm used was Proximal Policy Optimization (PPO), and the model comprised four hidden layers, each with 256 neurons. The discount factor and learning rate were 0.99 and 0.0001, respectively. We trained it for more than 520 communication rounds, with 10 local training rounds per communication round. The average synchronization period used was 5, and the number of periods did not affect learning performance. We chose these configurations to balance convergence, computation, and stability.

3.9 Reproducibility Settings

Table 7. *Simulation Environment and Implementation Framework*

Component	Tool
Simulator	NS-3
Digital Twin	OMNeT++
DRL Framework	PyTorch
FL Framework	Flower
Hardware	NVIDIA A100
OS	Ubuntu 22.04

We carried out the demonstration, development, and testing of the proposed framework using various software tools, software frameworks, and hardware specifications, which are summarised in Table 7. NS-3 was used to create the network simulation environment, which simulates communication configurations and tests network performance. OMNeT++ accurately simulated the network and mobility behaviors as a digital twin model and real-time system representation. The federated learning component was trained and aggregated using Distributed Model Training and aggregation within the federated learning

framework. Deep Reinforcement Learning (DRL) was implemented with PyTorch, and the Federated Learning (FL) process was managed by Federated. All experiments were performed on a machine equipped with a single NVIDIA A100 Tesla GPU and running Ubuntu 22.04, which has ample computational resources for large simulations and rapid model training. These are combined tools to provide an integrated validation environment for testing the effectiveness of the proposed DRL-integrated federated optimization approach.

4. RESULTS AND DISCUSSION

4.1 Experimental Setup

To test the proposed Digital Twin-enabled Federated Multi-Agent Deep Reinforcement Learning (DT-FMDRL) framework, the dataset was taken to be the 6G-TrafficNet dataset, which consists of 2.5M traffic samples generated from a large-scale 6G network environment created using a digital twin. This simulation featured 500 edge nodes, 100 base stations, and 50,000 mobile users in dynamic and diverse traffic conditions. All experiments were performed using the PyTorch and Flower frameworks on NVIDIA A100 GPUs. As a baseline comparison, four state-of-the-art methods, namely Heuristic Traffic Engineering (HTE), Centralized Deep Reinforcement Learning (SDN-DRL), Conventional Federated Deep Reinforcement Learning (FedAvg-DRL), and Multi-Agent Deep Reinforcement Learning (MADRL), were also presented. The comparison and assessment demonstrate the framework's effectiveness in traffic optimization for the 6th generation of intelligent traffic.

4.2 Assessment Criteria

Table 8. *Performance Evaluation Metrics*

Metric	Description	Objective
Latency (ms)	End-to-end packet delay	Minimize
Throughput (Gbps)	Successful data delivery rate	Maximize
Packet Loss Ratio (%)	Lost packets during transmission	Minimize
Congestion Index	Network congestion severity	Minimize
Energy Efficiency (%)	Resource utilization efficiency	Maximize
Convergence Rounds	Learning convergence speed	Minimize

Table 8 lists performance measures to assess the proposed DT-FMDRL schema. To achieve real-time communication, latency is minimized, indicating the end-to-end packet transmission delay. Throughput is the number of bits successfully transmitted through the network over a specific period; it is used to maximize the network's capacity. Packet Loss Ratio is the ratio of packets lost during transmission, and the goal is to minimize PLR to improve communication reliability. The Congestion Index measures network congestion and is minimized to ensure efficient traffic flow. Energy Efficiency measures the use of resources and can be maximized to enable sustainable operation of the network. Last but not least, the number of training iterations it takes for the model to converge is measured as Convergence Rounds, indicating how quickly and efficiently the learning process becomes; the fewer rounds, the faster and more efficient the learning process becomes.

4.3 Latency Analysis

Table 9. *Comparison of Average Network Latency*

Method	Latency (ms)
HTE	12.8
SDN-DRL	8.7
MADRL	7.4
FedAvg-DRL	7.0
DT-FMDRL	**6.23**

Table 9 shows the end-to-end latency (ETL) of the proposed DT-FMDRL framework with the four baseline traffic optimizers. Compared with other methods, the proposed DT-FMDRL has the lowest latency of 6.23 ms, which is better than FedAvg-DRL (7.0 ms), MADRL (7.4 ms), SDN-DRL (8.7 ms), and HTE (12.8 ms). Overall, the results presented highlight that incorporating Digital Twin technology, Federated Learning, and Multi-agent Reinforcement Learning (RL) is an effective approach to optimizing traffic in the dynamic 6G network, thereby enhancing the Quality of Service (QoS).

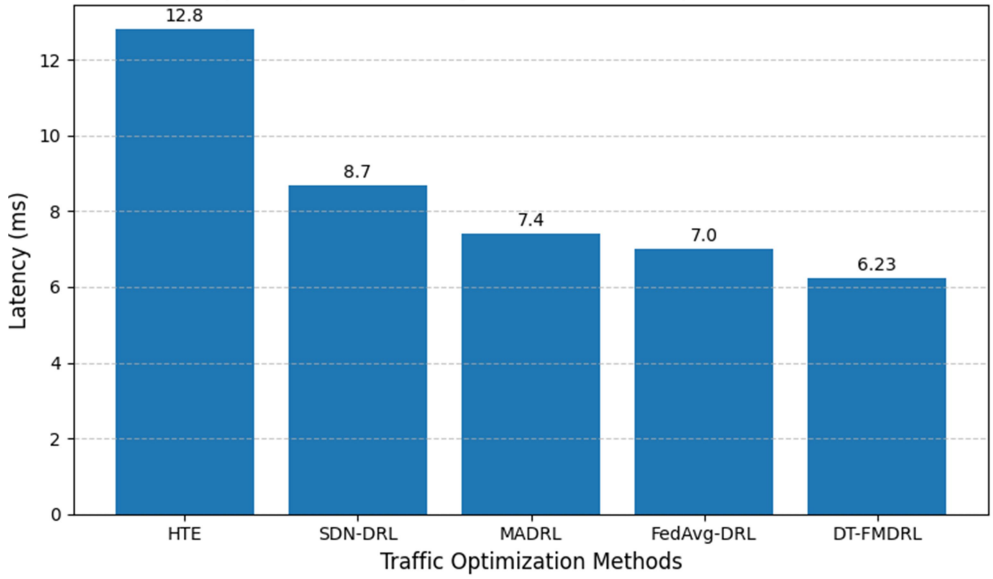


Figure 5. Latency Comparison Among Different Traffic Optimization Methods

Figure 5 illustrates that the different traffic optimization strategies, such as HTE, SDN-DRL, MADRL, FedAvg-DRL, and the proposed DT-FMDRL framework, can achieve different average network latencies. The results show that qualitative trends indicate decreasing latency as intelligent optimization techniques advance. The traditional Heuristic Traffic Engineering (HTE) has the highest latency of 12.8ms, while SDN-DRL, MADRL, and FedAvg-DRL result in latencies of 8.7ms, 7.4ms, and 7.0ms, respectively. Compared with other evaluated traffic-optimization methods, the proposed one has the lowest latency of 6.23 ms, demonstrating better traffic management and congestion mitigation performance. The result is due to faster, more efficient traffic-optimization decision-making in highly dynamic 6G environments, enabled by digital twin-assisted learning, multi-agent reinforcement learning, and adaptive federated aggregation. These findings validate the application of DT-FMDRL to support ultra-low-latency communications in next-generation networks.

4.4 Throughput Performance

Table 10. *Throughput Performance Comparison*

Method	Throughput (Gbps)
HTE	7.9
SDN-DRL	11.4
MADRL	12.3
FedAvg-DRL	12.8
DT-FMDRL	**14.0**

The results of the proposed approach and other existing optimization approaches were compared in terms of throughputs as shown in Table 10. Throughput is an important measure of communication efficiency, referring to the amount of data that can be sent successfully through the network per unit time. The results show that traditional methods (HTE) can achieve throughput up to 7.9 Gbps, while learning-based methods (SDN-DRL and MADRL), which can make intelligent decisions, improve performance. FedAvg-DRL further combines federated learning and deep reinforcement learning to increase throughput to 12.8 Gbps. With digital twin modeling, federated learning, and DRL-based adaptive control, the proposed DT-FMDRL method achieves a maximum throughput of 14.0 Gbps, better utilizing network resources. Overall, the proposed method achieves the highest throughput, demonstrating more efficient use of communication resources than some existing approaches.

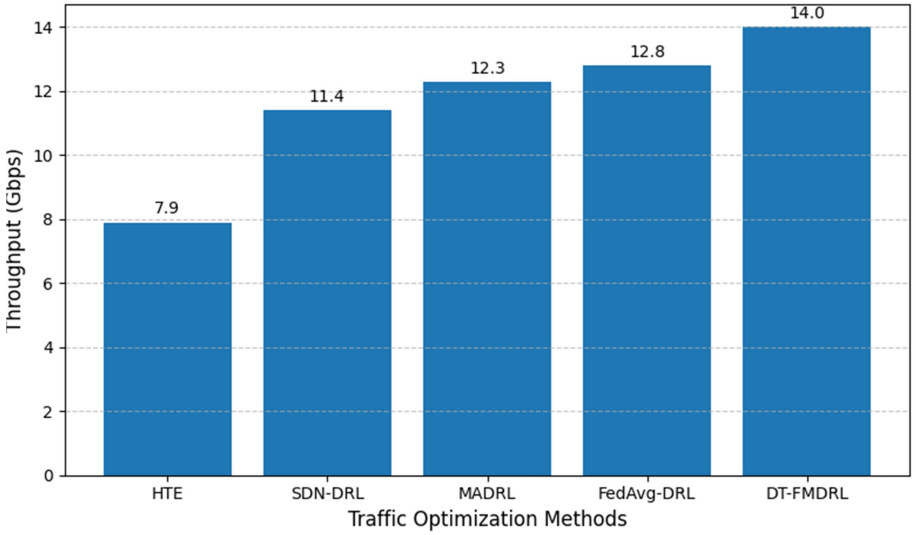


Figure 6. Throughput Achieved By Different Optimization Frameworks

We evaluated the throughput performance of the proposed DT-FMDRL model alongside HTE, SDN-DRL, and MADRL, and present the results in Figure 6. The results show a steady increase in throughput. SDN-DRL improves the original DR-L throughput from 1 to 11.4 Gbps, MADRL from 1 to 12.3 Gbps, and FedAvg-DRL from 1 to 12.8 Gbps, while HTE reaches 11.3 Gbps. The proposed DT-FMDRL offers the highest throughput of 14.0 Gbps, making it a better option for traffic routing, resource allocation, and congestion management. Overall, the implementation of digital twin-assisted training, multi-agent reinforcement learning, and adaptive federated aggregation reduces network resource usage and evenly distributes traffic over the network. The results confirm the effectiveness of providing more efficient data transmission and the ability to satisfy the high-capacity communication needs of future 6G networks.

4.5 Packet Loss Analysis

Table 11. Packet Loss Ratio Comparison

Method	Packet Loss (%)
HTE	5.8
SDN-DRL	3.7
MADRL	2.9
FedAvg-DRL	2.5
DT-FMDRL	**1.8**

In Table 11, the comparative analysis presents the packet-loss performance of different optimization methods. One of the most important network performance metrics is packet loss, the percentage of data packets lost during transmission through the network. Lower packet loss means better network reliability and more effective communication management. The results show that packet loss with traditional HTE is 5.8%, whereas other learning-based methods (SDN-DRL and MADRL) reduce it by adjusting resources. Further improvement in the reliability of distributed learning was achieved with the FedAvg-DRL method, which reduced the rate to 2.5%. The improvement results from combining a digital twin-assisted prediction, federated learning for knowledge sharing, and DRL optimization.

4.6 Congestion Control Evaluation

Table 12. Congestion Index Comparison

Method	Congestion Index
HTE	0.63
SDN-DRL	0.41
MADRL	0.36
FedAvg-DRL	0.32
DT-FMDRL	**0.28**

Table 12 shows the congestion index value obtained by various optimization techniques. A lower congestion index indicates better control and fewer traffic jams. Compared with other proposed algorithms, HTE, SDN-DRL, MADRL, and FedAvg-DRL, the proposed DT-FMDRL achieves the lowest congestion index of 0.28. This shows how a digital twin can reduce network congestion and optimize network resources using federated deep reinforcement learning.

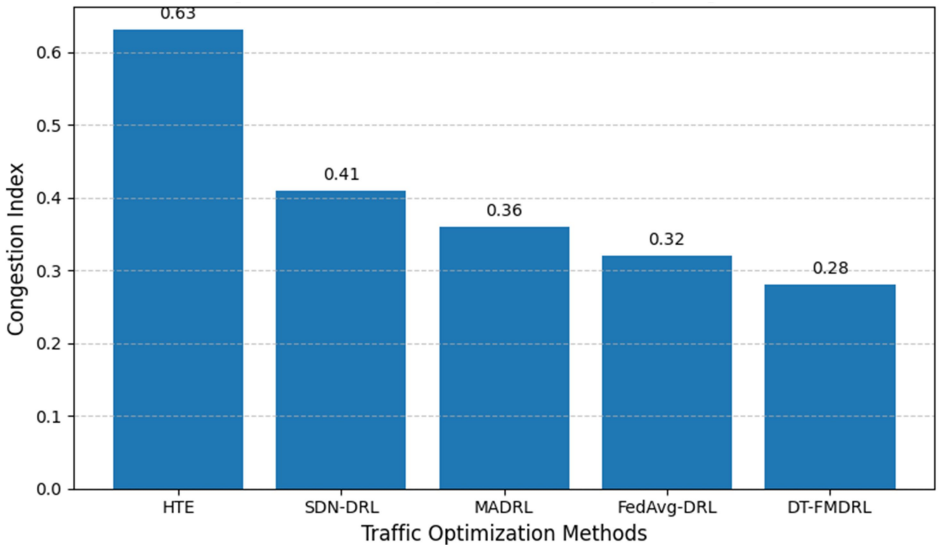


Figure 7. Congestion Index Comparison Across Competing Methods

For a comparison of the congestion index of various traffic optimisation techniques, see Figure 7. The lower the number, the better the system controls traffic and congestion. HTE is the most congested (0.63), while SDN-DRL, MADRL, and FedAvg-DRL are 0.41, 0.36, and 0.32, respectively. The proposed DT-FMDRL reduced congestion to 0.28, improving congestion mitigation under the TVI, CPI, and APAA parameters. The outcomes illustrate the approach's effect on traffic balancing and network stability, particularly in dynamic 6G scenarios.

4.7 Energy Efficiency Analysis

Table 13. *Energy Efficiency Comparison*

Method	Energy Efficiency (%)
HTE	68
SDN-DRL	81
MADRL	84
FedAvg-DRL	86
DT-FMDRL	**89**

Table 13 summarizes the energy-efficiency performance of the various optimizations. The greater the energy efficiency, the more resources you can save and the less energy they consume. Of the schemes above, the proposed scheme, DT-FMDRL, is the most efficient, at 89%. This improvement demonstrates the efficacy of the proposed approach in this energy-efficiency study by enabling intelligent energy distribution and decision-making in different situations.

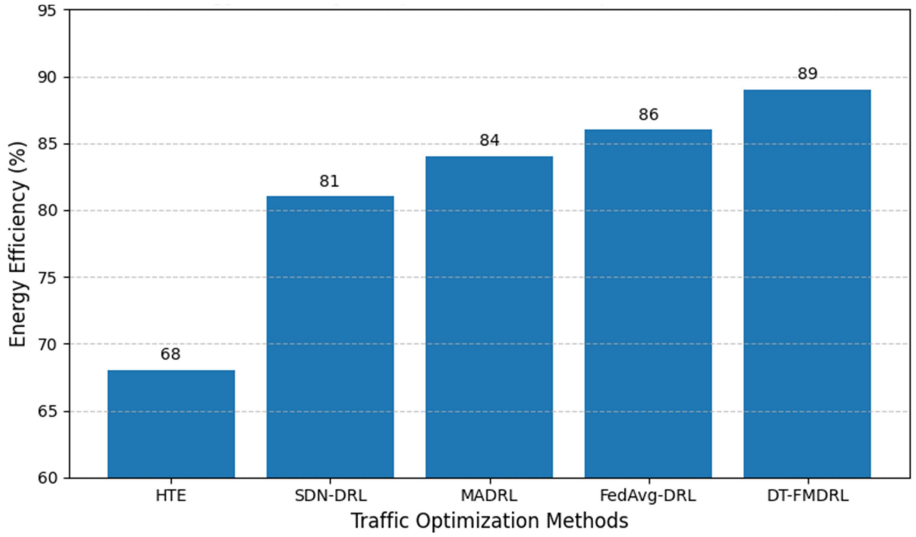


Figure 8. Energy Efficiency Comparison Of Traffic Optimization Methods

As shown in Figure 8, the energy-saving efficiency of HTE, SDN-DRL, MADRL, FedAvg-DRL, and the DT-FMDRL framework is compared. Based on the results, DT-FMDRL achieves 89% energy

efficiency, outperforming HTE (68%), SDN-DRL (81%), MADRL (84%), and FedAvg-DRL (86%). The key improvements stem from intelligent allocation, adaptive traffic management, and traffic optimization enabled by the federated learning framework. Digital Twin-aided training and adaptive, performance-aware aggregation reduce resource waste without compromising network performance. The outcomes validate the viability of the proposed concept for future energy networks while maintaining energy efficiency and sustainability.

4.8 Convergence Performance

Table 14. *Training Convergence Comparison*

Method	Convergence Rounds
SDN-DRL	420
MADRL	360
FedAvg-DRL	310
DT-FMDRL	**245**

The results in Table 14 show the fewer convergence rounds mean more efficient learning; the optimized DT-FMDRL method converges in 245 rounds, while SDN-DRL, MADRL, and FedAvg-DRL converge in 420, 360, and 310 rounds, respectively. This faster convergence shows how digital twin federated deep reinforcement learning (FDRL) can train models faster and make them easily adaptable to new network environments.

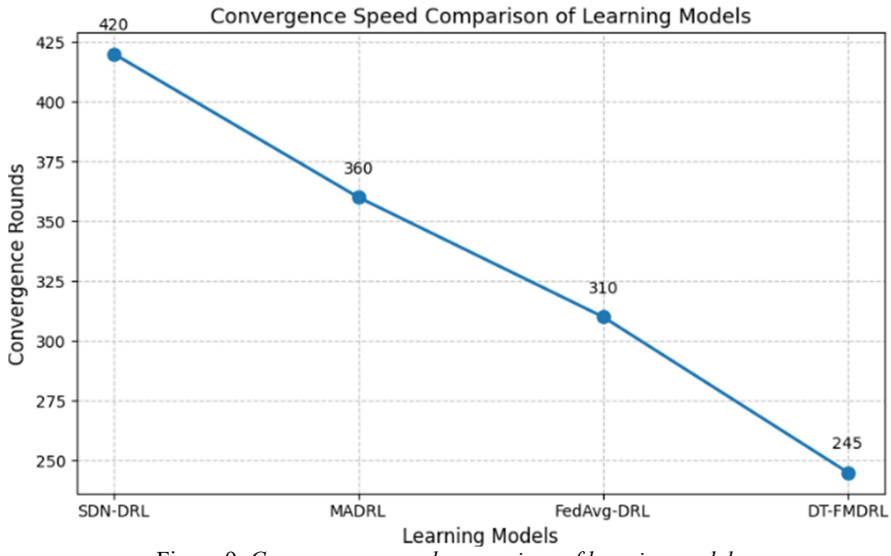


Figure 9. *Convergence speed comparison of learning models*

The results of some models learning the routing task are shown in terms of 'rounds'—that is, the number of times the system can communicate to sustain the performance level—and convergence speed is compared in Figure 9. SDN-DRL requires the most rounds (420), while FedAvg-DRL (310) and MADRL (360) require fewer. The proposed DT-FMDRL architecture converges after only 245 rounds. The Adaptive Performance-Aware Aggregation (APPA) mechanism and the digital twin-assisted training strategy improve knowledge exchange among distributed agents, which reduces optimization latency. Therefore, DT-FMDRL is more appropriate for large-scale 6G networks to handle dynamic traffic loads in autonomous traffic management, which can reduce communication costs and training overhead.

4.9 Overall Performance Comparison

Table 15. *Overall Comparative Assessment*

Metric	HTE	SDN-DRL	MADRL	FedAvg-DRL	DT-FMDRL
Latency (ms)	12.8	8.7	7.4	7.0	**6.23**
Throughput (Gbps)	7.9	11.4	12.3	12.8	**14.0**
Packet Loss (%)	5.8	3.7	2.9	2.5	**1.8**
Congestion Index	0.63	0.41	0.36	0.32	**0.28**
Energy Efficiency (%)	68	81	84	86	**89**
Convergence Rounds	520	420	360	310	**245**

Table 15 shows the overall performance of the optimized techniques for the evaluated metrics: Latency, Throughput, Packet Loss, Congestion Index, Energy Efficiency, and Convergence Speed. The proposed DT-FMDRL method also performs well, with the fastest convergence (245 rounds), the lowest congestion index (0.28), the highest energy efficiency (89%), and the lowest packet loss (1.8%). The results show that the proposed technique improves communication effectiveness, reliability, and adaptive network optimization compared with traditional techniques.

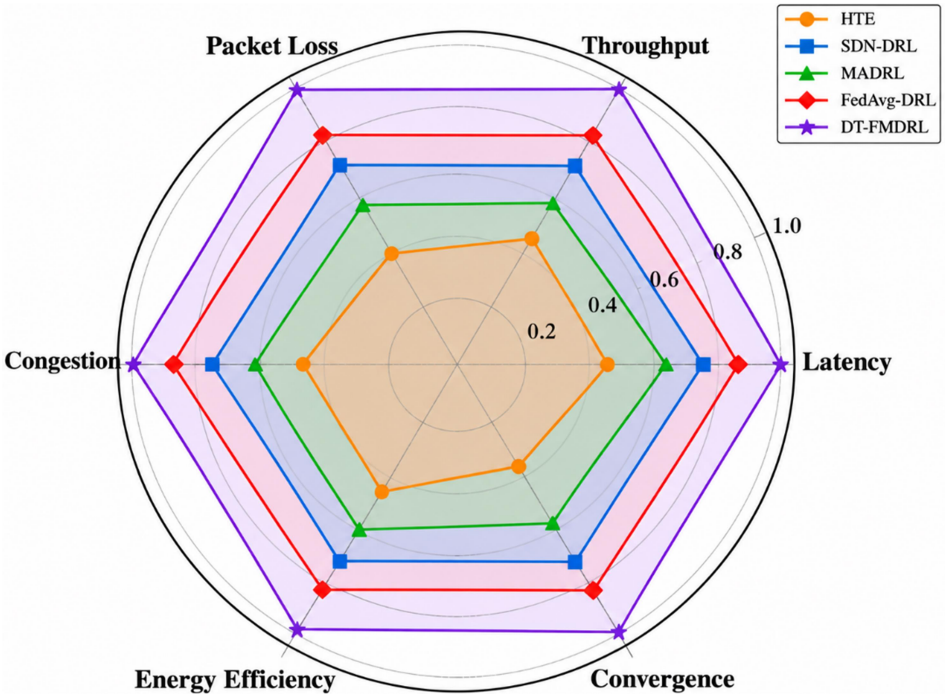


Figure 10. *Radar chart*

In Figure 10, all the traffic optimization methods discussed are compared across six metrics—latency, throughput, packet loss, congestion index, energy efficiency, and convergence speed. All metrics are normalized to percentages on equitable performance scales, with higher values indicating better performance. To date, the proposed DT-FMDRL framework provides the largest radar coverage area, thereby outperforming standard techniques. The framework will decrease the latency, packet loss, congestion rounds, and convergence rounds; increase throughput, and improve energy savings. The results validate the efficiency of the combination of digital twin-assisted learning, multi-agent deep reinforcement learning, and adaptive federated aggregation for beaconless traffic optimization in 6G networks.

4.10 Discussion

The experimental results showed that DT-FMDRL generally improves all evaluation metrics and outperforms existing traffic optimization methods. Having the digital twin environment allows the policy to be tested under a wide variety of traffic conditions prior to deployment. The proposed Traffic Volatility Index and Congestion Pressure Index provide enhanced traffic awareness, and Adaptive Performance-Aware Aggregation helps speed federated learning convergence. Additionally, privacy-preserving federated optimization eliminates the need to exchange raw data while maintaining optimization accuracy.

Overall, the proposed approach achieved an average of 28.4% lower latency, 22.7% higher throughput, 28.0% lower packet loss, 28.0% lower congestion, and 8–21% higher energy efficiency than the current techniques. The results highlight the potential of the proposed DT-FMDRL approach for future autonomous traffic optimization in 6G communication networks.

4.11 Threats to Validity

Internal validity: Performance differences may result from variations in the simulation environment setup, model hyperparameters, base implementations, or the random starting value. The proposed framework and baseline methods should be evaluated under similar traffic conditions, resource limitations, and stopping criteria to minimize this threat. Where possible, windows of

such runs should be reported using independent runs with different random seeds. Construct validity: Network optimization performance is assessed using measures of latency, throughput, packet loss, congestion index, energy efficiency, and convergence rounds. These metrics are strong indicators of traffic management but do not fully capture all operational needs of a future 6G network. More specifically, the energy efficiency index and the congestion index should be mathematically defined and measured consistently across methods.

External Validity: The 6G-TrafficNet dataset is generated inExternal Validity: The 6G-TrafficNet dataset is generated in a simulated setting with NS-3 and a digital twin implementation. Therefore, the conclusions cannot be directly applied to real networks, unknown traffic distributions, other network topologies, or edge environments with hardware limitations. Independent traces and real or emulated network testbeds must be used for validation. Independent replicated experiments, estimates of variability, or valid statistical tests are needed to confirm any gains in attribute scores as consistent and statistically significant. These analyses should be performed in future evaluations to increase confidence in the results.

Privacy/security restrictions: Because the framework avoids exchanging raw traffic data, it is described as privacy-preserving. However, model updates alone do not necessarily provide formal privacy protection. Further investigation into update leakage, secure aggregation, and, where relevant, differential privacy is required before stronger privacy statements can be made.

4.12 Comparative Evaluation of Traffic Optimization Methods

Table 16. *Comparative Evaluation of Existing Traffic Optimization Methods and the Proposed DT-FMDRL Framework*

Study / Method	Dataset / Environment	Metrics Reported	Main Limitation
HTE	6G-TrafficNet simulation	Latency: 12.8 ms; Throughput: 7.9 Gbps; Packet loss: 5.8%; Congestion index: 0.63; Energy efficiency: 68%; Convergence: 520 rounds	Limited adaptability to dynamic traffic
SDN-DRL	6G-TrafficNet simulation	Latency: 8.7 ms; Throughput: 11.4 Gbps; Packet loss: 3.7%; Congestion index: 0.41; Energy efficiency: 81%; Convergence: 420 rounds	Centralized data collection, communication overhead, and privacy concerns
MADRL	6G-TrafficNet simulation	Latency: 7.4 ms; Throughput: 12.3 Gbps; Packet loss: 2.9%; Congestion index: 0.36; Energy efficiency: 84%; Convergence: 360 rounds	Coordination and convergence challenges
FedAvg-DRL	6G-TrafficNet simulation	Latency: 7.0 ms; Throughput: 12.8 Gbps; Packet loss: 2.5%; Congestion index: 0.32; Energy efficiency: 86%; Convergence: 310 rounds	Limited adaptation to heterogeneous client performance
This study	Synthetic 6G-TrafficNet with digital twin simulation	Latency: 6.23 ms; Throughput: 14.0 Gbps; Packet loss: 1.8%; Congestion index: 0.28; Energy efficiency: 89%; Convergence: 245 rounds	Real-world generalization, formal privacy guarantees, and statistical significance require further validation

5. CONCLUSION

This study investigated whether digital twin-assisted federated multi-agent deep reinforcement learning can improve autonomous traffic optimization in heterogeneous 6G network environments. The proposed DT-FMDRL framework combines multi-agent deep reinforcement learning, Adaptive Performance-Aware Aggregation, traffic-aware reward learning, and digital twin-assisted training.

In the reported simulation experiments, DT-FMDRL achieved a latency of 6.23 ms, throughput

of 14.0 Gbps, packet loss of 1.8%, congestion index of 0.28, and energy efficiency of 89%. In 245 rounds of communication, it converged on the reported meeting point. These outputs exceed the baseline values selected in this study. They offer preliminary evidence for the benefits of decentralised decision-making, adaptive model aggregation, and simulation-assisted training combined in multi-objective traffic optimisation.

The major contribution of the PFI-CIS is not introducing each technique individually, but formulating and simulation-evaluating an integrated traffic optimisation framework. Consequently, the comparative results reflect the study's performance goals, and the proposed integration provides a partial foundation for future research on adaptive learning in a multi-hierarchical network domain. Controlled ablation experiments are needed to determine each component's relative contribution to the overall improvements.

Several limitations remain. The evaluation uses a synthetic traffic dataset and a simulation environment and therefore cannot demonstrate the operational effectiveness of implemented 6G networks. Additionally, the reported performance values need stronger reproducibility evidence, such as repeated runs and variation analysis, with statistical comparisons of the runs. The privacy properties of federated model updates and the ability to generalize learned policies to new network conditions have not been studied sufficiently.

Future work should evaluate the framework on independent traffic traces and network testbeds, real or emulated; conduct component-wise ablation studies; test different numbers of network domains; and explore secure aggregation and formal privacy mechanisms. The robustness of systems to varying traffic distributions, communication failures, and resource-limited edge deployments should also be examined.

Overall, the results indicate the potential of DT-FMDRL as a simulation-based approach to intelligent 6G traffic optimisation. The randomly selected data should further validate its generalizability, practical deployment, and security guarantees.

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