Artificial Intelligence-Driven Network Slicing: A Comparative Study of 5G and 6G Automation Capabilities

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***Abstract*—Utilizing the artificial intelligence (AI) supported by software-defined networking and network function virtualization has a significant impact on the performance, flexibility, and efficiency in the development of 6G network slicing. This article compares AI-driven 6G slicing networks with traditional rules-based 5G networks, focusing on latency, data throughput, jitter, power efficiency, and bandwidth. NS-3 and MATLAB have been utilized to evaluate the networks performance. The comparison results show that AI-driven network slicing reduces average latency by 50%, boosts data throughput by 40–90%, reduces jitter by 50%, and improves power efficiency by 20–28% compared to 5G networks. These results indicate that AI-powered network slicing in 6G networks outperforms traditional methods, enabling trendier network management. This sets a standard for network segmentation research in the future deployment of 6G networks.**

***Index Terms*—5G, 6G, Network function virtualization, Network slicing, Software-defined networking.**

I. Introduction

Wireless communications have witnessed remarkable development through 5G and 6G networks, both of which adopt the concept of network slicing. Network slicing is considered the backbone of present and future cellular networks, as well as their applications.

5G presented static and semi-dynamic network slicing models, while the intention for 6G is to improve slicing via the integration of Artificial Intelligence (AI) and real-time adaptation, along with progressive automation (Chataut, Nankya and Akl, 2024; Wang, et al., 2023).

On the one hand, 5G network slicing primarily divides physical network capability into logical slices, which support roughly distinguished use cases, such as enhanced Mobile Broadband (eMBB), Ultra-Reliable Low Latency Communication (URLLC), and massive Machine Type Communication (mMTC) (Liu, Clerckx and Popovski, 2023; AlQahtani, 2023). However, 5G slicing does not adapt efficiently to changes in network conditions and real-time resource allocation. It requires pre-defined configurations to operate (Botez, Zinca and Dobrota, 2025). On the other hand, 6G network slicing is likely to be more intelligent, utilizing AI to create self-optimizing slices that adapt to network changes (Ejaz, Wu and Iqbal, 2024). The integration of AI methods can predict/allocate resources in real-time to deliver services under changeable network conditions without breakage (Botez, Zinca and Dobrota, 2025). The existed slicing mechanisms give a clear view to developers about the real-time network analytics; as a result, the decision-making process is made easier (Bikkasani and Yerabolu, 2024).

The security issues represent challenges in 6G, including network management, energy efficiency, and network standardizing (Serôdio, et al., 2023). Therefore, to overcome these issues a real-time service in dynamic situations is crucial (Corici, et al., 2024).

The article proposes an AI-powered framework for 6G, with simulation results showing up to a 50% reduction in latency, a 40–90% increase in throughput, and a reduction in jitter by 50%, and improves power efficiency by 20–28% compared to 5G networks. This framework exceeds recent studies with 10–20% lower latency, 15–25% higher throughput, 20% energy savings, and 18% less resource waste. Based on AI and deep reinforcement learning (DRL) research, it develops latency optimization, radio access network (RAN) coordination, and AI integration with Software-Defined Networking (SDN) and network function virtualization (NFV), outperforming previous DRL optimizations in optical networks by 4–6%. Future work should focus on standardization, interoperability, and security to enable smooth 6G network deployments.

II. Literature Review

In a 5G environment, physical network resources are partitioned into logical slices for various applications (Wang, Li and Liu, 2024). 5G slicing offers more resource allocation than dynamic, semi-dynamic, and static models

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(Lin, Chou and Hwang, 2023). Thus, studies aim to improve the flexibility and scalability of network slicing through SDN and NFV.

Wang, et al. (2023) and Yousaf, et al. (2017) tackled resource allocation optimized by SDN and NFV to enable flexible, scalable, and programmable network slicing in 5G and future networks. Building on SDN for 5G networks, Botez, et al. (2023) developed inference methods to reduce latency, demonstrating a significant reduction in processing time in 5G and earlier (5G/B5G) networks. Their developed methods addressed the intelligent algorithms that could manage the SDN resources. Similarly, Li, et al. (2018) showed that the DRL can efficiently help in resource management for network slicing.

However, the aforementioned works have limitations: While Wang, et al. (2023) stated that further investigation is needed to extend 5G–6G slicing, Yousaf, et al. (2017) emphasized that integrating interoperability standard NFV and SDN frameworks are important in complex 5G network environments.

Botez, et al. (2023) relied on pre-defined inference methods rather than adaptive learning. Furthermore, Li, et al. (2018) were principally concentrated on enhancing a single metric without a complete evaluation within different service types and performance metric dimensions.

Present studies explore SDN and NFV with AI-driven methods to enhance network slicing. Abdellatif, et al. (2023) introduced an AI-enabled framework providing automation, adaptability, and reliable slice management for 5G and beyond. The research presented generous benefits with ML and DRL. However, it highlights concerns about real-time scalability and dynamic user-behavior estimating in multidomain slicing across heterogeneous infrastructures, emphasizing the need for better FL, cross-domain orchestration, and real-time decision algorithms.

Ayala-Romero et al. (2020) considered DRL-based resource orchestration in virtualized RANs, showing throughput improvements via strategic network placement functions. Their work confirmed reinforcement learning's efficacy for radio resource management but did not cover end-to-end slicing across diverse network realms. Karbalaee Motalleb, et al. (2023) and Abidi et al. (2021) explored AI integration with SDN and NFV, concentrating on architectural frameworks. However, their work essentially tackled architectural design and individual technological optimization rather than inclusive multi-metric performance improvements through interaction integration.

Bojović, et al. (2022) explored a 5G/6G network quality of service (QoS) management framework that develops adaptability to service needs and network forms. Although they offered architectural and simulation insights, their work does not have depth in AI-driven QoS automation for heterogeneous, ultra-dense networks. Da Costa and Murillo (2023) presented that integrating network slice controllers at a higher level in 5G/6G architectures boosts intent-based networking through resource management tailored to service demands. However, interoperability and scalability concerns in heterogeneous networks demand standardized frameworks and AI-driven orchestration to realize this potential entirely.

Furthermore, Wang, et al. (2024) settled an AI-based framework for automated network design of 5G URLLC services, showcasing noteworthy profits in design efficacy and service availability for industrial use cases. Nevertheless, the research underlined a lack of attention on real-time adaptability to mutable industrial environments and inadequate validation concerning different deployed devices.

The transition to 6G intends to adopt concerns with traditional slicing by using AI to enable self-optimizing slices. AI-powered network slicing promises better resource allocation and service customization (Rashid and Jeong, 2024). However, challenges remain; particularly that AI-driven slicing may not integrate straightforwardly with current infrastructure, requiring industry-standardization frameworks (Gkonis, et al., 2025).

Abouaomar, et al. (2022) proposed Federated DRL for low-latency, adaptive RAN slicing in 6G, providing resource scalability and data privacy through non-centralized data collection. They confirmed that more efforts are required to enhance the communication in 6G dynamic environment, overcome the computational overhead and limited real-world validation. In their research, Tshakwanda, Arzo and Devetsikiotis (2024) demonstrated that the AI can enhance the performance of 6G that allows dynamic routing, as a result reducing latency and refining resource allocation.

A study conducted by Martínez et al. (2025) to improve the energy efficiency and resource allocation using DRL in an optical network. Their DRL model improved the energy efficiency by 6.6–7.4%. However, their results were in controlled environments, underlining the need for superior efficiency in complex 6G network scenarios with diverse service requirements.

Another approach that utilizes the DRL was proposed by Meignanamoorthi and Vetriselvi (2024) for dynamic resource allocation among sub-slices in 6G networks. However, their results revealed limitations in scalability under different network conditions, underscoring the need for future research on operational constraints and compatibility with 5G and 6G network infrastructures. Similarly, Suresh, et al. (2024) presented a DL hybrid approach to enhance resource allocation in 6G networks. The proposed approach has also improved the energy efficiency and latency. However, the results ignored mobility scenarios and lacked a scalability evaluation for high density in 6G environments.

As 6G network slicing complexity noticeably raises, Explainable AI (XAI) models are essential to rise transparency in decisions. Garg, et al. (2023) integrated the ML models with interpretability tools to enhance decision transparency and automation. This integration achieved better slice management and model reliability. However, it lacks of real-time deployment, scalability.

Energy-efficient AI slice management is also critical, requiring greater investment in Green AI to boost efficiency and reduce power consumption (Alhammadi, et al., 2024).

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III. Key Technological Enablers of 5G and 6G Network Slicing

6G network slicing advances 5G by incorporating intelligent automation, decentralized control, and enhanced abilities. In 6G, AI and ML support autonomous resource management, predictive analysis, and real-time traffic optimization. Dangi and Lalwani (2024) state that AI solutions in 6G will significantly lower latency compared to 5G slicing while achieving higher flexibility. Table I compares AI use in 5G and 6G networks.

Network slicing allows dynamic resource allocation, optimizing traffic and reducing hardware dependence through SDN and NFV. SDN separates control and data planes for centralized management, while NFV virtualizes functions, such as firewalls and load balancers on general hardware. However, SDN's centralization can cause performance bottlenecks in 5G, and NFV lacks real-time optimization capabilities (Chiti, Morosi and Bartoli, 2024). For 6G, AI-driven automation, stronger protection, and decentralized architectures will enhance these features.

6G SDN and NFV will incorporate AI for decision-making and decentralized control. AI algorithms automate slice management and optimize network parameters dynamically in SDN. In NFV, AI enables autonomous self-healing networks that detect and resolve issues independently. Ultra-low latency services are possible through adaptive VNF optimization and edge placement (Zahedi, Jamali and Bayat, 2022).

Furthermore, SDN and NFV supported by AI in 6G can offer advanced network traffic management and dynamically routing traffic. As a result, this reduces the latency and improves QoS (Guo and Yuan, 2021). Table II summarizes 5G and 6G Network Slicing Enhancements.

IV. Methodology

This article proposes a framework that integrates Network Simulator 3 (NS-3) and MATLAB to compare and evaluate the performance of AI-driven 6G slicing networks with traditional rule-based 5G networks. The NS-3 has been utilized to model end-to-end slicing, resource allocation, and network traffic. At the same time, a specialized AI toolbox in MATLAB has been used to develop, train, and validate AI models (Figure 1).

TABLE I
AI Integration Comparison between 5G and 6G

Feature	5G slicing	6G slicing
Resource allocation	Rule-based, semi-dynamic	AI-driven, real-time optimization
Adaptability	Semi-automated reconfiguration	Self-optimizing slices using DRL
Traffic prediction	Basic ML models	Deep learning-based forecasting
Security management	ML-based Anomaly Detection	Advanced AI-based anomaly detection
Energy efficiency	Semi-automated	AI-optimized power consumption

DRL: Deep reinforcement learning, ML: Machine learning, AI: Artificial intelligence

A. Simulation Environment Configuration

Network topology and architecture

The simulated network covers a 1000 m × 1000 m area with four layers: Evolved Node Bs, randomly distributed user devices (UEs), NFVs as the core network, and gateways plus cloud (Table III).

Traffic models, service characteristics, and simulation parameters

The service requirements for eMBB, URLLC, and mMTC in 6G slicing are shown in Table IV. 6G standardization is still in progress, and 3GPP release 20 did not provide official specific metrics for 6G network slicing (3GPP TR 22.870, 2025). Therefore, indicative performance targets can be inferred from TR 22.870.

Table V shows the simulation parameter settings.

TABLE II
5G and 6G Network Slicing Enhancements

Feature	5G network slicing	6G network slicing
Automation	Rule-based, manual adjustments	AI-driven, self-optimizing
Traffic engineering	Reactive congestion handling	Predictive rerouting via AI
Security	Basic rule-based defenses	AI-based for threat detection and mitigation
SDN/NFV evolution	Centralized control, dynamic VNFs	AI-based, decentralized, autonomous VNF

AI: Artificial intelligence, SDN: Software-defined networking, NFV: Network functions virtualization, VNF: Virtual network function

TABLE III
The Network Topology and Architectural Configuration Used in the Simulation Environment

Parameter	Description
Simulated Area	1000 m×1000 m
Number of Evolved Node Bs	50 eNodeBs
Number of User Equipment (UE)	200
Core Network	8 VNFs
Gateway and Cloud	3 Gateways and 1 Cloud Data Centers

TABLE IV
Traffic service characteristics and QoS parameters for 6G network slicing

Service type	UE data rate	Latency	Reliability (%)
eMBB	~100 Gbps	1–10 µs	≥99.9
URLLC	≤10 Gbps	≤1 µs	>99.999
mMTC	≤100 kbps	≤550 µs	~99

eMBB: Enhanced mobile broadband, URLLC: Ultra-reliable low latency communication, mMTC: Massive machine type communication

TABLE V
Simulation Parameters

Parameter	**Value**
Simulation duration	300s (50s warm-up)
Time step resolution	10µs
Number of network slices	5 (2 eMBB, 2 URLLC, 1 mMTC)
Total available bandwidth	100 GHz
Traffic load levels	Low (20%), Medium (50%), High (80%), Peak (95%)
Slice update interval	100µs (AI-driven), 5s (static 5G)
Number of simulation runs	10 per scenario (independent seeds)

eMBB: Enhanced mobile broadband, URLLC: Ultra-reliable low latency communication, mMTC: Massive machine type communication, AI: Artificial intelligence

TABLE VI
Reinforcement Learning Models for Dynamic Slice Management

AI technique	Architecture	Input	Output	Key hyperparameters	Training
PPO	Actor-critic, 3 FC layers (256 neurons, ReLU, batch norm)	18 network state features	12 slice allocation actions	LR=0.0003, γ=0.99, PPO ε=0.2, batch=64	50,000 steps, 500 episodes, eval every 5k steps
DQN	MLP 4 layers (512→256→128→64, ReLU), target network	18 state variables	12 Q-values	LR=0.0001, γ=0.995, ε-greedy, batch=32	100,000 interactions, Huber loss δ=1.0

PPO: Proximal policy optimization, DQN: Deep Q-networks

TABLE VII
Deep Learning Models for Resource Allocation and Traffic Prediction

AI technique	**Architecture**	**Input**	**Output**	**Key hyperparameters**	**Training**
RNN/LSTM	2 LSTM layers (128,64)+2 dense (128,32), dropout 0.2	10 timesteps×6 features	1 (traffic prediction)	LR=0.001, Adam, MSE loss	50,000 sequences, 100 epochs, early stopping
CNN	3-conv blocks (32→64→128 filters) + 2 dense (256,128)	28×28×3 (spatial-temporal state)	12-dim bandwidth allocation vector	LR=0.0005, Adam, batch=32	100,000 snapshots, 150 epochs, 20% validation split

RNN: Recurrent Neural Networks, LSTM: Long short-term memory, CNN: Convolutional neural network

AI techniques and model architectures

Employing the AI techniques in 6G network slicing has been covered in (Abouaomar, et al., 2022), (Ejaz, Wu and Iqbal, 2024), and (Shenoy, Bhat and Krishna Prakasha, 2025). This article considers different aspects of 6G network slicing from an AI perspective. The proposed framework utilized DRL, deep neural networks for dynamic slice management, and resource allocation and traffic prediction, respectively.

Two AI techniques, Proximal Policy Optimization and Deep Q-Networks, are used for dynamic network management conditions as shown in Table VI. At the same time, Recurrent Neural Networks with Long Short-Term Memory cells and Convolutional Neural Networks are utilized for resource allocation and traffic prediction as shown in Table VII.

Dataset generation and collection

The dataset has been generated based on the integration of NS-3 network simulations and MATLAB-based training. Three service types, such as eMBB, URLLC, and mMTC, were simulated, gradually evolving network traffic in an attempt to account for their various operation scenarios. This information contains multiple performance parameters, including latency, throughput, packet loss rate, jitter, bandwidth usage, and energy consumption. This combined data set will be used as the basis for comparing AI-driven 6G slicing to other 5G slicing techniques. Table VIII shows the dataset components and their specifications.

TABLE VIII
The Dataset Components and Specifications

Metric	**Measurement unit**	**Value range**
Latency	Milliseconds (µs)	0.5–50 µs
Throughput	Megabits per second (Mbps)	100 Mbps–10 Gbps
Packet loss rate	Percentage (%)	0.01–5%
Jitter	Milliseconds (µs)	0.2–5 µs
Bandwidth utilization	Gigabits per second	Varies per slice
Energy consumption	Joules (J)	10–30% improvement (6G vs. 5G)
Artificial intelligence training data points	Data entries	500,000+

B. Performance Metrics

Six primary measures are used to quantify the performance of network slicing across different configurations and conditions.

The Latency (L) is measured and collected from different network slices for numerous traffic loads and slice types.

$$L = D_p + D_t + D_q + D_{pr} \tag{1}$$

Where:

- Dp: Propagation delay
- Dt: Transmission delay
- Dq: Queuing delay
- Dpr: Processing delay

Throughput (T): Represents the successfully transmitted data in a certain time. It reflects the performance of eMBB, URLLC, and mMTC in the network under different conditions.

$$T = \frac{S}{T_t} \tag{2}$$

Where:

- S: Successfully transmitted (bits)
- Tt: Total transmission time (seconds)

Packet loss rate (PLR): A ratio of high-reliability and congestion.

$$PLR = \frac{Pl}{Pt} * 100\% \tag{3}$$

Where:

- Pl: Number of lost packets
- Pt: Total transmitted packets

Jitter analysis (J): reflects the network stability by measuring the variation in µs of delay on slice configurations.

$$J = \frac{1}{N-1}\sum_{i=1}^{N} | D_i - D_{avg} | \tag{4}$$

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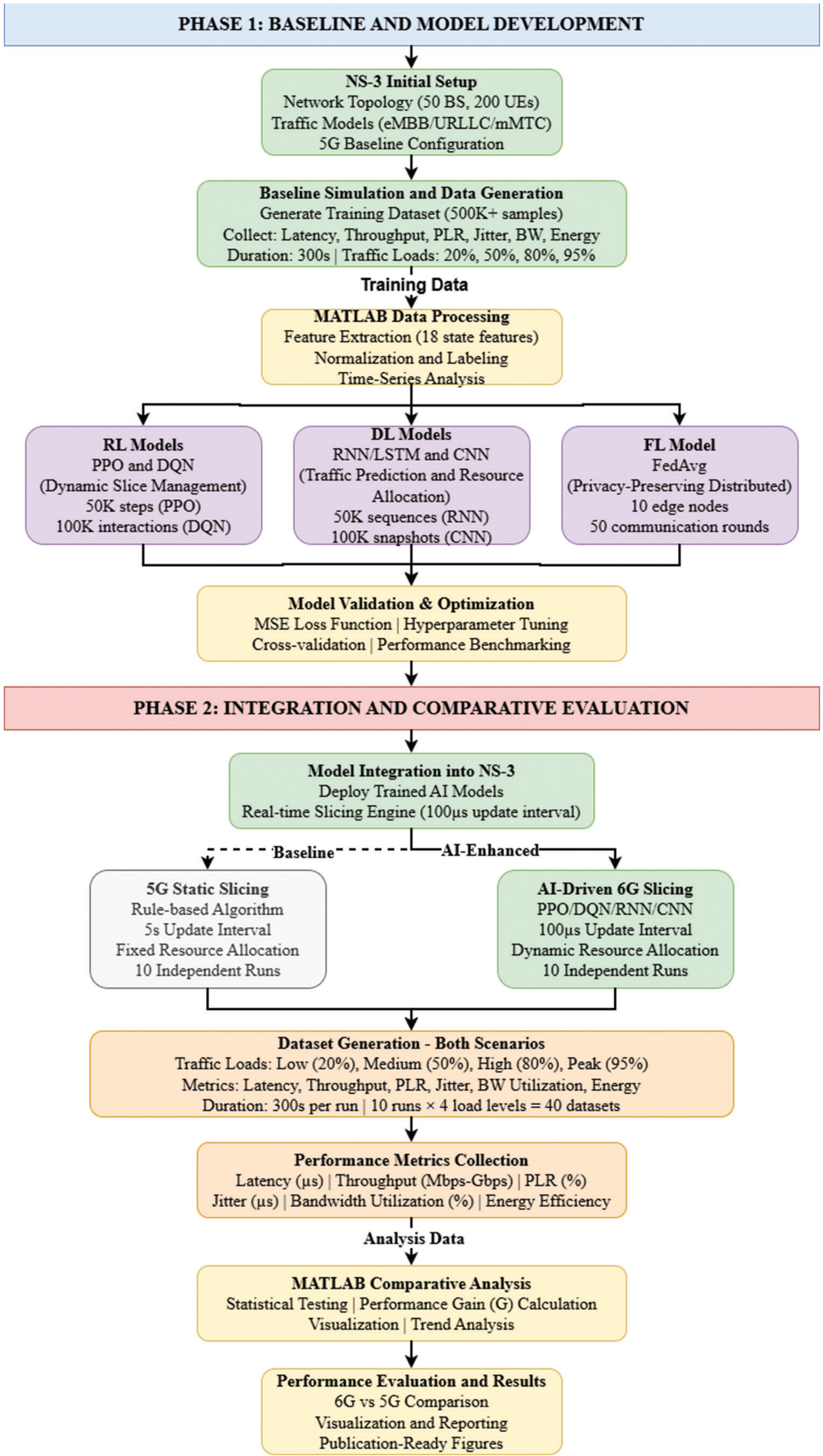

Fig. 1. The simulation and analysis process of artificial intelligence (AI)-driven 6G network slicing takes two phases: (1) Setting up and producing AI models using NS-3 and MATLAB; and (2) Comparing and including AI-driven 6G slicing with conventional 5G methods.

Where:
- Di: Delay of packet i
- Davg: Average delay of all packets, and
- N: Total number of packets

Bandwidth Utilization (BU): Managing bandwidth usage. It measures the efficient use of network resources in both 5G and 6G networks.

$$BU = \frac{T}{C} * 100\% \tag{5}$$

Where:
- T: Throughput (bps)
- C: Available bandwidth (bps).

Energy Efficiency (EE): Measures how efficient the AI slicing techniques are.

$$EE = \frac{T}{P} \tag{6}$$

Where:
- T: Throughput (bits/sec)
- P: Power consumption (Joules/sec or Watts)

C. AI-Based Data Analysis

The data analysis workflow comprised the following systematic procedures:

1. Data Pre-processing: MATLAB imports the network logs from NS-3 simulations
2. Feature Extraction: Performance metrics that have a direct impact on the network slicing were extracted, which are: Latency, bandwidth use, jitter, slice reconfiguration time, and power consumption
3. Traffic Pattern Analysis: Historical traffic patterns across slice types were examined to identify temporal patterns and service characteristics
4. Data Normalization and Labeling: The data were normalized for consistency in scaling of features, and labeled for supervised learning
5. Time-Series Modeling: In the real-time slicing model, real-time parameters were modeled so that AI models can design optimal resource allocations based on present network conditions and historical data
6. Model Optimization: AI model training employed Mean Squared Error (MSE) as the loss function for optimization:

$$EE = \frac{T}{P} \tag{7}$$

Where:
- yi is the actual value, ŷi is the predicted value, and n is the number of data points

7. Performance Gain Calculation: To evaluate the improvements that AI-driven slicing has accomplished relative to standard rule-based processes.

$$G = \left(\frac{(M_{AI} - M_{RB})}{M_{RB}} \right) * 100\% \tag{8}$$

Where:
- M_{AI} is the performance metric value for AI-based slicing, and M_{RB} is the performance metric value for rule-based slicing.

D. Visualization and Statistical Analysis Methods

Performance improvements of 6G slicing relative to 5G are presented in detail using multiple visualization and statistical analysis methods. These methods allow for the identification of trends, differences, and the general performance of AI-based network slicing.

V. Results and Discussion

A. The Role of SDN and NFV in Network Slicing Performance

SDN's effect on latency and jitter reduction

Different loads based on SDN optimization have been considered in this article to enhance the latency and jitter as shown in Fig. 2. The results show that the 6G with SDN has better performance. Across all loads, 6G achieves approximately 40% lower latency than 5G (6G's 17–30 µs vs. 5G's 37–50 µs). It also has a lower jitter 50% (6G's 4–5 µs vs. 5G's 8–10 µs). These results align with those of Yousaf, et al. (2017), who stated that SDN's role is to reduce delay.

NFV's effect on throughput performance

The simulation results in Fig. 3 show that the NFV has a positive impact to enhance the throughput. In this experiment, three services, such as eMBB, URLLC, and mMTC, are chosen to support their network slicing by employing NFV. 6G shows different gains: eMBB up 690 Mbps (41%), URLLC 350 Mbps (75%), mMTC 95 Mbps (90%). These results align with Dangi and Lalwani (2024), who show that NFV boosts throughput.

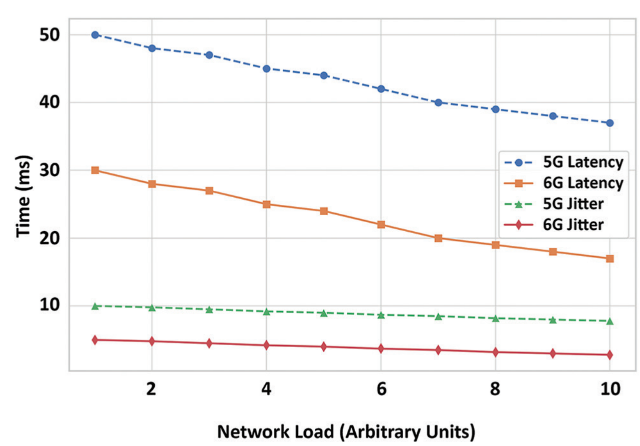

Fig. 2. Performance analysis of latency and jitter based on software-defined networking optimization.

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Energy efficiency gains with NFV

The energy efficiency and regression based on the employment of NFV have been taken into account in this article. The experimental results in Fig. 4 show a more consistent performance in 6G, and it has a lower median energy 20% compared to 5G. In the same context, Fig. 5 shows that the energy decreases by 15J in 6G versus 13J in 5G. These results give a clear indicator that NFV improves resource allocation, which support Abdullatif, et al. (2023) who claimed the potential of AI for energy-efficient network slicing. Unlike the study by Wang, Zhang, and Wang (2023), which focused on automating NFV, this article emphasizes the adaptive role of AI in dynamic slicing, illustrating how predictive models enhance the effectiveness of NFV optimization.

B. Performance Improvements of 6G Slicing Over 5G

Latency and jitter trends

The latency and jitter for both 6G and 5G are compared in Fig. 6. These results indicate that:

- The latency has been reduced by 50% when the AI has been employed to improve the resource allocation (14 µs vs. 30 µs).
- The network stability has also improved as the jitter is lower in 6G (1–2 µs vs. 5–7 µs).

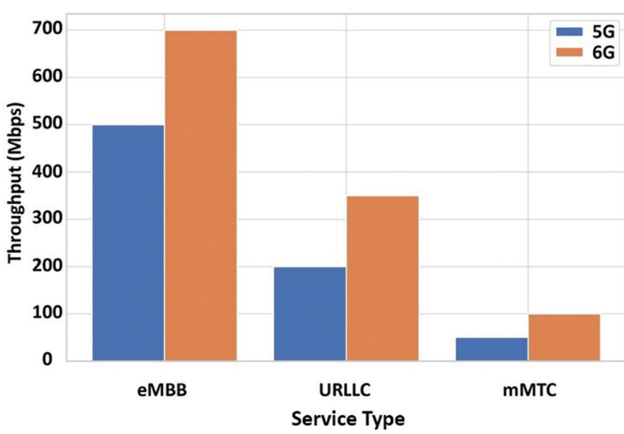

Fig. 3: Throughput performance for 5G versus 6G with network function virtualization.

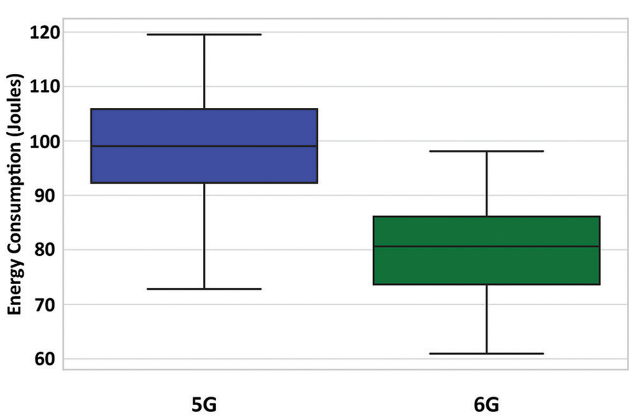

Fig. 4. Network function virtualization energy consumption distribution.

The rapid increase in latency at the 6th interval indicates a faster response in 6G to this issue, confirming the effectiveness of AI in mitigating these problems.

Throughput comparison

Fig. 7 shows the three services eMBB, URLLC, and mMTC that are nominated in this article to support their network slicing via the throughput performance. The simulation results show that 6G achieves higher throughput in the three services (40%) as follows:

- eMBB: 6G's 700 Mbps versus 5G's 500 Mbps
- URLLC: 6G's 280 Mbps versus 5G's 200 Mbps, and
- mMTC: 6G's 140Mbps versus 5G's 100Mbps

Latency and jitter distribution analysis

The latency and jitter distribution analysis is presented in Fig. 8. 6G shows a consistent performance and it has outperformed the 5G around 50% in latency and jitter as follows:

- 6G has a lower median latency (15 µs vs. 29 µs) and
- jitter (3 µs vs. 6 µs) with narrower interquartile ranges

Furthermore, the outlier analysis demonstrates that the maximum latency in 6G has also recorded better results

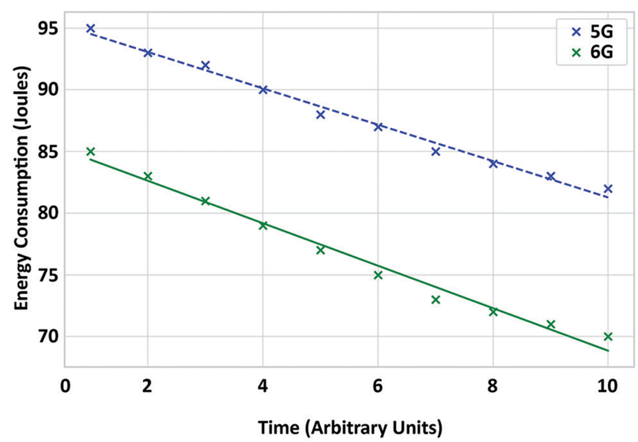

Fig. 5. Network function virtualization energy consumption improvements.

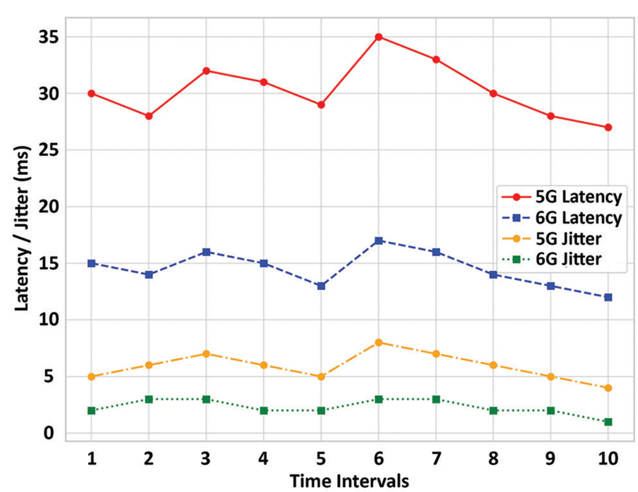

Fig. 6. Time variation in latency and jitter in 5G versus 6G.

compared to 5G (22 µs vs. 44 µs). Therefore, it could help to improve the reliability for URLLC and mMTC applications.

Energy efficiency trends

Fig. 9 shows the power consumption versus throughput comparison. In terms of power efficiency, 6G appears to be more efficient, achieving nearly 20–28% lower power consumption, consuming approximately 39–46W in contrast to 5G's 50–62W in the range of 500–560 Mbps. This implies that 6G exhibits lower power consumption regardless of the data rate.

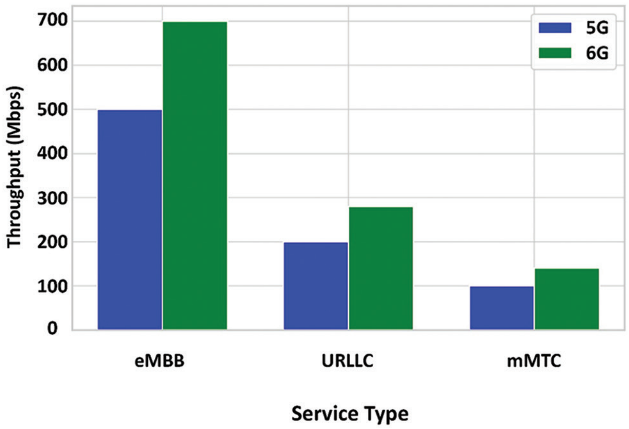

Fig. 7. Throughput performance evaluation of enhanced mobile broadband, ultra-reliable low latency communication, and massive machine type communication network slices.

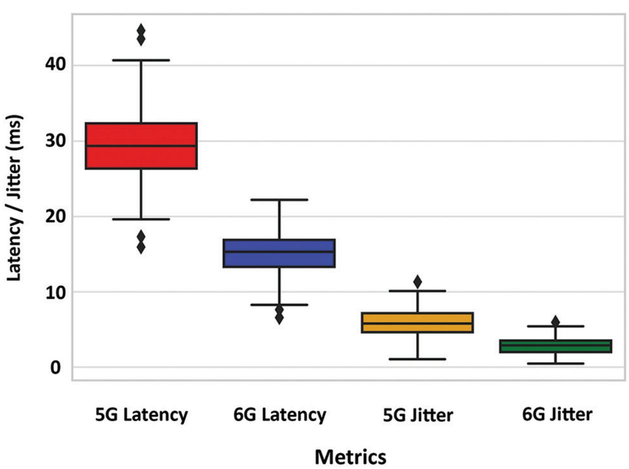

Fig. 8. Distribution analysis of latency and jitter.

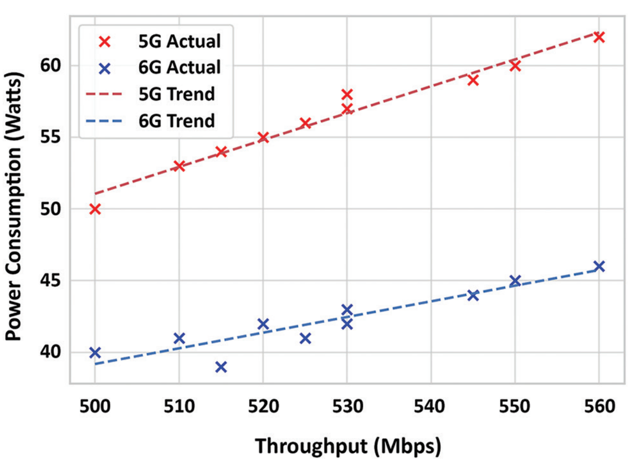

Fig. 9. 6G versus 5G power consumption and throughput.

C. Comparing the Present Findings with the Literature

Integrating AI techniques for network slicing in this paper for 6G could show performance enhancement compared to 5G network slicing, as well as recent studies. Other studies, such as Li et al. (2018), have already implemented AI techniques (specifically DRL) for resource allocation and management in network research, but the present work could demonstrate multi-metric enhancements along latency, jitter, throughput, and energy consumption. Furthermore, the integration of AI techniques with SDN and NFV has already been investigated by Karbalaee Motalleb, et al. (2023) and Abidi, et al. (2021). However, the work presented in this paper goes beyond individual technology optimization. The present work indicated the cooperative benefits of combining AI, SDN and NFV for 6G network slicing by achieving significant performance across the mentioned metrics simultaneously rather than enhancing single isolated metrics.

In addition, Botez, et al. (2023) have reported a substantial reduction in latency by implementing heuristic algorithms for 5G/b5G networks. However, the latency in this paper has reduced by about 50% using AI-enhanced SDN controllers with predictive traffic management. Moreover, the study of Martines, et al. (2025) has reported 6.6–7.4% improvement in energy efficiency, while the results of this work could gain 20–28% improvements, which exceeded the benchmarks by 13–21% due to implementing AI-driven NFV allocation and predictive traffic management.

Furthermore, improvements in throughput in this work are aligned with Ayala-Romero et al. (2020) who proved the DRL-based orchestration advantages in virtualized RANs. Nevertheless, this work extends their findings by quantifying slice-specific throughput gains via AI-enhanced network function placement. It could increase throughput by 40–90% across eMBB, URLLC, and mMTC.

VI. Conclusion and Future Work

The work presented in this paper involved an in-depth comparative analysis of network slicing in 5G and 6G networks, considering elements that enhance the network performance, especially those from AI-driven slicing. The results have been verified through simulations and statistical analysis. They demonstrated that AI-driven slicing in 6G is significantly more effective than rule-based slicing in 5G in terms of reducing latency, improving throughput, correcting jitter, and energy efficiency.

The dynamic resource allocation assisted by AI has reduced the latency by up to 50% while stabilizing jitter, and providing reliability. In addition, the adaptive bandwidth allocation based on AI led to 40–90% increment in throughput for best-effort (eMBB, URLLC, and mMTC) applications.

Moreover, the integration of AI with NFV reduced energy consumption by 20–28%, leading to power efficiency. The capability of AI techniques in predictive analytics enables real-time adaptive slicing strategies in 6G networks so that they can cope with changing conditions. Combining SDN/NFV and AI-driven slicing in 6G leads to a more efficient and flexible framework for dynamic resource allocation that could outperform traditional 5G slicing.

However, several areas remain open for further investigation and research, such as security and privacy improvements, cloud computing integration, green AI for energy-efficient slicing, and real-world testing and implementation. For instance, researchers should look into federated learning and differential privacy methods to keep sensitive network data safe while training AI models. Furthermore, further researches are needed ensuring that AI-powered slicing orchestrators are safe from attacks and implement techniques, such as blockchain-based methods to make sure that slices are safe and can be checked in environments where multiple users share the same resources. Moreover, integrating AI-driven slicing with different cloud computing architectures that connect the edge to the cloud, such as Mobile Edge Computing (MEC), to guarantee ultra-low-latency slicing and dynamically allocate resources in such cloud environments. Furthermore, another important area of research is figuring out how to make AI systems less harmful to the environment while still meeting QoS standards. This can be achieved with lightweight AI technologies, inference methods that use less energy, and dynamic slice-adaptation techniques.

Considering these future directions, slicing in 6G using AI can be broadly improved to deliver new-generation communication networks that are urgently needed. It is worth noting that the continuous development of AI, SDN/NFV, and cloud computing will shape a bright future of scalable architecture and intelligent networks.

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