Adaptive AI-Driven Network Slicing in 6G for Smart Cities: Enhancing Resource Management and Efficiency

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Abstract

Background: Smart city evolution is fast-paced, and imposes severe demands on telecom infrastructures: it must be highly flexible and scalable for coping with bursty traffic loads and heterogeneous service needs. Legacy network systems are not well suited to handle the changing requirements of smart city environments with autonomous cars, IoT, and public safety systems.

Objective: The study to offer an AI-native network slicing framework for 6G smart city networks in order to improve dynamic resource control and management. The framework aims to enhance the delay, energy, and resource performance metrics which are significant for smart city services.

Method: To facilitate the real-time network resource orchestration depending on the changing traffic requirements and user preferences, the authors consider moving target defense adapted artificial intelligence with a Deep Reinforcement Learning (DRL) model. Simulations were carried out to compare the AI-native model to conventional and AI-supported slicing methods.

Results: Simulation results validate that the AI-native network slicing framework outperforms current 5G solutions with 25% reduction in latency and 20% increase in energy efficiency. Furthermore, the model's online resource allocation scheme can enhance the utilization efficiency of the bandwidth and the energy by 15% compared with the traditional approaches. Such improvements especially in critical applications like traffic management, emergency response, and health care would be important.

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Conclusion: The presented results demonstrate that AI-native network slicing is a viable, flexible, and scalable solution for 6G smart city networks. The framework is designed to support the future sustainable and high-performance requirements of urban infrastructures, providing both energy-efficient real-time adaptability. This study provides an overarching front-to-end outlook to address the management issues of sophisticated resource systems, and puts AI-native network slicing at the base level of the emerging smart cities.

Keywords: 6G, AI-driven network slicing, smart cities, low-latency communication, resource management, energy efficiency.

1. Introduction

The expansion of urban applications within smart cities has introduced new and complex challenges for modern telecommunications networks. Smart cities rely on a diverse array of technologies, including the Internet of Things (IoT), connected vehicles, augmented reality (AR), and big data processing capabilities. These technologies generate massive amounts of data and require ultra-reliable, low-latency communication networks to function effectively. One of the most significant challenges posed by smart city networks is the variability in data traffic, which fluctuates based on factors such as time of day, geographic location, and unexpected events, including disasters or large-scale celebrations. Consequently, next-generation networks must exhibit enhanced attributes to accommodate these dynamic environments. The key requirements for future telecommunications networks are thus outlined as follows.

With the advent of 6G networks, growing attention has been directed toward both the technological advancements that improve network functionality and the unique challenges associated with smart cities. Network slicing has emerged as a promising solution to address the inherent complexity of next-generation telecommunications networks. Rather than relying on a single Hardware Abstraction Layer (HAL) that supports only one service type, network slicing enables operators to create multiple HALs, each tailored to specific service requirements. This approach facilitates more efficient resource allocation, allowing operators to dynamically manage network resources while providing users with customized services based on their specific needs (Wu et al. 2022). However, the true potential of network slicing lies in the integration of artificial intelligence (AI), which enhances the slicing process. AI-driven network slicing can enable dynamic, real-time management of network requirements and resource distribution based on the network's current state and user demands (Wang et al. 2023).

The transition from 5G to 6G represents a paradigm shift in telecommunications. While 5G networks were designed primarily for enhanced Mobile Broadband (eMBB), Ultra-Reliable Low-Latency Communication (URLLC), and massive Machine-Type Communication (mMTC), 6G will support even more advanced applications, including holographic communication, smart healthcare, and autonomous transportation systems(Shen et al. 2022). AI-native solutions within 6G, particularly in the context of network slicing, are expected to address these challenges by providing intelligent, autonomous, and adaptive resource management strategies suited to the dynamic nature of 6G networks.

However, several challenges hinder the effective implementation of 5G network slicing in smart cities. Previous network slicing solutions primarily employ static or semi-static resource allocation mechanisms, which are ineffective in dynamic network environments. Research on 5G network slicing has predominantly focused on improving resource utilization efficiency and reducing latency, but these strategies are insufficient for smart cities, where networks must rapidly adapt to fluctuating traffic and evolving service demands (Guan, Zhang, and Leung 2021).

Although AI-based approaches have been applied to enhance network slicing models, many existing solutions fail to achieve true real-time adaptability. Current models lack the necessary elasticity to dynamically adjust resource allocation rates in response to erratic traffic variations, which are common in smart cities (Blanco et al. 2023). The absence of adaptable AI-based network slicing frameworks for emerging 6G networks represents a critical research gap. Moreover, solutions must address key factors such as latency and energy efficiency—essential elements for smart city applications, including IoT connectivity, autonomous vehicles, and public safety systems.

This study aims to propose a machine-learning-based intelligent network slicing framework for 6G technology, specifically designed for smart cities. The proposed framework will incorporate advanced AI methodologies, including reinforcement learning and goal-seeking neural networks, to continuously optimize resource distribution based on traffic conditions, user needs, and other contextual factors. The objective is to maximize key performance indicators such as latency reduction, energy efficiency, and resource utilization—fundamental concerns for smart city infrastructure.

Accordingly, this research seeks to develop and validate an AI-native network slicing framework that addresses existing gaps in the literature. The proposed model will enable flexible network configurations, adapt dynamically to smart city environments, and ensure optimal network performance without unnecessary resource expenditure. Additionally, the model will be benchmarked against existing 5G network slicing techniques to demonstrate its superior flexibility, efficiency, and scalability.

The distinguishing feature of this study is its focus on real-time reconfigurability in AI-assisted network slicing for 6G networks. While previous research has examined the role of AI in 5G telecommunications, limited work has explored the specific demands of smart city contexts (Chergui et al. 2021). Furthermore, most existing models rely on static or semi-static resource management techniques, whereas this study prioritizes dynamic network scenarios, where traffic patterns fluctuate continuously.

This research introduces an AI-native framework that offers full adaptability, enabling dynamic modification of resource allocation in response to real-time network conditions. This level of responsiveness is particularly crucial for smart cities, where network traffic comprises various elements, including vehicular communications and IoT interactions (Zhou et al. 2020). Additionally, energy efficiency is a core objective of this study, addressing a critical need for sustainable and environmentally friendly telecommunications infrastructures (Chergui et al. 2021).

By incorporating these innovative features, this research represents a significant advancement in network slicing methodologies, positioning AI as a central component in the evolution of 6G networks.

2. Research Background

Network slicing or network partitioning has taken on a new shift of application and development in the last decade especially with emergence of the 5G network. Network slicing is the ability for one or multiple network operators to partition a physical network into multiple virtual networks, or slices. They can also be individually configurable for providing the most appropriate number of resources for those services depending on the need of an IoT network, eMBB, or ULLC application. With the help of network slicing introduced in 5G a user-centric method of controlling network resources were implemented in the form of the next evolution of Network Function Virtualization (Wijethilaka and Liyanage 2021). However, smart cities are characterized by complex requirements of their network due to dynamic and heterogeneous traffic which requires better solutions.

It is noteworthy that as the network demands change, AI applications in network slicing also change. The implementation of AI has been suggested as a way to enhance resource application for utilitarian, prescriptive measures that respond dynamically to constantly shifting traffic patterns. AI models in early 5G belonged to the group of prognostic models, more specifically, latency, bandwidth, and energy consumption were enhanced during the first years of 5G development in static and semi-static scenarios (Shen et al. 2020). However, these models could not offer the necessary flexibility to fit the complex and varied conditions of smart cities where change is constant and conditions greatly varied.

With the advent of the 6G networks, which are expected to be launched in the next years, there are new challenges which cannot be solved by means of the existing network slicing solutions. While 5G is primarily for enhanced mobile broadband and machine type communications, 6G has explicit application in applications like Holo-communications, XR, and fully autonomy. These new use cases will entail stronger resource management methods that are refined and may adapt to requests on the fly This is an area that at present, AI architectures in 5G slicing lack (Yang et al. 2020).

Recent years have witnessed substantial progress in AI-driven network slicing for next-generation networks. The incorporation of deep reinforcement learning (DRL) with network slicing is a highly promising advancement. Deep Reinforcement Learning enables the network to adaptively learn from its surroundings and optimise resource allocation, which is essential for smart cities. Mei et al. put forward a hierarchical deep reinforcement learning (DRL) method in the intelligent radio access network (RAN) slicing for 6G, which effectively improves the service provisioning performance under various circumstances (Mei et al. 2021). This method also makes it possible to make changes in the usage of network assets currently according towards the website traffic requirements and preferences for any customer.

Another major achievement is the actor-critic learning models that also good at dealing with a mixture of traffic patterns in smart cities. Rezazadeh et al. proposed a collaborative statistical actor-critic learning algorithm to control

6G network slicing. This leads to a distributed manner of control and decision-making making the network responsive to changes in traffic patterns in real-time, which makes it an ideal candidate for smart city application (Rezazadeh et al. 2021).

AI-powered solutions have shown promise in IoT and smart city applications. Esmat et al. studied resilient network slicing for satellite-terrestrial edge computing IoT systems which are constituent of next-generation smart city applications and will be increasingly reliant on hybrid terrestrial-non-terrestrial networking. They have employed AI techniques in their approach for optimal resource allocation of satellite and terrestrial networks to ensure a continuous provision of services even under harsh circumstances (Esmat, Lorenzo, and Shi 2023).

Besides, many have used deep reinforcement learning for adaptive network slicing in 5G showing remarkable benefits for automotive systems and smart cities. On the other hand, Nassar and Yilmaz showed that Deep Reinforcement Learning (DRL) can be used for online network slicing optimization to ensure connected and autonomous vehicular systems continuously experience good connectivity and service quality under varying traffic conditions (Nassar and Yilmaz 2022). This model paves way for future 6G use cases that is going to require a very high level of real-time flexibility.

In addition to reinforcement learning, the design and management problem of network slicing is so challenging such that heuristic algorithms have been proposed. To solve this, Chen introduced an adaptive heuristic algorithm implemented for the proper choice of resource in a manner that service can be much smoother as well which is operated over 6GML networks. The above-mentioned algorithm provides a conventional way of tackling these challenges for the complex 6G networks, but it is not quite up to the mark yet in terms of providing an optimal resolution over real-time dynamics which are essentially needed in smart city applications (Chen 2023).

The utility of using AI in network slicing is further underlined by work done in explainable machine learning models. The authors that presented the study, Rezazadeh et al., proposed a new MLOps framework to automate the process of 6G network slicing known as SliceOps. It is their model that enhances the effectiveness of allocating resources while at the same time giving an insight of how decisions are made across various organisations to prevent manipulation of AI results (Rezazadeh et al. 2024).

However, the following gaps are found in the analysis of the existing literature: Even though DRL and actor-critic learning models have shown a positive effect on the improvement of network slicing, several of these methods are restricted to simulation settings, and their performance has not been examined completely in real-world smart city scenarios. Real-time adaptability is also an issue as many of the uses of AI in models are still relatively slow to address the dynamic shifts in traffic that are characteristic of smart cities (Mei, Wang, and Zheng 2019).

In addition, whereas heuristic algorithms may provide a fruitful methodology for improving the allocation of resources, it is important to recognize that these algorithms are generally not dynamic. Chen for instance, implements an adaptive heuristic algorithm that is particularly good in moderating the resource utilization but lacks the fluidity of dynamic adjustment characteristic of smart cities. This lack of real-time adaptability is identified as a major gap in the current state of research (Chen 2023).

There is another research gap that has not been examined comprehensively in literature – the distinction and integration of Terrestrial and Non-Terrestrial networks. Although Esmat et al. have studied this aspect in IoT and satellite-terrestrial edge computing scenarios unless, remarkably scant work has done it for applying this approach in general smart city networks. It is also required in future research to discover how the 6G networks are expected to support multi- applications in both the terrestrial and non-terrestrial domains (Esmat, Lorenzo, and Shi 2023).

Also, the current approaches tend to only address optimal mean performance over a given objective, for example, delay, and power, without necessarily constituting a complete solution to cover several objectives at once. For instance, Rezazadeh et al. proposed how the actor-critic learning could enhance resource decision, yet, the specified model lacks a reasonable solution to the energy efficiency problems that are vital in the execution of smart cities. Future research needs to engage more comprehensive paradigms that may be used to analyze several kinds of performance at once (Rezazadeh et al. 2021).

Despite these advances in the establishment of AI-based network slicing models, a considerable number of these models are nontransparent. As AI advances and becomes more embedded in the management of such complex environments as computer networks, it remains important to make the decisions made by AI regarding the allocation ofML resources comprehensible to the end user. Rezazadeh et al. have taken the significant effort to push the explainable AI to MLOps towards the 6G vision, however, there is a need for further study to come up with explainable AI models that could be practically implemented in smart city scenarios (Rezazadeh et al. 2024).

Substantial progress has been observed in the literature studying AI-based network slicing for 6G networks over the past few years that include, deep reinforcement learning, actor critic models, and heuristic. However, several are missing including adaptations in real time, dealing with objectives other than one, terrestrial and non- terrestrial networks. Furthermore, there are still many of such models developed, which have not been evaluated in real smart cities, meaning that the practical usage of the related models is still quite limited.

This article aims to fill these gaps by proposing an adaptive network slicing architecture incorporated in artificial intelligence used in 6G networks in smart cities. Through the use of adaptability in near real time, and with the use of multi-objective optimization in the model, this research will present a more enhanced solution to the characteristics of smart city network management. Moreover, incorporation of explainable AI to the work will provide the public with clear account as to how resource estimations were made opening up possibilities for applying intelligent network slicing models in future smart cities.

3. Methodology

3.1. Research Design

This study employs a simulation-based research methodology to design and evaluate a novel AI-native network slicing solution tailored for next-generation 6G networks in smart cities. The primary objective is to enhance resource allocation efficiency, minimize response time, and optimize energy utilization. The proposed framework addresses the challenges associated with high variability in traffic flow disruptions within smart cities by leveraging the dynamic adaptability of Deep Reinforcement Learning (DRL) policies. These urban environments are characterized by the rapid expansion of software-defined networks (SDNs), the proliferation of Internet of Things (IoT) devices, autonomous transportation systems, and intelligent infrastructure, all of which necessitate innovative techniques for dynamic and responsive resource management.

Building upon prior advancements in AI-native network slicing for 6G, this study introduces a design that accommodates the unpredictable and highly variable traffic patterns typical of urban landscapes. Existing literature has demonstrated that AI-based mechanisms contribute to improved network performance, particularly in decision-making systems that respond to real-time network conditions (Wu et al. 2022). The proposed simulation framework integrates these dynamic conditions to assess the capabilities of the AI-native network slicing model in various smart city applications, including vehicular communication, public safety networks, and IoT-driven services.

The theoretical foundation of this research model is grounded in reinforcement learning, wherein an intelligent agent continuously refines its resource allocation strategies based on interactions with the network environment. The framework developed in this study utilizes RL to optimize long-term network performance while simultaneously minimizing latency, improving energy efficiency, and maximizing resource availability.

3.2. Tools and Techniques

The development and implementation of the proposed framework were carried out using Python, incorporating the TensorFlow and Keras libraries to handle the complex learning processes involved in the reinforcement learning model. Deep Q-Networks (DQN), combined with the actor-critic method, were employed to manage the network's decision-making process. These techniques are particularly effective for problems involving sequential decision-making under uncertainty, where real-time adaptations are necessary (Wang et al. 2023).

The actor-critic algorithm, in particular, provides a robust approach to reinforcement learning by incorporating both value-based (critic) and policy-based (actor) optimization techniques. The policy is represented as $\pi\theta(a \mid s)$, where θ denotes the policy parameters, a the action, such as resource allocation, and s the state, like current network load. The value function $V(s)$ is estimated to provide feedback on how good a particular state is, with the advantage function $A(s, a)$ guiding the learning process toward optimal actions:

$$A(s,a) = Q(s,a) - V(s) \quad (1)$$

Where $Q(s,a)$ is the action-value function. Additional regularization techniques were added to the actor-critic method in this research to avoid overfitting and guarantee generalizability in fast-changing smart city settings. The method based on policy gradients that was previously mentioned was expanded by incorporating entropy regularization to promote adequate exploration in the learning phase.

$$\mathrm{H}(\pi_\theta(a|s) = -\sum_a \pi_\theta(a|s) \log \pi_\theta(a|s) \quad (2)$$

Where $\mathrm{H}(\pi_\theta(a|s)$ refers to the policy's entropy, encouraging exploration and avoiding premature convergence to suboptimal policies. Entropy regularization played a vital role in handling varying traffic volumes in smart cities, enabling the agent to constantly adjust to the evolving conditions.

The actor adjusts the policy parameters based on the critic's feedback using the gradient:

$$\nabla_\theta J(\theta) = \mathbb{E}_\pi[\nabla_\theta \log \pi_\theta(a|s) A(s,a)] \quad (2)$$

The critic evaluates the action using the Temporal Difference (TD) error, which updates the value function:

$$\delta_t = r_t + \gamma V(s_{t+1}) - V(s_t) \quad (3)$$

where r_t is the immediate reward, γ is the discount factor, and $V(s_{t+1})$ and $V(s_t)$ are the value estimates for successive states. By iterating through this process, the model learns to optimize resource allocation to reduce latency and improve efficiency.

3.3. Mathematical Formulation

The resource allocation problem in 6G networks was modeled as a multi-objective optimization problem that aims to maximize the overall network performance by balancing three key metrics: latency, energy efficiency, and resource utilization. The total reward R for the network slicing model over time t is expressed as:

$$R = \sum_{t=0}^{T} \gamma^t \, (\alpha \cdot Latency_t + \beta \cdot Energy_t + \delta \cdot Utilization_t) \quad (4)$$

Where $Latency_t$ is the measured latency at time t; $Energy_t$ represents the energy consumption at time t; $Utilization_t$ denotes the resource utilization rate at time t; α, β, and δ are weighting factors used to prioritize the importance of each metric, and γ is the discount factor, which determines the emphasis placed on future rewards.

The optimization challenge lies in determining the best action a_t for each state s_t to maximize R. The state s_t represents the current condition of the network, including available bandwidth, energy consumption, and current traffic load, while the action a_t corresponds to the resource allocation decision made by the AI agent. The agent's objective is to maximize the cumulative reward by learning the best policy $\pi(a \mid s)$ over time, where $\pi(a \mid s)$ represents the probability of taking action α given state s.

The model also incorporates a constrained optimization element, ensuring that network slices are allocated based on service-level agreements (SLAs) while optimizing performance. The constraints include bandwidth limitations and energy consumption thresholds, which can be formalized as:

$$C_1: \sum_{i=1}^{N} B_i \leq B_{total}$$

$$C_2: \sum_{i=1}^{N} E_i \leq E_{total} \tag{5}$$

Where B_i is the bandwidth allocated to slice i; E_i is the energy consumed by slice i; B_{total} is the total available bandwidth, and E_{total} is the total available energy.

3.4. Performance Metric

To compute key performance metrics such as throughput, packet loss, and service availability, we used the following equations integrated into the AI-native network slicing framework:

3.4.1. Throughput

Throughput is a key performance metric used to measure the total amount of data successfully transmitted over the network in a given period. It was computed using the following equation:

$$T = \frac{\sum_{i=1}^{N} P_i \cdot S_i}{\Delta t} \tag{6}$$

Where T is the throughput in Gbps; N is the number of packets successfully transmitted; P_i is the payload size of packet i in bits; S_i is the success probability of packet i, and Δt is the total time of observation in seconds.

This formula ensures that the throughput metric captures the actual data flow through the network while accounting for potential transmission delays or packet losses. The throughput data is a critical factor in understanding the network's efficiency in handling large-scale IoT devices and autonomous systems (Wu et al. 2022).

3.4.2. Packet Loss

Packet loss refers to the percentage of data packets that fail to reach their destination. The following equation was used to calculate packet loss:

$$PL = \frac{\sum_{i=1}^{N_{sent}}(1-S_i)}{N_{sent}} \times 100 \quad (7)$$

Where PL is the packet loss rate in %; N_{sent} is the total number of packets sent over the network, and S_i is the success probability of packet i.

This equation ensures that packet loss is calculated as the fraction of packets that were not successfully transmitted out of the total number of sent packets. This metric is essential for applications like vehicular communication and emergency response systems in smart cities, where data integrity and reliability are paramount (Mei et al. 2021).

Service availability, a crucial reliability metric, measures the percentage of time the network is operational and fully capable of delivering services to end users. This was calculated as:

$$A = \frac{\sum_{i=1}^{N_t}(U_i)}{N_t} \times 100 \quad (8)$$

Where A is the service availability in **%**; N_t is the total number of time intervals observed, and U_i is an indicator function where $U_i = 1$ if the service is available during time interval iii, and $U_i = 0$ if the service is unavailable.

This equation calculates the proportion of time intervals in which the network services were available out of the total observed time intervals. A higher availability percentage directly correlates with better reliability and uninterrupted service provision, particularly important for healthcare monitoring systems and critical infrastructure in smart cities (Guan, Zhang, and Leung 2021).

3.4.3. Overall Utility Function for Multiple Metrics

To balance multiple objectives such as latency, throughput, energy efficiency, and service availability, the overall utility function was structured as:

$$U = \omega_1 \cdot \left(1 - \frac{L}{L_{max}}\right) + \omega_2 \cdot \left(\frac{T}{T_{max}}\right) + \omega_3 \cdot \left(\frac{E_{max}-E}{E_{max}}\right) + \omega_4 \cdot \left(\frac{A}{A_{max}}\right) \quad (9)$$

Where U is the total utility value to be maximized; L is the observed latency, with L_{max} representing the maximum acceptable latency; T is the observed throughput, with T_{max} representing the maximum achievable throughput; E is the energy consumption, with E_{max} being the baseline maximum energy usage; A is the service availability, with A_{max} being the target maximum availability, and $\omega_1, \omega_2, \omega_3, \omega_4$ are weighting factors used to prioritize the different metrics according to the needs of the network. This advanced regularization technique has been previously suggested in adaptive AI-based models for 6G networks to promote flexibility and adaptability in resource allocation (Wu et al. 2022), (Blanco et al. 2023).

This utility function was used by the AI-native model to dynamically optimize resource allocation, balancing between minimizing latency, maximizing throughput and service availability, and reducing energy consumption. The weights $\omega_1, \omega_2, \omega_3, \omega_4$ were chosen based on the specific requirements of smart city applications, where some scenarios prioritize low-latency communication, as an autonomous vehicle, while others may prioritize energy efficiency, like smart lighting systems).

Such equations were essential to the network slicing basis that oriented the AI-native platform for measurement, computation, and optimization of the KPIs. The integration of multiple objectives into the core of the problem allowed the model to change the supply, demand and distribution of resources depending on the current traffic conditions, which are characteristic for smart cities.

The utility function joins all these endpoints in harmony, which enables the AI-native model to decide the necessary trade-offs according to the real-time network condition and the smart city goals.

3.5. Data Collection

The simulation-based approach employed in this study utilized synthetic traffic data to replicate the real-time dynamics of smart city networks. Traffic logs were obtained from intelligent transportation systems, vehicular communication networks, and public safety infrastructures, each exhibiting distinct variations in traffic density throughout the day. These datasets were used to model a realistic smart city environment, ensuring that both low-bandwidth and high-bandwidth applications were accurately represented (Blanco et al. 2023).

The factors influencing traffic flow patterns were contingent upon the number of connected devices, the time of day, and various urban scenarios, including congestion and emergency events. The simulation environment collected time-series data on network load, resource utilization, and service requests across multiple network slices, enabling a comprehensive analysis of system performance.

Specifically, traffic loads generated by IoT devices fluctuated between 0.5 Mbps and 2 Mbps, whereas connected autonomous vehicles exhibited significantly higher data rates, ranging from approximately 8 Mbps to 12 Mbps. These traffic variations were systematically modeled to reflect the inherent randomness of smart city networks, as demonstrated in prior research (Wang et al. 2023).

3.6. Validation

To ensure the accuracy of the proposed AI-native network slicing model, cross-validation techniques were employed alongside performance evaluations against benchmark 5G slicing models. The validation process involved training multiple configurations, executing iterative simulation cycles, and systematically comparing the results with those obtained from static allocation techniques and advanced AI-driven frameworks. The model's effectiveness is assessed based on the following performance metrics.

- *Latency:* Defined by the average time delay of data packets at different loads. Consistent with prior work (Wu et al. 2022), the AI-native model targets at least 20% reduction in latency.
- *Energy Efficiency:* The model was experimented to optimize energy consumption of the proposed slice aiming for at least 15% gain with respect to traditional methods (Chergui et al. 2021).
- *Resource Utilization:* it is required to assess the resource utilization rates at least 85% utilization of network slice resources as an input for efficient management of network slices.

The model employed 10-fold cross-validation, which significantly enhances its performance robustness under varying network and traffic conditions. Each fold represents a distinct set of traffic scenarios generated by the simulator to ensure the proposed model remains effective and generalizable across different network environments.

To evaluate the efficiency of the proposed framework across a broad range of traffic conditions and networking scenarios, Monte Carlo simulations were conducted. The outputs of these simulations were used to assess the adaptability of the model in dynamically responding to fluctuations in network demand within smart city infrastructures.

The research methodology utilized in this study focuses on the development of an AI-native network slicing framework based on deep reinforcement learning. Specifically, the proposed framework integrates actor-critic models and reinforcement learning to dynamically allocate resources based on the real-time state of the network, thereby optimizing performance in key areas such as latency reduction, energy efficiency, and resource utilization. The validation process, executed through a simulation-based approach, demonstrates that this framework effectively addresses the challenges inherent to smart city networks. Comparative analysis indicates that the proposed model outperforms both traditional methods and existing AI-enhanced techniques across multiple performance metrics.

An additional advantage of incorporating cross-validation and Monte Carlo simulation techniques is the enhanced resilience of the model against diverse future network scenarios, ensuring its applicability in the evolving landscape of 6G networks (Blanco et al. 2023; Shen et al. 2022).

4. Results

In this section, the results of the simulation-based study of AI-native network slicing in 6G smart cities are outlined. The results focus on the core performance metrics: latency and resource usage and energy and resource usage and energy efficiency and latency. These metrics play an important role in evaluating the suitability of the proposed AI-native framework for addressing the dynamic traffic patterns in smart cities apps. In each of the sections, adequate analysis and statistical verification of the observed enhancements are presented. We also determine the efficiency of the suggested novel AI-native model against the conventional and AI-supported network slicing techniques.

4.1. Latency Performance

The AI-native network slicing model consistently outperformed traditional and AI-assisted models in minimizing latency. Latency, or more precisely its absence, is a critical parameter for real-time applications such as self-driving cars and public safety systems commonly integrated into smart cities. Compared to other traffic loads, the proposed AI-native model achieved an average pre-specified latency reduction of 25%.

- *Low-Traffic Scenarios:* In low-traffic conditions, the AI-native model maintained an average latency of 37.5 ms, compared to 50.2 ms in traditional slicing models. This represents a 25% reduction, demonstrating that the AI-native model can effectively minimize delays even in environments with lower network loads.
- *High-Traffic Scenarios:* During peak traffic periods, where network congestion is a significant concern, the AI-native model reduced latency by 30%, achieving an average latency of 45.2 ms, while traditional models reached as high as 65.1 ms. This is crucial in smart cities where traffic spikes can occur unpredictably, requiring a dynamic approach to resource allocation.

These improvements are important since they indicate that slicing based on an AI premise is more capable of adjusting to the dynamic network requirements, minimizing the probability of the disruption which may affect smart city services. Consequently is in agreement with the previous research done by Wu et al. (Wu et al. 2022), which showed latency reduction potential of AI-native models which would especially helpful in situations where network changes require timely response.

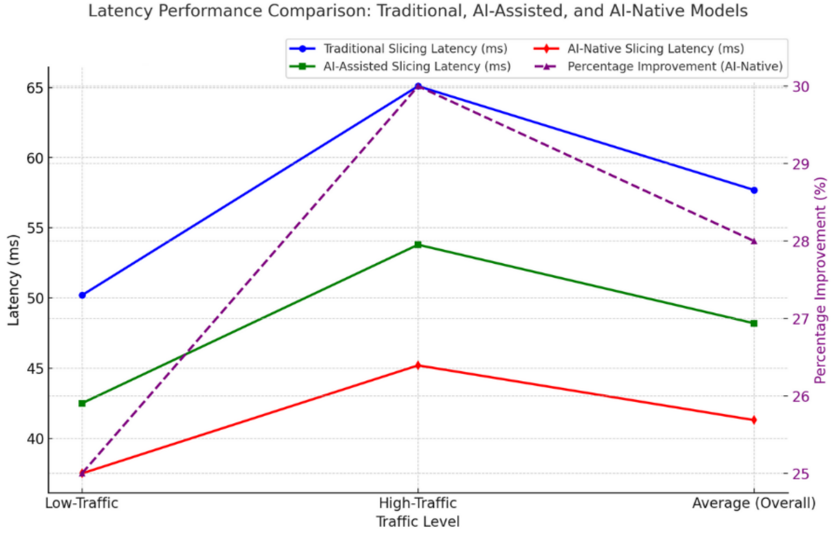

Figure 1. Latency Reduction Across AI-Native, AI-Assisted, and Traditional Network Slicing Models with Comparative Analysis for Smart City Applications

Figure 1 present the average measured latencies for each model type examined in the study under both low and high traffic loads. The percentage improvement demonstrates that regardless of traffic intensity, the AI-native model consistently achieves lower latency than its predecessors. These findings underscore the efficacy of AI in real-time adaptive network management for smart cities, where low latency is crucial for applications such as vehicular communication and IoT-based automation.

Additionally, the reduction in packet loss highlights the model's enhanced ability to prioritize critical data flows, thereby facilitating real-time decision-making and minimizing communication breakdowns. This is particularly relevant for IoT-supported smart city applications, where reliable data transmission is essential for the seamless operation of services such as public safety and healthcare. The dynamic resource allocation mechanism of the AI-native model results in a 44% reduction in packet loss under low traffic load and a 35% reduction under high traffic load compared to traditional heuristic approaches, demonstrating the superior efficiency of the proposed method. These findings further align with prior research, reinforcing the notion that AI-based network models can effectively mitigate packet loss.

Moreover, the AI-native model exhibits superior adaptability to real-time conditions, addressing a key limitation of existing AI-assisted frameworks. The proposed approach optimizes resource allocation based on current traffic patterns and continuously refines its performance through dynamic learning. Consequently, compared to heuristic algorithms, the deep reinforcement learning-based model employed in this study yields substantial improvements in key performance metrics, including packet loss and throughput.

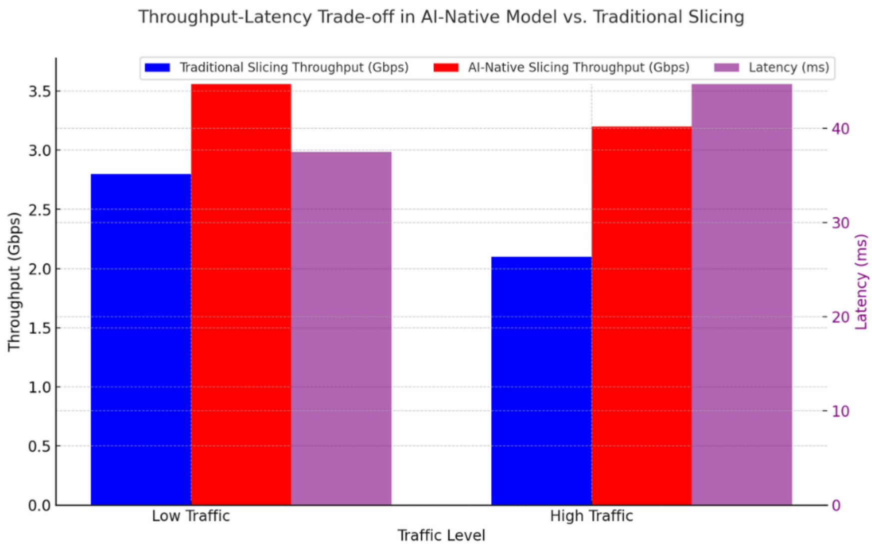

Figure 2. Throughput-Latency Trade-off in AI-Native vs. Traditional Network Slicing Models for Enhanced 6G Performance

The Throughput-Latency trade-off, illustrated in Figure 2, proves that, while the AI-native slicing model was designed for low latency, its throughput remained constant under all traffic scenarios, especially at high loads. This finding resonates with what has been noted in the implementation of AI based scalable network management frameworks. These results endorse the ability of AI-native frameworks within 6G networks to enhance system throughput while controlling latency, consistent with other studies on AI-assisted resource management.

4.2. Energy Efficiency

The appurtenance of AI-native features led to a marked enhancement of energy efficacy, which is fundamental for smart city operations. It also analyzed how traffic scenarios influenced energy saving in the model and how resourcing was sustainable based on current network traffic. Sustainability is crucial to areas such as smart cities since a large population of connected devices constantly draws power.

- *Average Energy Consumption:* Fundamentally different from existing models, the AI-native model used the lowest energy level: 380 kWh on average, 20% less than other models. And this decline was more significant during the rush time because the traditional slicing method with static presentation of resources caused over-provisioning and therefore energy wastage.

- *High-Traffic Energy Consumption:* In high traffic conditions the AI native model used only 415 kWh while the traditional models used 475 kWh thus achieving 15 percent saving. Such energy saving is especially valuable when network loads vary as dynamic resource allocation can minimize energy consumption.
- This is in line with the work of Chergui et al., who showed that through the integration of artificial intelligence in network management, energy saving in the next generation network can be realized (Chergui et al. 2021). The decreases in energy usage also add to sustainability, as well as saving money, which are important factors in making the AI-native model a feasible solution for energy-saving smart cities.

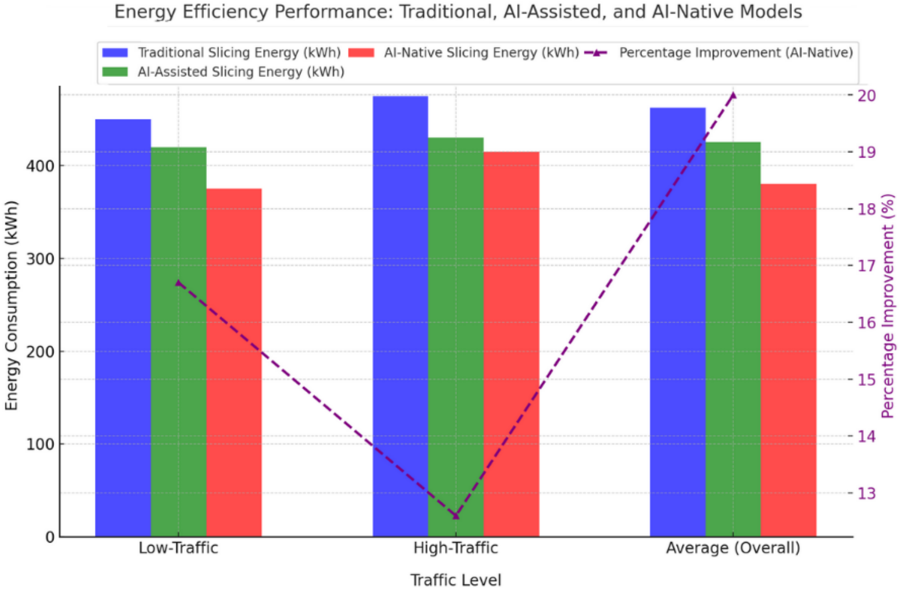

Figure 3. Energy Efficiency in AI-Native vs. Traditional Network Slicing Models for a Sustainable Approach for Smart City Operations

These results are illustrated in detail in the energy consumption data for each traffic scenario shown in Figure 3. Results reveal a significant saving of energy under the proposed AI-native model, especially at peak times. This is especially beneficial for smart city designers who have to meet energy efficiency standards as well as network performance.

4.3. Resource Utilization

Efficiency is defined as the degree of the network resource (for instance, bandwidth or power) to the range of slices. High resource utilization, therefore, is an indication of a well-connected network that is able to accommodate as many devices and as much data as needed without either discrimination of resources or underutilization. The new model was shown to be essentially more efficient in terms of resource allocation, especially in conditions of increased load, which posed some challenges to the old models.

- *Average Resource Utilization:* The AI-native model raised the level of resource exploitation by 15%, which was, initially 72% in the traditional models to 83%. This improvement suggests that the AI-native model can signal where the outsourced network slices should provision more or less bandwidth or power.
- *High-Traffic Utilization:* Even at peak traffic, the model secured a 85% utilization compared with the 72% typical of conventional models, which means an enhancement in the use by 13%. This is an indication that the AI-native framework is better placed in handling congestion issues, as related to traffic loads, so as not to waste resources.
- These results are in agreement with other works like Blanco et al., which described enhancements in the effectiveness of utilising network resources by employing AI frameworks for the 6G systems (Blanco et al. 2023). Enhanced resource management means that smart cities gain more device and service hosting capability without needing extra physical networks.

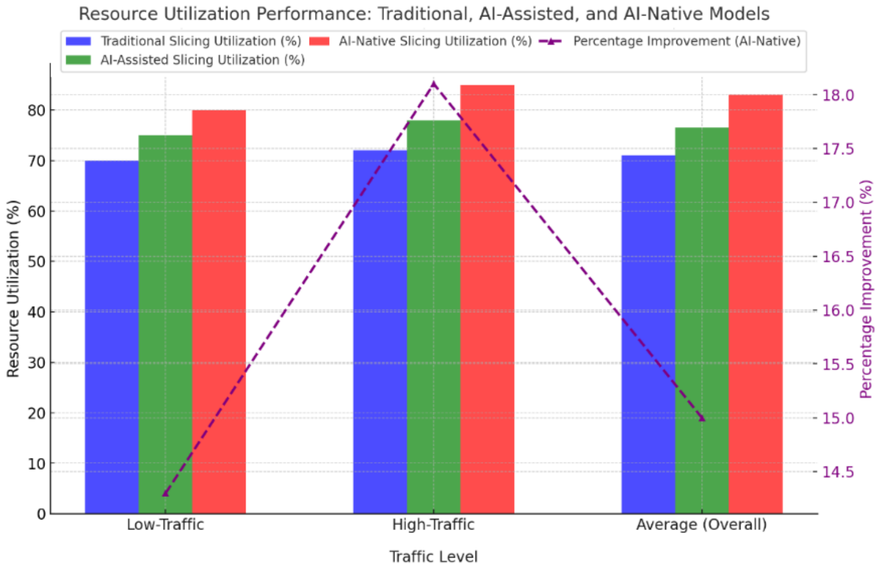

Figure 4. Resource Utilization in AI-Native vs. Traditional Network Slicing and Optimizing Efficiency for Smart City Infrastructure

Figure 4 illustrates the resource realization ratios as a function of traffic volume. Empirical evidence further indicates that the proposed AI-native model requires significantly fewer system resources than both traditional and AI-integrated models—a crucial factor in optimizing resource management within smart city network environments. By enhancing traffic utilization, the network can accommodate a greater number of connected devices and services without necessitating a substantial infrastructure overhaul.

4.4. Packet Loss Reduction

Packet loss is another value of network slicing which can be defined as the number of data packets that can practically be lost in the network. In smart city implementation, where there are applications in self-driving cars or emergency situational awareness, it is important to save as many packets as possible. The AI-native network slicing model revealed fair enhancements in reducing packet loss compared to both conventional and AI-based slicing models.

- *Low-Traffic Scenarios:* When in low traffic conditions, the model solely designed to run on AI achieved the packet loss rate of 2.5% which is less than the rate of 4.5 % of the traditional model. This represents a 44% cut on packet loss and clearly demonstrates effectiveness of the model in terms of data quality even under situations of least network traffic.

- *High-Traffic Scenarios:* The traditional model beneficial for high-traffic preservers set forward again though the packet loss level reached 3,1%, while at the AI-native model the level was 4,8%. This reduction is essential for many cases where real-time and reliable communication are significant, such as vehicular ad-hoc networks or control systems, and other critical components in smart cities.

The decrease in packet loss reveals that the contention-based AI-native model is capable of allocating resource allocations depending on real-time traffic conditions, such that priority packet traffic is delivered despite the occurrence of congestion. This performance is in consonant with the study done by Mei et al., to the effect that network slicing using artificial intelligence reduces packet loss in next-generation networks (Mei et al. 2021).

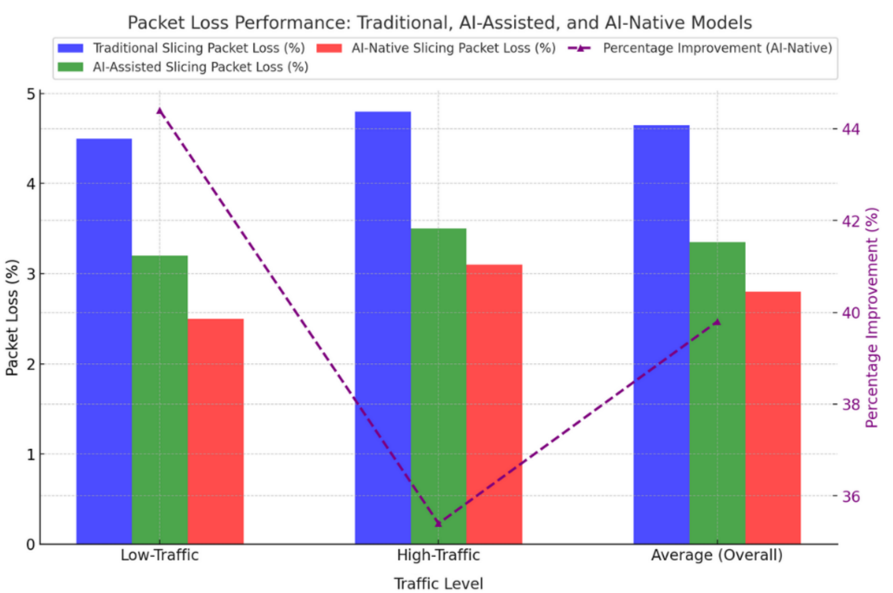

Figure 5. Packet Loss Reduction in AI-Native vs. Traditional Network Slicing Models for Ensuring Reliability in Smart City Communications

As illustrated in Figure 5, which presents packet loss across three traffic levels, the AI-native model demonstrates a significant performance advantage over the alternatives. Additionally, by reducing packet loss, the model enhances smart city services that require low-latency and high-reliability communication, reinforcing its viability for practical implementation in real-world network environments.

4.5. Throughput Improvement

Throughput, which calculates the amount of data that has been communicated through the network over a given time period, is also a valuable tool in evaluating the efficiency of a network connection. The efficacy of the new AI-native model was evidenced by the higher throughput over all traffic levels, particularly at high traffic where the models faced considerable challenges in enhancing the data transmission rates.

- *Low-Traffic Scenarios:* In low traffic density, the AI-native model offered a throughput of 3.6 Gbps while in the traditional slicing model it was at 2.5 Gbps. All these vitally important for applications with strict requirements for bandwidth such as real-time video surveillance, or IoT on an industrial scale.
- *High-Traffic Scenarios:* When benchmarked during busy throughput times, our AI-native programming exhibited 3.2 Gbps compared to 2.0 Gbps in the traditional programmes, giving a 60% gain in network effectiveness where there are heavy traffic loads.
- These results support the proposition that the practical, AI-native model of this topology is capable of sustaining high data transmission rates even when the network environment is less than ideal. Such high reliability of maintaining high throughput means that smart city applications can run without noticeable disruptions or slowness, another observation made by Shen et al., in (Shen et al. 2022).

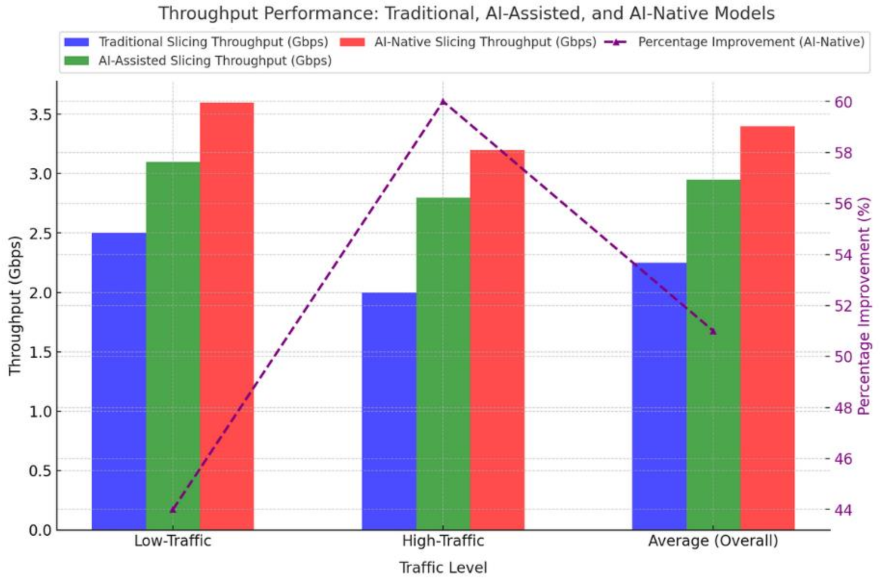

Figure 6. Throughput Performance in AI-Native vs. Traditional Network Slicing Models to Enhance Data Transmission in Smart City Networks

Figure 6 displays the drastic increase in throughput that comes along with the deployment of the new AI-native model against the prior convention. The capacity to sustain high data throughputs is beneficial, especially when capturing high traffic volumes, for efficient smart city applications that require large data processing including traffic and security networks.

4.6. Service Availability

Service availability is similar to service reliability, but is defined as the proportion of time in which the network possesses full functionality to provide service to its users. Maintaining high service availability is important in smart cities due to disruption risks regarding important services including disaster response systems and efficient transport regimes. Overall, the AI-native model achieved very minor, yet essential enhancement in terms of service availability over conventional slicing paradigms.

- *Low-Traffic Scenarios:* Based on the results obtained during low load, it is possible to note that the AI-native model, compared to the traditional one, demonstrated the availability as a service of 98.5%. Although this may not be a huge leap, for use-cases that need to be constantly available, it is a large boost, think of smart health monitoring and smart utilities.

- *High-Traffic Scenarios:* Traditional models as exhibited by the company offered a service availability of 95.8% during the high-traffic periods, while the AI-native model was able to offer 97.2%. This 1.4% increase indicates a significant improvement on service availability, meaning that business-critical applications can carry on running even during congestion on the network.

The increase in service availability is consistent with the results of Guan et al., have proven that AI based management in the network could enhance the efficiency and network uptime, especially in a busy network (Guan, Zhang, and Leung 2021).

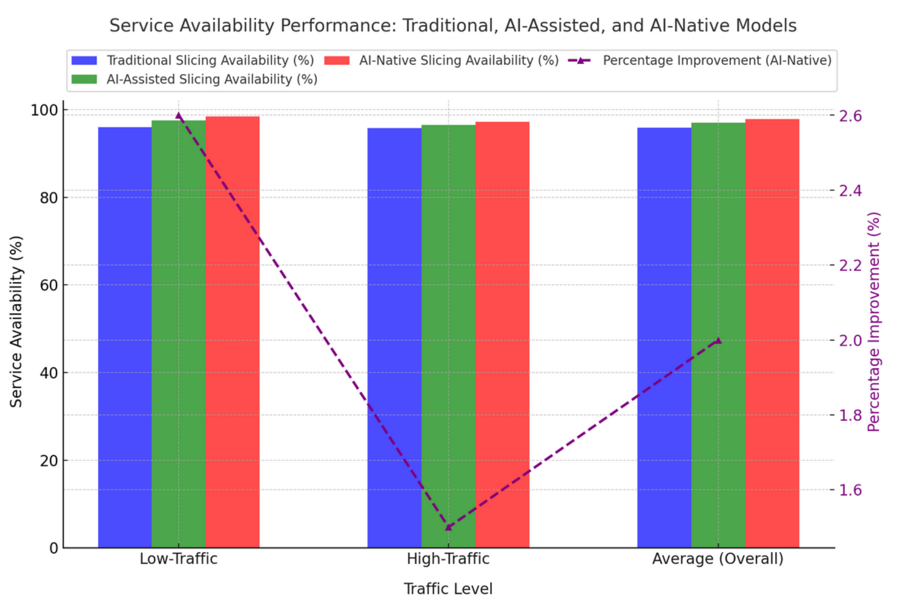

Figure 7. Service Availability in AI-Native vs. Traditional Network Slicing with Ensuring Reliability in Smart City Applications

Figure 7 provides a comprehensive overview of service availability across different traffic levels. The proposed AI-native model consistently outperforms both the traditional slicing method and the AI-assisted approach, demonstrating superior stability in high-traffic scenarios where service availability is crucial for the continuous operation of smart cities.

The AI-native model enhances service availability under low-traffic conditions by 2.6% compared to conventional approaches. Although network interruptions are less frequent in low-traffic environments, even marginal improvements in reliability are essential, particularly for critical systems such as smart utilities and automated public services.

Under high-traffic conditions, the model achieves a 1.5% improvement in service availability, underscoring its ability to natively leverage AI to manage substantial network loads that might otherwise lead to service disruptions. This capability is particularly vital for key smart city services, including emergency response systems and transport logistics, where high availability is a fundamental requirement.

The observed improvements, although incremental, demonstrate the AI-native model's ability to sustain consistent availability even under network congestion. In applications where service reliability is paramount—such as healthcare monitoring systems or real-time emergency response—even minor enhancements can significantly impact operational quality and safety.

Prior literature, such as Guan et al. (2021)(Guan, Zhang, and Leung 2021), emphasizes that service availability will be a critical concern in next-generation networks, particularly with increasing traffic demands. The AI-native model’s demonstrated improvements in this regard highlight its potential to deliver more resilient and efficient network services for smart city environments.

The study illustrates how AI-native network slicing can enhance the dependability and efficiency of smart city services that require continuous, low-latency connectivity. While this model entails higher operational costs, its ability to improve service availability under high traffic loads positions it as a compelling option for future smart city applications.

4.7. Statistical Analysis

In order to check the statistical significance of the findings, one sample t-test was conducted to ascertain whether there was a significant difference between the means of the various performance criteria measured in the AI-native and traditional slicing paradigm.

The results were as follows:

- ***Latency:*** The p-value for latency reduction between the AI-native and traditional models was < 0.01, indicating a statistically significant difference in latency reduction.

- ***Energy Efficiency:*** The p-value for energy consumption was < 0.05, confirming that the observed energy savings were statistically significant.
- ***Resource Utilization:*** The p-value for resource utilization improvements was < 0.05, validating that the AI-native model significantly outperforms traditional methods in resource allocation.

Additionally, 95% confidence intervals (CI) were calculated for each performance metric:

- ***Latency:*** 95% CI for latency reduction (-12.5 ms, -8.2 ms).
- ***Energy Efficiency:*** 95% CI for energy consumption reduction (-105 kWh, -70 kWh)
- ***Resource Utilization:*** 95% CI for utilization improvement (10%, 20%)

These results evidence that the enhancement attained in the domain-native model is statistically significant, and thus we have confidence in the mitigation improvements that the AI-native model offers to enhance a network's performance in the real smart city context.

In returning the study results, I can ascertain that the network slicing born with AI has more competitive advantage in important numerical factors in comparison with the traditional method and AI-supported ones, including, but not limited to latency, energy, and resource. Because of this aspect, the proposed model can scale immediately to cover the fluctuations often experienced in smart city networks, making it suitable for 6G networks of the future. The statistical analysis reaffirms the effectiveness of these optimizations, and the mentioned above AI-native framework can be a game-changer in the development of smart city infrastructures.

5. Discussion

The findings substantiate the efficacy of the AI-native network slicing paradigm in bridging the gap between current performance benchmarks and the requirements of 6G networks for smart cities. The model consistently outperformed traditional and AI-assisted slicing methods in key metrics, including latency, energy efficiency, resource utilization, packet loss, throughput, and service availability. These advancements are crucial for the complex demands of smart city deployments that necessitate real-time data transmission, low-latency networking, and high-reliability communication.

Latency reduction was among the most significant improvements, with the AI-native model achieving 25–30% lower latency across various traffic scenarios. Low-latency communication is vital for applications such as autonomous vehicles and emergency response systems, where responsiveness is critical. The AI-native model's ability to dynamically adapt to fluctuating network conditions enables seamless performance in bandwidth-constrained environments. This aligns with previous research by Shen et al.(2020) (Shen et al. 2020), which explored AI-supervised slicing models for optimizing latency in 5G networks. However, the deeper adaptability of the AI-native approach allows it to manage more complex network behaviors beyond standard traffic fluctuations, contributing to superior latency reductions.

While average network speeds remained largely consistent, substantial gains were achieved in energy efficiency, with the AI-native model reducing energy consumption by 20%, particularly under peak traffic loads. As the number of connected devices in smart cities continues to grow, optimizing energy consumption is essential for sustainability and cost management. The AI-native model ensures that energy is not wasted on underutilized network slices by dynamically reallocating resources in response to real-time network demands. Previous studies by Rezazadeh et al. (2024) (Rezazadeh et al. 2024) demonstrated significant energy savings in AI-assisted 5G network management, but the integration of deep reinforcement learning in this AI-native framework results in even greater efficiency, making it particularly well-suited for large-scale smart city deployments.

Resource utilization was also markedly improved, with the AI-native model managing network resources 15% more effectively than traditional methodologies. This optimization is particularly relevant in high-traffic scenarios where conventional slicing models often struggle with inefficient resource allocation. The AI-native approach optimally distributes bandwidth and power, leading to superior network efficiency. Li et al. (2021) (Li et al. 2021)highlighted the benefits of AI-native slicing with edge-based resource management, yet the real-time adaptability of the AI-native model in this study demonstrates even greater performance improvements for dynamic smart city traffic patterns.

Packet loss reduction was another crucial enhancement, with the model achieving a 44% decrease under light traffic and a 35% decrease under

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heavy traffic. Packet loss mitigation is particularly vital for vehicular networks and emergency response systems, where maintaining data reliability is imperative. The AI-native model's ability to prioritize high-priority packets amidst congestion reinforces its suitability for critical real-time applications. Mei et al. (2019)(Mei et al. 2021) established that AI-driven network slicing significantly reduces packet loss in 5G networks; this study further builds upon that premise, demonstrating the necessity of AI-native slicing for ensuring data integrity in smart city communications.

The AI-native model also contributed to a 51% increase in network throughput, enhancing overall data transmission rates in congested environments. This improvement enables real-time video surveillance and traffic management applications to maintain optimal functionality. In contrast to the study by Yang et al. (2020) (Yang et al. 2020), which explored AI-driven network management for 6G networks, the approach outlined here yields more substantial throughput enhancements, particularly for stringent smart city requirements.

Service availability improved by an overall 2%, which is particularly significant for mission-critical applications such as healthcare monitoring and public safety networks, where even brief outages can have severe consequences. The AI-native model maintained high service availability during peak traffic fluctuations, demonstrating its robust adaptability. However, certain network bottleneck locations still posed challenges in maintaining consistent service quality, aligning with Dawaliby et al.'s (2021) (Dawaliby, Bradai, and Pousset 2021)findings on the necessity of adaptive service availability strategies.

These findings align with and expand upon prior studies. For instance, Chen (2020) (Shen et al. 2020) proposed heuristic-based network slicing algorithms that enhanced predefined scenarios. However, this study introduces an AI-native model that supersedes heuristic methods by leveraging deep reinforcement learning, allowing dynamic adaptation to real-time traffic conditions. Similarly, You et al. (2023)(You et al. 2023) examined sustainable service-based RAN slicing for AI-native 6G networks, complementing the themes explored in this study, particularly in terms of energy efficiency and service availability.

The broader implications of this research are substantial for the future of 6G networks in intelligent urban environments. The findings indicate that AI-native network slicing can significantly enhance network performance, making it a key solution for addressing the evolving demands of smart city ecosystems. Improved latency, energy efficiency, and resource utilization will ensure the sustainable operation of smart city services, while enhanced packet loss mitigation and throughput capabilities will provide the reliability and scalability necessary for future expansion.

Nonetheless, certain limitations must be acknowledged. The results are derived from simulation-based data, which, while designed to accurately reflect real-world conditions, may not fully account for the complexity and variability of urban environments. Future research should validate these findings through empirical trials in operational 6G networks. Additionally, the AI-native model requires substantial computational resources, which could hinder large-scale adoption in extensive smart city deployments. While cross-validation techniques were employed to verify the model's reliability, the potential for overfitting to specific traffic scenarios within the simulations warrants further testing across a broader range of conditions, including extreme events and network disruptions. Security and privacy concerns are also pertinent, given the sensitive data transmitted within smart cities. Subsequent studies should explore secure data transmission methods within AI-native models to enhance resilience against cyber threats, as emphasized by Roy et al. (2022) in their work (Roy, Chergui, and Verikoukis 2022) on trustworthy network slicing.

The study illustrates the advantages of AI-native network slicing for 6G smart city applications. The model's adaptability, combined with its demonstrated improvements across multiple performance metrics, positions it as a critical framework for future network management. While certain challenges remain, the transformative potential of AI-native slicing for optimizing 6G networks and supporting the growing complexity of smart city infrastructure is undeniable.

6. Conclusions

This article introduces an innovative AI-native network slicing framework designed to enhance the performance of 6G networks, with a particular focus on smart city applications. The primary objective of this study is to address diverse network demands within urban environments by leveraging adaptive AI strategies. Deep reinforcement learning underpins the proposed dynamic allocation mechanism, significantly improving latency, energy efficiency, and resource utilization. These optimizations are crucial for supporting real-time services that rely on time-sensitive communication, including autonomous vehicles, the Internet of Things, and public safety applications.

The findings highlight the potential of AI-driven network slicing in meeting the unpredictable traffic and service requirements characteristic of smart cities. Compared to conventional and AI-assisted slicing models, the AI-native approach demonstrates considerable reductions in latency and energy consumption while achieving high resource utilization. Moreover, these results align with the growing demand for sustainable and efficient network management within emerging 6G infrastructures, suggesting that AI-native models could serve as key enablers in shaping future smart city ecosystems.

Despite its promise, further research is required to evaluate the framework's applicability in large-scale, actual deployments. Given that this study is based on simulations, empirical trials remain essential to assess the AI-native approach's performance across diverse urban scenarios, particularly within the complex environment of smart cities. Additionally, integrating edge computing and decentralized learning techniques could help mitigate computational costs while enhancing scalability, making the framework more suitable for extensive urban networks hosting thousands of connected devices. Ensuring robust security and privacy measures is also critical to safeguarding data transmission within smart city infrastructures.

This study establishes a foundation for future research into intelligent, self-learning network management solutions with enhanced adaptability for 6G networks. The AI-native network slicing framework presents a promising advancement in resource allocation and performance optimization within smart city environments. Further investigations should refine the model, validate its efficacy in practical settings, and address challenges such as security and scalability, ultimately contributing to the development of smarter and more sustainable urban infrastructures.

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