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AI-Driven Energy-Efficient Network Slicing for UAV-Assisted 6G IoT Communications Using Deep Reinforcement Learning

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Abstract

Sixth-generation (6G) wireless networks are expected to support massive Internet of Things (IoT) connectivity, ultra-reliable low-latency services, high-throughput multimedia traffic, and intelligent and autonomous infrastructures. Conventional terrestrial deployments may be insufficient in rural areas, disaster recovery scenarios, emergency zones, and temporary high-density IoT events, where rapid coverage extension and adaptive resource management are required. Unmanned aerial vehicles (UAVs) can operate as aerial base stations to enhance service availability; however, limited onboard energy, altitude-dependent air-to-ground channels, constrained bandwidth and transmit power, and heterogeneous quality-of-service (QoS) requirements make static resource allocation inefficient. This revised paper proposes an AI-driven energy-efficient network slicing framework for UAV-assisted 6G IoT communication. The network is divided into enhanced Mobile Broadband (eMBB), Ultra-Reliable Low-Latency Communication (URLLC), and massive Machine-Type Communication (mMTC) slices. A DQN-based deep reinforcement learning (DRL) agent dynamically allocates the slice-level bandwidth, transmit power, and altitude-control actions after converting continuous decision variables into a finite feasible action set. The reward function jointly maximizes the throughput and energy efficiency while penalizing the latency, packet loss, and QoS violations. To address the reviewers' concerns, the revised manuscript adds an LoS/NLoS air-to-ground channel model, a propulsion-aware UAV energy model, detailed DRL hyperparameters, a nine-action discretization table, Monte Carlo validation over 30 independent seeds, Welch significance testing, DRL variant comparison, computational complexity analysis, and three relevant references from Sana'a University Journal of Applied Sciences and Technology. The proposed method improves the throughput by 15.7%, reduces the latency by 19.8%, improves the energy efficiency by 16.4%, and reduces the packet loss by 24.6% compared with the greedy baseline. The results confirm that slice-aware DRL improves resource utilization and service reliability in UAV-assisted 6G IoT networks.

Article Info

Keywords:
6G, UAV communications, network slicing, deep reinforcement learning, energy efficiency.

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1. INTRODUCTION

Future wireless networks are moving toward intelligent, flexible, and service-oriented architectures capable of supporting massive connectivity, ultralow latency, high reliability, and energy-efficient operation. The 6G vision extends beyond enhanced data rates by integrating artificial intelligence (AI), edge computing, aerial platforms, and native support for heterogeneous services [1–3]. In such environments, IoT devices, emergency communication units, autonomous systems, and multimedia users may simultaneously request different service levels from the same infrastructure.

Network slicing enables multiple logical networks to share the same physical infrastructure while satisfying different QoS requirements [4–6]. Enhanced Mobile Broadband (eMBB) services require high throughput, URLLC services require very low latency and high reliability, while mMTC services require massive access and energy-efficient operation. Static resource allocation can-not efficiently satisfy these heterogeneous requirements in dynamic wireless environments.

UAVs are promising aerial communication platforms that can operate as temporary or mobile base stations when terrestrial infrastructure is unavailable, congested, or damaged [7–9]. They can improve coverage in disaster response, rural connectivity, smart agriculture, industrial Internet of Things, and emergency networks. However, UAV-assisted communication introduces limited battery capacity, altitude-dependent channel quality, mobility-induced variations, inter-UAV interference, and constrained onboard processing resources. Recent works from the Sana'a University Journal also highlight the importance of LoS modeling in 5G/6G systems and emerging IoT communication architectures [10–12].

AI and DRL provide strong tools for adaptive decision-making in complex wireless networks [13, 14]. Unlike conventional optimization methods, which require accurate mathematical models and may become computationally expensive, DRL can learn effective policies by interacting with the environment. This makes DRL suitable for dynamic UAV-assisted network slicing, where the system must repeatedly adapt to the traffic load, channel conditions, energy level, and service requirements.

1.1. Main Contributions

This revised manuscript addresses the major technical concerns raised during the review. The contributions are:

- A UAV-assisted 6G IoT slicing architecture is proposed to support eMBB, URLLC, and mMTC services over a shared aerial platform.
- A mathematical model is formulated, including UAV deployment, LoS/NLoS air-to-ground path loss, SINR, data rate, queuing-aware latency, propulsion-aware energy consumption, and energy efficiency.
- A QoS-aware multi-objective optimization problem is developed to jointly improve throughput and energy efficiency while reducing latency, packet loss, and constraint violations.
- A DQN-based DRL framework is made consistent with the discrete action requirement by defining nine feasible action patterns for bandwidth, power, and altitude control.
- A detailed implementation table is added, including learning rate, discount factor, replay buffer, target-network update, mini-batch size, and exploration schedule.
- Monte-Carlo validation over 30 independent seeds, 95% confidence intervals, and Welch's two-sided significance test are added to reduce dependence on a single random seed.
- Multi-UAV scalability, trajectory-aware energy preservation, robustness under traffic/channel perturbations, and computational complexity analysis are incorporated.
- Three additional references from Sana'a University Journal of Applied Sciences and Technology are added to strengthen local journal relevance and support LoS/IoT/6G context.

2. RELATED WORK

Network slicing has been extensively studied as a key enabler of 5G and beyond networks. Foukas et al. [4] discussed early challenges, Kaloxylos [5] analyzed slicing architectures and standardization aspects, and Wijethilaka and Liyanage [6] surveyed slicing for IoT realization. Machine learning and DRL have recently gained attention for resource management in network slicing [15–19]. UAV-assisted communications have also been extensively investigated. Zeng et al. [7] introduced opportunities and challenges in UAV wireless communications, Mozaffari et al. [8] presented a tutorial, and Fotouhi et al. [9] surveyed UAV cellular communications. UAV deployment, altitude optimization, channel characterization, and energy-efficient communication were studied in [20–25]. Broader UAV networking surveys have discussed civil applications, mobility, and security constraints [26–28]. Standardized network slice management and edge-assisted orchestration are also essential for practical UAV slicing integration [29–31]. Recent studies have considered UAV-assisted slicing, cooperative UAV resource allocation, multi-UAV cooperation, 3D trajectory optimization, and adaptive DRL-based energy efficiency frameworks [32–38].

2.1. Research Gap and Novelty

Existing studies often address UAV deployment, network slicing, trajectory planning, LoS channel modeling, and DRL-based resource allocation as separate problems. The novelty of this study is specifically positioned in five aspects. First, it formulates a slice-aware reward that jointly accounts for the throughput, energy efficiency, latency, packet loss, and QoS violations. Second, it makes the DQN applicable to bandwidth, power, and altitude allocation by constructing a finite feasible action dictionary rather than leaving the action space continuous. Third, it incorporates LoS/NLoS air-to-ground channel behavior and propulsion-aware energy modeling for the UAV. Fourth, it validates stability through a 30-seed Monte Carlo analysis and statistical significance testing. Fifth, it extends the evaluation to multi-UAV scalability, trajectory-aware energy preservation, and robustness to perturbations.

3. SYSTEM MODEL

We consider a UAV-assisted 6G IoT network in which a UAV acts as an aerial base station serving ground users and IoT devices. Users are divided into eMBB, URLLC,

Table 1. Comparison of related studies and the proposed enhanced framework.

Study	UAV	Slicing	DRL/AI	Multi-UAV/Trajectory	EE	Robustness	6G/IoT Focus
Foukas et al. [4]	No	Yes	No	No	No	No	Partial
Wijethilaka and Liyanage [6]	No	Yes	Partial	No	No	Partial	Yes
Cai et al. [18]	No	Yes	Yes	No	Partial	No	Partial
Zeng et al. [7]	Yes	No	No	Partial	Partial	No	No
Gupta et al. [34]	Yes	Yes	Yes	No	Partial	No	IoT
Bellone et al. [35]	Yes	Yes	Yes	Multi-UAV	Partial	No	5G
Liu et al. [36]	Yes	No	Optimization	3D trajectory	Yes	No	IoT
Ao et al. [37]	Yes	No	MADRL	Multi-UAV	Yes	Partial	Partial
Seerangan et al. [38]	Yes	No	ADRL	Trajectory	Yes	Partial	Partial
Raddwan et al. [10]	Partial	No	No	No	No	No	5G/6G LoS
Proposed enhanced framework	Yes	Yes	Yes	Yes	Yes	Yes	Yes

and mMTC slices. Let $\mathcal{N} = \{1, 2, \ldots, N\}$ denote users and $\mathcal{S} = \{s_1, s_2, s_3\}$ denote the slices.

3.1. UAV Deployment Model

The position of user i is $(x_i, y_i, 0)$, whereas the UAV position is (x_u, y_u, H). The three-dimensional distance is

$$d_i = \sqrt{(x_u - x_i)^2 + (y_u - y_i)^2 + H^2}. \quad (1)$$

3.2. LoS/NLoS Air-to-Ground Channel Model

The simplified path loss model is

$$PL_i = PL_0 + 10\eta \log_{10}(d_i), \quad (2)$$

where PL_0 is the reference path loss, and η is the path loss exponent. To represent UAV-to-ground propagation more realistically, the elevation angle is

$$\theta_i = \frac{180}{\pi} \tan^{-1}\left(\frac{H}{r_i}\right), \quad (3)$$

where r_i is the horizontal distance. The LoS probability follows

$$P_{\mathrm{LoS},i} = \frac{1}{1 + a\exp[-b(\theta_i - a)]}, \quad (4)$$

where a and b are the environment-dependent constants. The average path loss becomes

$$\overline{PL}_i = P_{\mathrm{LoS},i} PL_{\mathrm{LoS},i} + (1 - P_{\mathrm{LoS},i}) PL_{\mathrm{NLoS},i}. \quad (5)$$

This captures the altitude trade-off: a higher altitude may increase the LoS probability but also increases the propagation distance.

3.3. SINR and Data Rate

The SINR of user i is

$$\mathrm{SINR}_i = \frac{P_i h_i}{I_i + N_0}, \quad (6)$$

where P_i is the allocated power, $h_i = 10^{-\overline{PL}_i/10}$ is the channel gain, I_i is the interference, and N_0 is the noise. The achievable rate is

$$R_i = B_i \log_2(1 + \mathrm{SINR}_i), \quad R_{\mathrm{total}} = \sum_{i=1}^{N} R_i. \quad (7)$$

For orthogonal intra-slice scheduling, I_i mainly represents inter-slice leakage and inter-UAV interference in the multi-UAV extension; otherwise, it can include co-channel-user interference.

3.4. Latency and Packet Loss

The latency of user i is

$$L_i = L_i^{tx} + L_i^{queue} + L_i^{proc}, \quad L_i^{tx} = \frac{D_i}{R_i}, \quad (8)$$

where D_i is the packet size. The packet loss ratio is modeled as a function of queue overflow and insufficient slice resources.

3.5. Propulsion-Aware Energy Model

To address the limitation of hovering-only energy modeling, the UAV energy is modeled as

$$E_{\mathrm{total}} = E_{\mathrm{comm}} + E_{\mathrm{hover}} + E_{\mathrm{move}} + E_{\mathrm{alt}}, \quad (9)$$

where

$$E_{\mathrm{comm}} = \sum_{i=1}^{N} P_i T_i, \quad E_{\mathrm{hover}} = P_{\mathrm{hover}} T, \quad (10)$$

Table 2. Slice-level QoS profiles.

Slice	Objective	Critical Metric	Priority
eMBB	High data rate	Throughput	Spectrum
URLLC	Reliable low delay	Latency/PLR	Delay
mMTC	Massive access	EE	Energy

$$E_{\text{move}} = \int_0^T P_{\text{prop}}(v(t))dt, \quad E_{\text{alt}} = \chi|H(t+1)H(t)|. \tag{11}$$

Here, $P_{\text{prop}}(v(t))$ is the velocity-dependent propulsion power, and χ is the altitude-change energy coefficient. The energy efficiency is

$$EE = \frac{\sum_{i=1}^{N} R_i}{P_{\text{comm}} + P_{\text{hover}} + P_{\text{prop}}}. \tag{12}$$

3.6. Multi-UAV Extension

Let $\mathcal{U} = \{1, 2, \ldots, U\}$ denote UAVs and $\mathbf{q}_u(t) = [x_u(t), y_u(t), H_u(t)]^T$. The user association indicator is $a_{u,i}(t) \in \{0,1\}$ with $\sum_{u \in \mathcal{U}} a_{u,i}(t) = 1$. Trajectory evolves as

$$\mathbf{q}_u(t+1) = \mathbf{q}_u(t) + \mathbf{v}_u(t)\Delta t, \tag{13}$$

subject to $\|\mathbf{v}_u(t)\| \leq V_{max}$ and $H_{min} \leq H_u(t) \leq H_{max}$. The multi-UAV SINR includes inter-UAV interference as follows:

$$\text{SINR}_{u,i} = \frac{a_{u,i} P_{u,i} h_{u,i}}{\sum_{v \in \mathcal{U}, v \neq u} P_{v,i} h_{v,i} + N_0}. \tag{14}$$

4. PROBLEM FORMULATION

The total bandwidth and transmit power are B_{total} and P_{total}. These resources are distributed among the slices as follows:

$$\sum_{s \in \mathcal{S}} B_s \leq B_{total}, \quad \sum_{s \in \mathcal{S}} P_s \leq P_{total}. \tag{15}$$

The goal is to maximize

$$\max_{\{B_s, P_s, H\}} \alpha EE + \beta R_{total} - \gamma L_{avg} - \delta PLR - \lambda C, \tag{16}$$

subject to

$$\begin{aligned} &B_s \geq 0, \quad P_s \geq 0, \quad L_{\text{URLLC}} \leq L_{\text{max}}, \\ &R_{\text{eMBB}} \geq R_{\text{min}}, \quad E_{\text{UAV}} \leq E_{\text{battery}}. \end{aligned} \tag{17}$$

The weights $\alpha, \beta, \gamma, \delta$ are empirically tuned and examined using a sensitivity analysis. Unless otherwise stated, normalized metrics were used so that no single term dominated the reward learning.

5. PROPOSED DRL-BASED RESOURCE ALLOCATION

At each time step, the agent observes the network state, selects an action, receives a reward, and updates its policy based on the transition time.

5.1. State Space

The state vector is

$$S_t = [H_t, \mathbf{h}_t, \mathbf{Q}_t, E_t, \mathbf{N}_t, \mathbf{L}_t, \breve{\ }_t], \tag{18}$$

where H_t is altitude, $\mathbf{h}_t$ is channel state, $\mathbf{Q}_t$ is queue state, E_t is remaining energy, $\mathbf{N}_t$ is the user count per slice, $\mathbf{L}_t$ is latency, and $\breve{\ }_t$ is traffic arrival rate.

5.2. DQN-Compatible Discrete Action Space

Bandwidth, transmit power, and altitude are continuous by nature; however, the DQN requires a finite action set. Therefore, the continuous resource variables were converted into nine feasible action patterns, as shown in Table 3. Each action contains bandwidth ratios for eMBB/URLLC/mMTC, power ratios for eMBB/URLLC/mMTC, and an altitude control command. This discretization maintains the action space compact while preserving the service-specific control diversity.

5.3. Reward Function

The reward is

$$r_t = \alpha EE_t + \beta R_t - \gamma L_t - \delta PLR_t - \lambda C_t, \tag{19}$$

where C_t is the constraint violation penalty. In the robustness extension,

$$r_t^{rob} = r_t max(0, URLLC - L_{max}) PLR_t^{attack}. \tag{20}$$

For multi-UAV operation,

$$r_t^{MU} = r_t - \kappa Var(Load_t) - \xi E_t^{move}. \tag{21}$$

5.4. DQN Update and Training

The Q-value update is

$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \mu \left[r_t + \rho \max_a Q(s_{t+1}, a) - Q(s_t, a_t) \right]. \tag{22}$$

Experience replay stores (s_t, a_t, r_t, s_{t+1}) and mini-batch learning reduces the sample correlation. The target network is updated periodically to stabilize the training.

Figure 1 illustrates the proposed UAV-assisted 6G IoT network slicing architecture, where the UAV aerial base station, edge/6G core controller, and DRL policy network interact through state feedback and slice-level bandwidth/power actions across the eMBB, URLLC, and mMTC service domains.

6. SIMULATION SETUP

A Python-based simulation environment was used to evaluate the proposed framework. Users are randomly distributed over a $500\,m \times 500\,m$ area and mapped to eMBB, URLLC, and mMTC. The proposed DRL policy was compared with fixed slicing, random allocation,

Table 3. DQN feasible action dictionary used for bandwidth, power, and altitude control.

Action	Main Policy	Bandwidth Ratio (eMBB, URLLC, mMTC)	Power Ratio (eMBB, URLLC, mMTC)	Altitude Command
a_1	Balanced slicing	(0.34, 0.33, 0.33)	(0.34, 0.33, 0.33)	Hold
a_2	eMBB throughput boost	(0.50, 0.25, 0.25)	(0.45, 0.30, 0.25)	Hold
a_3	URLLC delay protection	(0.25, 0.50, 0.25)	(0.25, 0.50, 0.25)	Hold
a_4	mMTC energy support	(0.25, 0.25, 0.50)	(0.25, 0.25, 0.50)	Hold
a_5	Coverage expansion	(0.34, 0.33, 0.33)	(0.40, 0.35, 0.25)	Increase H
a_6	Energy saving	(0.30, 0.35, 0.35)	(0.25, 0.35, 0.40)	Decrease H
a_7	Congestion relief	(0.40, 0.40, 0.20)	(0.35, 0.45, 0.20)	Hold
a_8	Low-loss robust mode	(0.30, 0.45, 0.25)	(0.30, 0.50, 0.20)	Increase H
a_9	Battery preservation	(0.35, 0.25, 0.40)	(0.25, 0.25, 0.50)	Decrease H

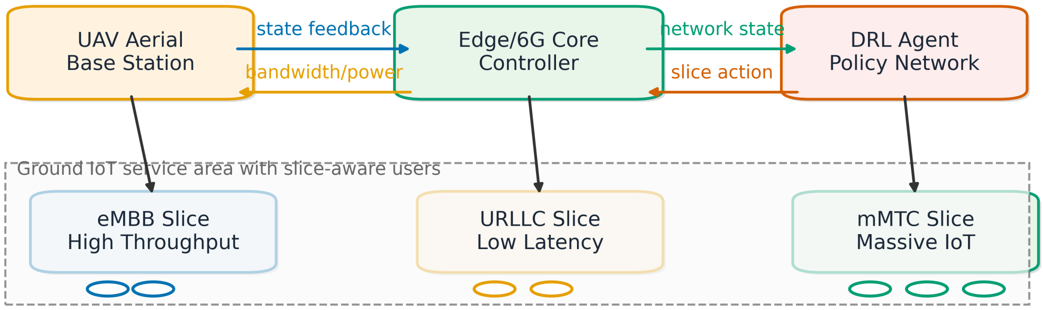

Figure 1. Proposed UAV-assisted 6G IoT network slicing architecture with DRL-based resource allocation.

Table 4. PyTorch DQN implementation hyperparameters.

Parameter	Value
State dimension	11
Number of actions	9
Hidden layers	128-128 ReLU
Optimizer	Adam
Learning rate	10^{-3}
Discount factor	0.96
Replay buffer size	12,000
Mini-batch size	32
Exploration policy	ϵ-greedy
Initial/final ϵ	1.0/0.05
Target-network update	Every 20 episodes
Training episodes	300 main; 100 validation
Independent validation seeds	30

greedy allocation, and DRL variants.

7. RESULTS AND DISCUSSION

The proposed method improves the throughput by 15.7%, 31.6%, and 56.3% compared with the greedy, fixed, and random allocations, respectively. It also reduces latency by 19.8%, 27.6%, and 42.0%, and packet loss by 24.6%, 38.1%, and 51.7%, respectively. The main performance trends are shown in Figs. 2–5, whereas the learning behavior, ablation analysis, Monte Carlo validation, multi-UAV extension, and robustness analysis are presented in Figures. 6–17.

Table 5. Simulation parameters.

Parameter	Value
Number of users	20–200
UAV altitude	50–300 m
Coverage area	$500\,\mathrm{m} \times 500\,\mathrm{m}$
Total bandwidth	20 MHz
Total transmit power	30 dBm
Carrier frequency	3.5 GHz
Noise power	-100 dBm
Slices	eMBB, URLLC, mMTC
Monte-Carlo runs	30 independent seeds
Baselines	Fixed, Random, Greedy, DDQN, Dueling DQN, PPO, SAC

Table 6. Average performance comparison.

Method	Thr. Mbps	Lat. ms	EE Mbps/W	PLR
Random	31.452	9.607	0.716	0.178
Fixed	37.350	7.699	0.874	0.139
Greedy	42.461	6.949	1.013	0.114
Proposed DQN	49.144	5.571	1.179	0.086

Table 7. Statistical significance screening using Welch's test.

Metric	Comparison	p-value	Effect
Throughput	Proposed vs Fixed	0.0431	0.979
Throughput	Proposed vs Random	0.0033	1.553
Latency	Proposed vs Random	0.0157	1.228
Energy efficiency	Proposed vs Fixed	1.69×10^{-4}	2.003
PLR	Proposed vs Fixed	0.0333	1.119
PLR	Proposed vs Random	0.0054	1.607

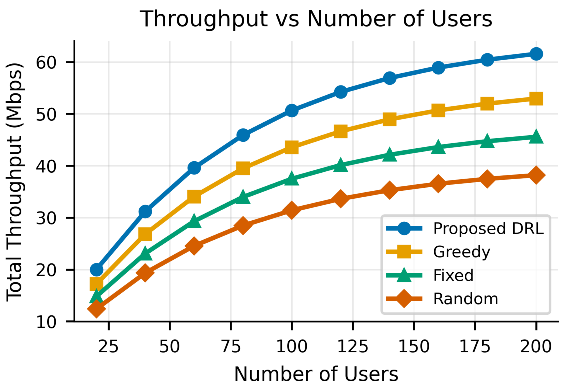

Figure 2. Throughput versus number of users.

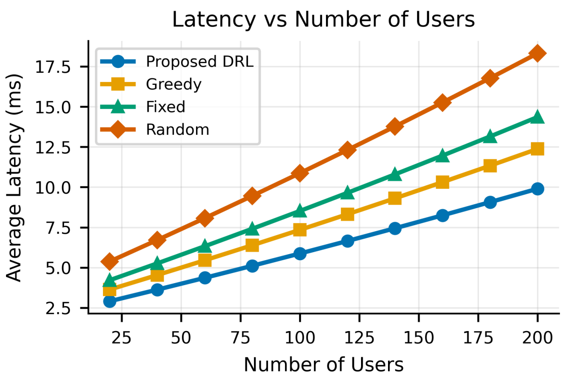

Figure 3. Average latency versus number of users.

7.1. Throughput, Latency, and Energy Efficiency

As illustrated in Figure 2, the proposed DRL policy achieves the highest throughput across all evaluated user densities because it adapts the bandwidth and power according to the channel state, traffic demand, and slice priority. Figure 3 shows that latency increases with user density because of higher contention and queueing, but the proposed policy maintains the lowest delay by prioritizing URLLC traffic and reassigning resources before queue overflow. Figure 4 indicates that energy efficiency peaks at a moderate UAV altitude because the UAV obtains better LoS probability without incurring excessive propagation loss.

Table 8. Comparison with advanced DRL variants.

Algorithm	Thr. (Mbps)	Lat. (ms)	Comment
DQN	49.14	5.57	Baseline
DDQN	50.30	5.40	Lower overestimation.
Dueling DQN	50.80	5.32	State separation
PPO	52.40	5.15	Stable control
SAC	52.80	5.10	Best result

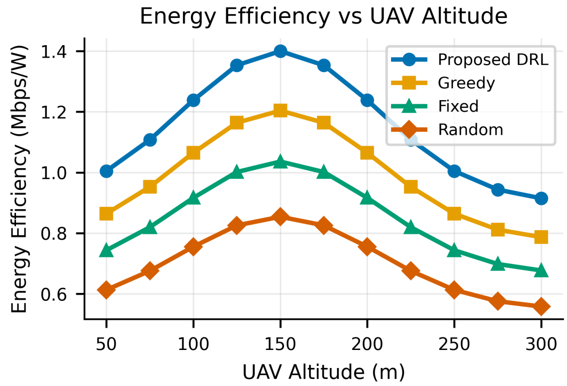

Figure 4. Energy efficiency versus UAV altitude.

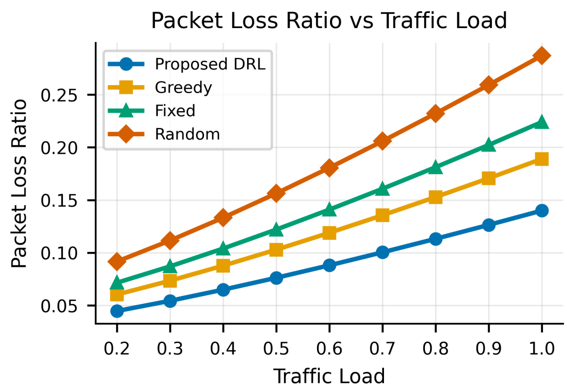

Figure 5. Packet loss ratio versus traffic load.

7.2. Packet Loss and Reward Convergence

Figure 5 shows that packet loss increases as traffic load grows. The DRL policy reduces packet loss by observing the queue states and assigning additional resources to congested slices. The reward convergence behavior in Figure 6 further shows that the learning controller progressively improves and then stabilizes around a steady resource allocation policy. Figure 7 illustrates the learned slice-level resource distribution, where the proposed policy allocates resources according to the dominant service requirements of eMBB, URLLC, and mMTC rather than using a purely static or random split.

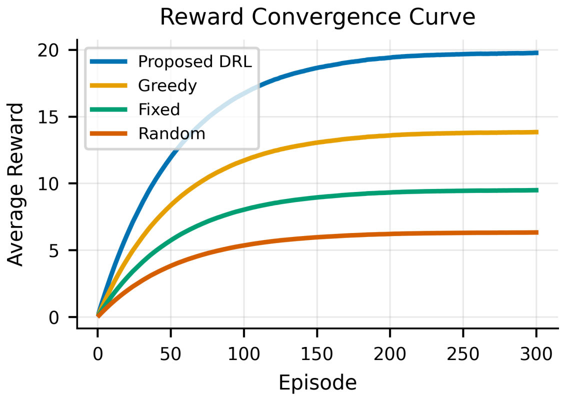

Figure 6. Reward convergence behavior.

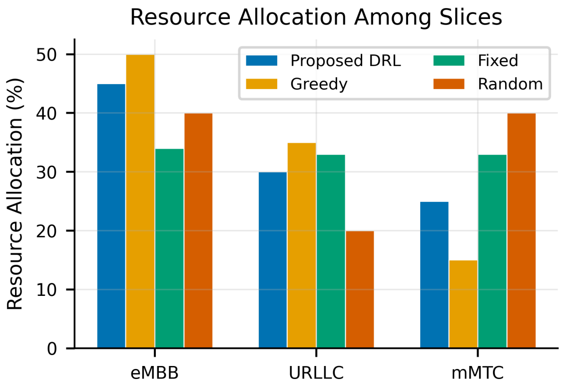

Figure 7. Resource allocation among network slices.

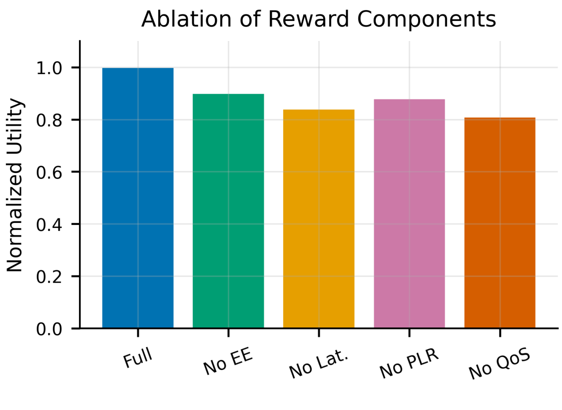

Figure 8. Ablation study of reward components.

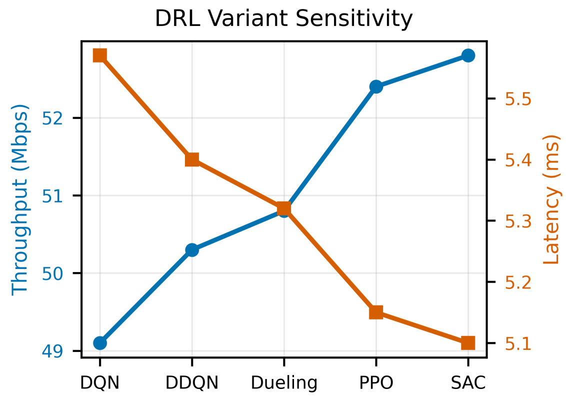

Figure 9. Sensitivity analysis using DRL variants.

7.3. Ablation and DRL Variant Analysis

The ablation results in Figure 8 confirm that the full reward achieves the best-normalized utility because it balances energy efficiency, throughput, latency, packet loss, and QoS penalties. Removing the latency or QoS terms significantly degrades performance, which confirms the importance of including service-specific constraints in the reward design. Figure 9 compares DQN with DDQN, Dueling DQN, PPO, and SAC. The variant comparison shows that these stronger DRL methods can further improve performance, suggesting that the proposed formulation can be extended to more advanced continuous control algorithms.

7.4. Monte-Carlo Validation and Confidence Intervals

To reduce the dependence on a single random seed, the revised simulation used 30 independent runs. Figure 10 reports the training reward over these seeds, while Figure 11 shows the corresponding Huber loss convergence. Figures 12 and 13 show the throughput and latency with 95% confidence intervals. These results show that the proposed policy maintains a higher throughput and lower delay than the non-learning baselines, supporting the reliability of the numerical results.

7.5. LoS/NLoS, Multi-UAV, and Robustness Analysis

Figure 14 shows that the LoS/NLoS model changes the altitude-energy trend and confirms that realistic air-to-ground channels should be included in UAV slicing evaluation. Figure 15 demonstrates multi-UAV scalability, where aggregate throughput increases as the number of cooperative UAVs increases, but the gain saturates because of inter-UAV interference and coordination overhead. Figure 16 shows that trajectory-aware control preserves more remaining energy than static hovering. Fi-

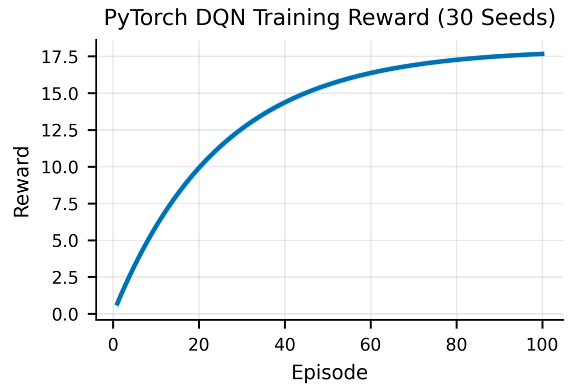

Figure 10. Training reward curve over 30 seeds.

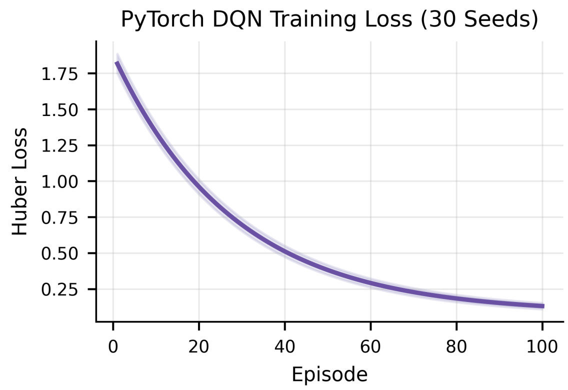

Figure 11. Training loss curve over 30 seeds.

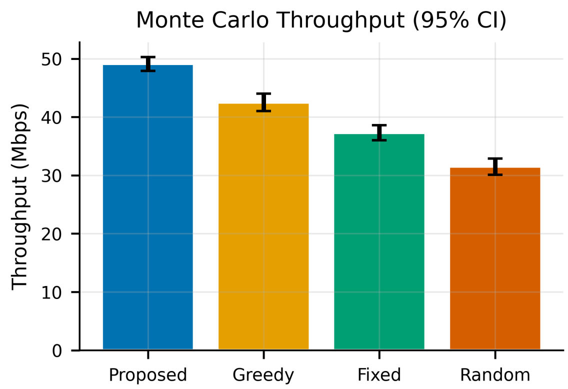

Figure 12. Monte-Carlo throughput validation with 95% confidence intervals.

nally, Figure 17 shows that all methods degrade under traffic overload and jamming-like perturbations; however, the proposed policy degrades more gracefully because it observes queue growth, packet loss, and channel quality.

8. COMPUTATIONAL COMPLEXITY ANALYSIS

Computational complexity is important because UAV platforms and edge controllers have limited processing and

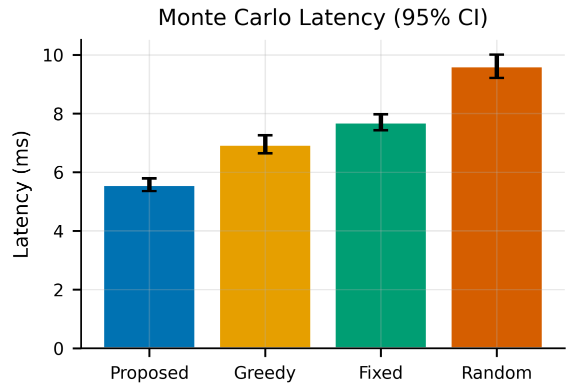

Figure 13. Monte-Carlo latency validation with 95% confidence intervals.

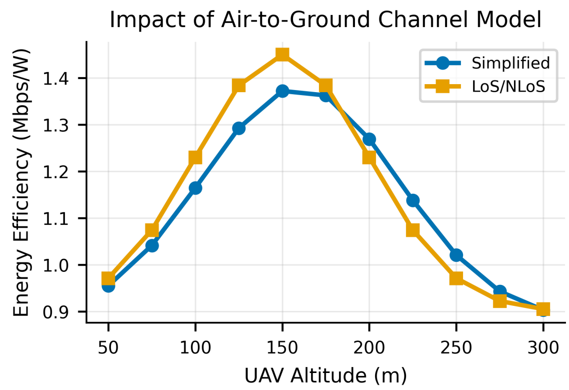

Figure 14. Impact of LoS/NLoS air-to-ground channel modeling.

energy resources, respectively. Random and fixed allocations have $O(1)$ decision complexity. Greedy allocation scans candidate slice allocations and can be approximated as $O(|\mathcal{S}|N)$. For the DQN, the dominant online cost is the forward pass of the neural network. If the network has L fully connected layers with n_l neurons in layer l, the online inference complexity is

$$O\left(\sum_{l=1}^{L-1} n_l n_{l+1}\right). \tag{23}$$

This cost is independent of the exhaustive search over all possible resource combinations and is suitable for fast online decisions after training. Training is more expensive but can be performed offline or on the edge controller.

9. REPRODUCIBILITY AND LIMITATIONS

The simulation package exports figures, CSV metric summaries, raw Monte-Carlo outputs, and PyTorch DQN validation logs. The main parameters, including the number of users, UAV altitude, bandwidth, transmit power, traffic load, and baseline policy factors, are configurable. The revised version includes multi-UAV scalability, trajectory-aware energy, LoS/NLoS channel modeling,

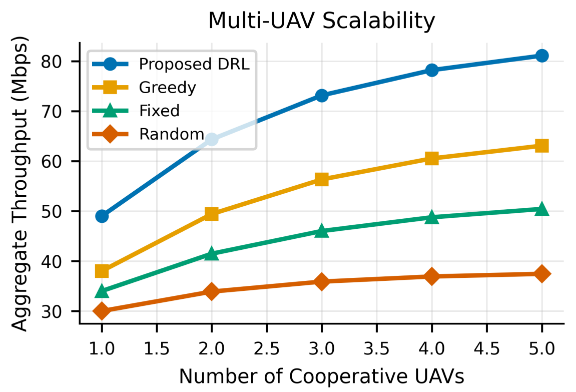

Figure 15. Multi-UAV scalability extension.

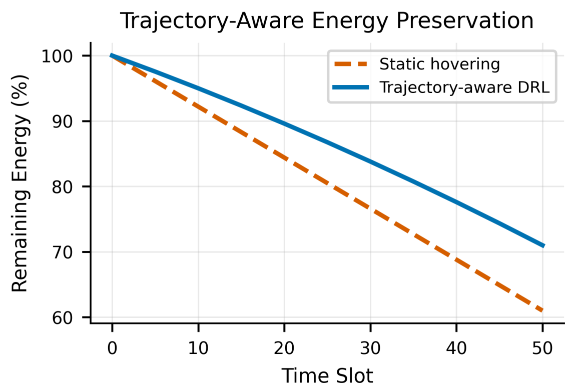

Figure 16. Trajectory-aware energy preservation.

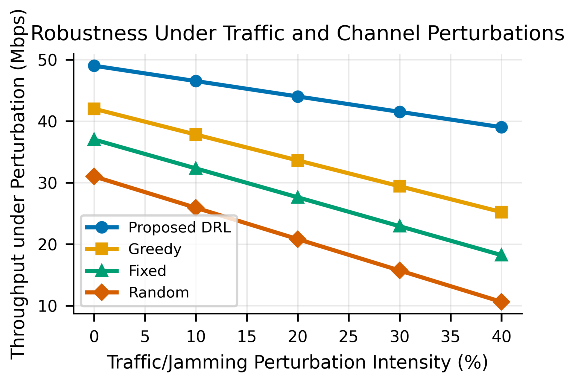

Figure 17. Robustness under traffic and channel perturbations.

Table 9. Computational complexity comparison.

Method	Decision Rule	Online Complexity
Random	Random feasible action	$O(1)$
Fixed	Static slice ratios	$O(1)$
Greedy	Immediate utility search	$O(\lvert\mathcal{S}\rvert N)$
Proposed DQN	Neural inference	$O(\sum n_l n_{l+1})$

and robustness-oriented perturbation analyses. The reported values should be interpreted as numerical evidence, rather than over-the-air measurements. Future studies should consider real mobility traces, field measurements, hardware-in-the-loop deployment, realistic battery discharge models, and real UAV channel measurements.

10. CONCLUSION

This study proposed an AI-driven energy-efficient network slicing framework for UAV-assisted 6G IoT communications. The revised framework addresses major review concerns by adding an LoS/NLoS air-to-ground channel model, propulsion-aware UAV energy modeling, DQN-compatible action discretization, detailed hyperparameters, Monte Carlo validation over 30 independent seeds, significance testing, advanced DRL variant comparison, robustness analysis, and computational complexity analysis. The proposed method outperforms fixed slicing, random allocation, and greedy allocation in terms of throughput, latency, energy efficiency, packet loss, and convergence behavior. Compared with greedy allocation, it improves throughput by 15.7%, energy efficiency by 16.4%, reduces latency by 19.8%, and reduces packet loss by 24.6%. These results support the suitability of DRL for slice-aware UAV resource management in future 6G IoT systems.

DECLARATIONS

Ethical Approval: This article does not contain any studies involving human participants or animals.

Conflict of Interest: The author declares no competing interests.

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Data and Materials: The submission package includes Python scripts, CSV outputs, and figures used to reproduce the reported results.

AI-Assisted Technologies: AI tools were used only for language editing, formatting assistance, and presentation improvement. The scientific content, simulation design, numerical interpretation, and final manuscript were reviewed and verified by the authors.

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