Machine Learning-Based Resource Allocation and Offloading Strategies for Next-Generation Satellite-Terrestrial and IRS-Assisted Networks

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***Abstract*—This paper presents a reinforcement learning-based framework for joint task offloading and resource allocation in hybrid satellite-terrestrial networks enhanced with Intelligent Reflecting Surfaces (IRS). The proposed approach leverages a Deep Q-Network (DQN) agent to optimize the trade-off between energy consumption and latency for multiple users and edge nodes. Through extensive simulations and comparative analysis, we demonstrate that our model adapts to complex wireless environments and significantly improves system performance across key metrics, including reward, latency, and energy efficiency. The results validate the effectiveness of integrating IRS with satellite-terrestrial networks using deep reinforcement learning, providing insights for the future development of heterogeneous wireless infrastructures.**

***Index Terms*—Task Offloading, Reinforcement Learning, Satellite-Terrestrial Networks, Intelligent Reflecting Surface (IRS), Resource Allocation, Edge Computing**

I. INTRODUCTION

The demand for ubiquitous connectivity and computational offloading has surged with the rise of latency-sensitive and computation-intensive applications. Traditional terrestrial wireless networks often fall short in delivering seamless service in remote or mobility-constrained regions. Satellite-terrestrial networks (STNs) offer a promising solution by integrating satellite coverage with terrestrial infrastructure. However, STNs face challenges such as signal degradation, high latency, and limited capacity. Intelligent Reflecting Surfaces (IRS), composed of programmable passive elements, have emerged as a low-power solution to reconfigure wireless propagation environments, improving signal strength and spectral efficiency when integrated with STNs. Optimizing these dynamic systems requires adaptive strategies.

This paper proposes a Deep Reinforcement Learning (DRL) framework that dynamically allocates resources and offloads tasks while leveraging IRS-enhanced links. A Deep Q-Network (DQN) agent is trained to learn optimal actions under fluctuating channel conditions, user demands, and IRS configurations.

A. Related Work

Recent research has explored resource allocation in edge computing and satellite networks using various techniques:

- **Resource Allocation in Edge Computing**: Chen et al. [1] and Liu et al. [2] used convex optimization for Mobile Edge Computing (MEC), achieving optimal results under static assumptions. Zhang et al. [3] applied game theory with Stackelberg games, capturing competitive dynamics but assuming perfect information. Wang et al. [4] employed heuristic algorithms like genetic algorithms for near-optimal solutions with lower complexity. - **Machine Learning for Wireless Networks**: Regression models predict traffic and mobility [5], while clustering groups users by requirements [6]. Reinforcement learning, including Q-learning and DQN, has been used for spectrum access [7] and power control [8], showing adaptability but slow convergence. - **IRS in Wireless Communications**: Wu et al. [9] modeled IRS-assisted channels, Huang et al. [10] improved energy efficiency, and Di et al. [11] extended coverage. - **Satellite-Terrestrial Integration**: Works like [12], [13] proposed architectures, Zhang et al. [14] managed spectrum sharing, and Liu et al. [15] ensured service continuity.

Research Gaps: Most studies focus on either IRS-terrestrial or satellite-terrestrial systems, not the integrated three-component system we propose. Few incorporate IRS into satellite-terrestrial settings with DRL for joint offloading and allocation, and dynamic IRS optimization under uncertainty remains underexplored. Our work addresses these gaps.

To position our work relative to prior studies, we compare it with five key papers: - **Paper 1** [16]: Optimizes IRS-assisted IoT networks for throughput using static methods, unlike our dynamic DRL approach for latency and energy in satellite-terrestrial-IRS systems. - **Paper 2** [17]: Uses RL for IRS-aided MISO downlink rate maximization, while we focus on uplink task offloading with task-oriented metrics. - **Paper 3** [18]: Addresses satellite-terrestrial resource allocation statically, lacking IRS and DRL, which we integrate. - **Paper 4** [19]: Maximizes energy efficiency in IRS-assisted radar-communication systems statically, whereas we target broader offloading with DRL. - **Paper 5** [20]: Employs multiagent DRL for satellite-terrestrial offloading, improved by our IRS integration and single-agent DQN.

Table I summarizes these distinctions.

B. Contributions

This paper offers the following contributions: - **Novel Integration Framework**: A unified approach combining terrestrial networks, satellite links, and IRS for optimized resource allocation. - **Dynamic DRL Solution**: Adapts to changing

TABLE I
COMPARISON WITH PRIOR WORKS

Aspect	Our Paper	Paper 1	Paper 2	Paper 3	Paper 4	Paper 5
Network Scope	Sat-Ter-IRS	Ter-IRS	Ter-IRS	Sat-Ter	Ter-IRS	Sat-Ter
Optimization Method	DRL (DQN) + IRS Opt	Static	RL	Static	Static	Multiagent DRL
Objectives	Latency, Energy, Tasks	Throughput	Data Rate	Rate, Interference	Energy Efficiency	Energy, Delay
Dynamic Adaptation	High	Low	Moderate	Low	Low	High
IRS Optimization	Yes	Yes	Yes	No	Yes	No

conditions using a sophisticated DRL architecture. - **IRS Configuration Optimization**: Dynamically adjusts IRS settings based on network states. - **Extensive Performance Analysis**: Compares our approach against baselines across multiple metrics. - **Scalability Assessment**: Evaluates performance with increasing system complexity.

II. SYSTEM MODEL

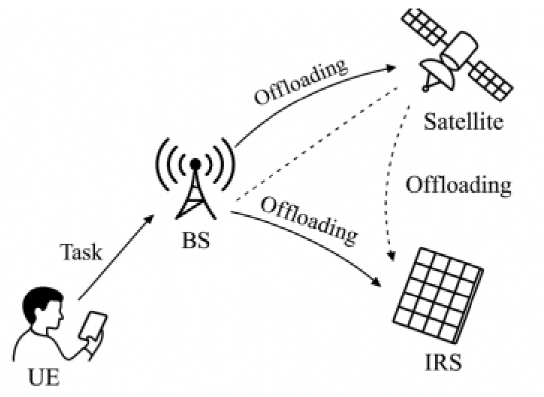

Fig. 1. Total Reward over 300 Episodes.

We present a detailed system model for a multi-user hybrid satellite-terrestrial network augmented with Intelligent Reflecting Surfaces (IRS) to facilitate efficient computation offloading and resource allocation for mobile users.

A. Network Model

The system comprises a hybrid network integrating terrestrial and satellite components, enhanced by IRS to optimize connectivity. It includes:

- **Users**: A set of $N = 5$ mobile users, denoted as $\mathcal{N} = \{1, 2, \ldots, N\}$, each capable of generating computational tasks.
- **IRS Nodes**: A set of $M = 3$ IRS nodes, denoted as $\mathcal{M} = \{1, 2, \ldots, M\}$, each equipped with $K = 100$ passive reflecting elements. These nodes enhance connectivity by reflecting signals.
- **Edge Servers**: A set of $E = 3$ edge servers, denoted as $\mathcal{E} = \{1, 2, \ldots, E\}$, each with a maximum computational capacity of $f_e^{\max} = 20$ GHz, providing resources for task offloading.
- **Satellite**: A single Low Earth Orbit (LEO) satellite, denoted as s, orbiting at 550 km with a coverage radius of 1,000 km. It offers a computational capacity of $f_s^{\max} = 10$ GHz, operates with a 500 MHz bandwidth, and employs 10 spot beams for extended coverage.

Each IRS element has a reflection coefficient $\theta_{m,k} = \beta_{m,k} e^{j\phi_{m,k}}$, where $\beta_{m,k} = 1$ (perfect reflection) and $\phi_{m,k} \in [0, 2\pi)$ is the adjustable phase shift. Tasks can be processed locally or offloaded to edge servers or the satellite based on system requirements.

B. Mobility Model

Users adhere to the Random Waypoint Mobility Model, with their positions and movements defined as follows:

- **Position**: Coordinates (x_i, y_i) for user $i \in \mathcal{N}$ evolve over time with updates:

$$x_{i,t+1} = x_{i,t} + v_i \cos(\theta_i) \cdot \Delta t \tag{1}$$

$$y_{i,t+1} = y_{i,t} + v_i \sin(\theta_i) \cdot \Delta t \tag{2}$$

- **Velocity**: $v_i \in [0, 5]$ m/s.
- **Direction**: $\theta_i \in [0, 2\pi)$, with a probability $p_{\text{change}} = 0.2$ of random alteration per time step.

This mobility introduces dynamic variations in channel conditions, influencing offloading decisions.

C. Task Model

Each user $i \in \mathcal{N}$ generates computational tasks modeled as tuples (d_i, c_i, t_i), arriving via a Poisson process with rate $\lambda_i = 0.5$ tasks per second. Task attributes include:

- **Data Size**: $d_i \in [0.1, 2]$ MB.
- **Computational Requirement**: $c_i \in [0.5, 2]$ gigacycles (CPU cycles).
- **Delay Tolerance**: t_i, exponentially distributed with a mean of 500 ms.

For each task at time t, an offloading decision $a_{i,t} \in \{0, 1, 2\}$ is made:

- $a_{i,t} = 0$: Local processing on the user device.
- $a_{i,t} = 1$: Offloading to an edge server.
- $a_{i,t} = 2$: Offloading to the satellite.

D. Channel Model

The communication channels consist of direct, IRS-assisted, and satellite links, with gains defined as:

- **Direct Link**: Channel gain between user i and edge server e, $h_{i,e} = \sqrt{\alpha_{i,e}} g_{i,e}$, where $\alpha_{i,e} = \alpha_0 \left(\frac{d_{i,e}}{d_0}\right)^{-\gamma}$ accounts for large-scale fading, and $g_{i,e}$ follows Rayleigh fading.

- **IRS-Assisted Link**: Effective gain, $h_{i,e}^{\text{IRS}} = \sum_{m=1}^{M} \mathbf{h}_{i,m}^{H} \boldsymbol{\Theta}_m \mathbf{g}_{m,e}$, where $\boldsymbol{\Theta}_m = \text{diag}(\theta_{m,1}, \ldots, \theta_{m,K})$ is the IRS reflection matrix.
- **Satellite Link**: Gain, $h_{i,s} = \sqrt{\alpha_{i,s}} g_{i,s}$, with $\alpha_{i,s} = \alpha_0 \left(\frac{d_{i,s}}{d_0}\right)^{-2}$, and $g_{i,s}$ follows Rician fading.

Data rates are computed using Shannon's formula:

$$R_{i,e} = B \log_2 \left(1 + \frac{P_i |h_{i,e} + h_{i,e}^{\text{IRS}}|^2}{\sigma^2}\right) \tag{3}$$

$$R_{i,s} = B_s \log_2 \left(1 + \frac{P_i |h_{i,s}|^2}{\sigma_s^2}\right) \tag{4}$$

E. Computation Model

Task computation varies based on the offloading decision:

- **Local Processing** ($a_{i,t} = 0$):
  - Latency: $T_i^{\text{local}} = \frac{c_i}{f_i^{\text{local}}}$
  - Energy: $E_i^{\text{local}} = \kappa (f_i^{\text{local}})^2 c_i$
- **Edge Offloading** ($a_{i,t} = 1$):
  - Transmission time: $T_i^{\text{tx}} = \frac{d_i}{R_{i,e}}$
  - Computation time: $T_i^{\text{comp}} = \frac{c_i}{f_e}$
  - Waiting time: $W_{i,e}$ (queue-dependent)
  - Total latency: $L_i = T_i^{\text{tx}} + T_i^{\text{comp}} + W_{i,e}$
  - Energy: $E_i = P_i \frac{d_i}{R_{i,e}}$
- **Satellite Offloading** ($a_{i,t} = 2$):
  - Transmission time: $T_i^{\text{tx,s}} = \frac{d_i}{R_{i,s}}$
  - Computation time: $T_i^{\text{comp,s}} = \frac{c_i}{f_s}$
  - Waiting time: $W_{i,s}$
  - Total latency: $L_i = T_i^{\text{tx,s}} + T_i^{\text{comp,s}} + W_{i,s}$
  - Energy: $E_i = P_i \frac{d_i}{R_{i,s}}$

Queue waiting times $W_{i,j}$ depend on the queue length at the processing node.

F. Optimization Problem Formulation

To provide a rigorous foundation for our Deep Reinforcement Learning (DRL) framework, we formulate a joint task offloading and resource allocation problem aimed at minimizing latency and energy consumption while ensuring task completion within delay constraints. For each task i, the cost function is:

$$C_i = \alpha L_i + \beta E_i \tag{5}$$

where:

- L_i: Total latency for task i (seconds),
- E_i: Energy consumption for task i (Joules),
- α, β: Weighting coefficients (e.g., $\alpha = 1\,\text{s}^{-1}$, $\beta = 0.1\,\text{J}^{-1}$).

The expressions for L_i and E_i depend on the offloading decision a_i as detailed in the computation model. Given the system's dynamic nature (e.g., user mobility, task arrivals, and channel variations), we model it as a Markov Decision Process (MDP) with:

- **State** ($\mathbf{s}_t$): Channel gains, queue lengths, task attributes (data sizes, computational requirements, delay tolerances), and user positions.
- **Action** ($\mathbf{a}_t$): Offloading decisions $a_{i,t} \in \{0, 1, 2\}$ for all users.
- **Reward** (r_t): $r_t = \sum_{i \in \mathcal{C}_t} (\beta_c - \alpha L_i - \beta E_i)$, where $\mathcal{C}_t$ is the set of tasks completed at time t, and β_c is a constant baseline reward.
- **Transition Probabilities**: Governed by user mobility, task arrivals, channel fading, and queue dynamics.

The objective is to maximize the expected cumulative discounted reward:

$$\max E \left[\sum_{t=0}^{\infty} \gamma^t r_t\right] \tag{6}$$

where $\gamma \in (0, 1)$ is the discount factor. A Deep Q-Network (DQN) approximates the optimal action-value function:

$$Q^*(\mathbf{s}, \mathbf{a}) = E\left[r_t + \gamma \max_{\mathbf{a}'} Q^*(\mathbf{s}_{t+1}, \mathbf{a}')\right] \tag{7}$$

The DQN is trained by minimizing the loss:

$$\mathcal{L}(\theta) = E\left[\left(r_j + \gamma \max_{\mathbf{a}'} Q(\mathbf{s}_{j+1}, \mathbf{a}'; \theta^-) - Q(\mathbf{s}_j, \mathbf{a}_j; \theta)\right)^2\right] \tag{8}$$

This formulation ties the system parameters to the DRL solution, ensuring a comprehensive optimization framework for the hybrid network.

III. Proposed Methodology

We use a DQN-based agent to optimize offloading and allocation, enhanced with IRS phase shift optimization to maximize system performance.

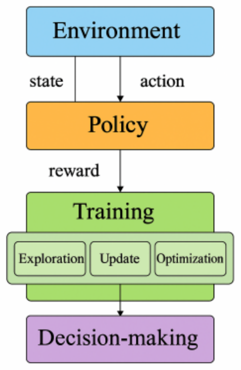

Fig. 2. Workflow of the Reinforcement Learning (RL) agent.

A. Algorithm Description

The problem is formulated as an MDP $(\mathcal{S}, \mathcal{A}, \mathcal{P}, \mathcal{R}, \gamma)$, as detailed in Section II.F: - State Space: $\mathbf{s}_t = [\mathbf{h}_t, \mathbf{q}_t, \mathbf{e}_t, \mathbf{d}_t, \mathbf{c}_t, \mathbf{t}_t, \mathbf{p}_t]$ - Action Space: $\mathbf{a}_t = [a_{1,t}, \ldots, a_{N,t}]$, $a_{i,t} \in \{0, 1, 2\}$ - Reward: $r_t = \sum_{i=1}^{N} (\beta_c \cdot \mathbf{1}\{\text{task } i \text{ completed}\} - \alpha \cdot L_{i,t} - \beta \cdot E_{i,t})$ - **DQN**: Two hidden layers (256, 128 neurons, ReLU), trained with experience replay (buffer 5000, batch 64), ϵ-greedy exploration.

The updated algorithm integrates DQN-based offloading with IRS optimization:

Algorithm 1 DQN-Based Offloading and IRS Optimization

```
Initialize replay memory $D$ to capacity 5000
Initialize $Q$ with random weights $\theta$
Initialize target $\hat{Q}$ with $\theta^- = \theta$
**for** episode = 1 to 300 **do**
    Initialize state $s_1$
    **for** $t = 1$ to 100 **do**
        With probability $\epsilon$ select random $a_t$
        Otherwise $a_t = \arg\max_a Q(s_t, a; \theta)$
        Execute $a_t$, observe $r_t$, $s_{t+1}$
        Store $(s_t, a_t, r_t, s_{t+1})$ in $D$
        Sample mini-batch from $D$
        Set $y_j = r_j + \gamma \max_{a'} \hat{Q}(s_{j+1}, a'; \theta^-)$ or $r_j$ if terminal
        Gradient descent on $(y_j - Q(s_j, a_j; \theta))^2$
        Update $\hat{Q}$ every 100 steps
    **end for**
    Optimize IRS phase shifts for edge-offloaded users using gradient ascent
**end for**
```

B. IRS Phase Shift Optimization

After determining offloading decisions, we optimize the IRS phase shifts $\Phi = \{\phi_{m,k}\}$ to maximize the sum rate for edge-offloaded users:

$$\max_{\Phi} \sum_{i \in \mathcal{I}} R_{i,e_i} \tag{9}$$

where $\mathcal{I} = \{i \mid a_{i,t} = 1\}$ represents the set of edge-offloaded users, and R_{i,e_i} is the data rate as defined in (3). We employ gradient ascent to iteratively update the phase shifts:

$$\phi_{m,k}^{(t+1)} = \phi_{m,k}^{(t)} + \eta \frac{\partial}{\partial \phi_{m,k}} \sum_{i \in \mathcal{I}} R_{i,e_i} \tag{10}$$

where η is the step size. This two-stage approach—DQN for offloading followed by IRS optimization—ensures efficient resource utilization and enhanced link quality, adapting dynamically to the network state.

IV. Numerical Simulations

A. Simulation Settings

Implemented in Python with TensorFlow, parameters include: - $N = 5$, $M = 3$, $E = 3$, $K = 100$ - CPU frequencies: 1 GHz (user), 20 GHz (edge), 10 GHz (satellite) - Bandwidth: 20 MHz, Episodes: 300, Steps: 100

TABLE II
Simulation Parameters

Parameter	Value
Number of users (N)	5
IRS nodes (M)	3
Edge servers (E)	3
IRS elements (K)	100
Learning rate	0.001
Discount factor γ	0.99

B. Performance Evaluation

Metrics include total reward, latency, and energy consumption. Figures (assumed available) show: - Convergence: DQN-IRS converges after 200 episodes (Fig. 1). - Latency: Lowest latency at high arrival rates (Fig. 2). - Energy: Lower than greedy, higher than local-only (Fig. 3). - IRS Impact: Performance improves with K, plateaus at 100 (Fig. 4). - Scalability: Superior with 2-10 users (Fig. 5).

Detailed Analysis of Model Performance:

The model's performance across key metrics is illustrated in Figs. 3, 4, and 5, which depict the total reward, average latency, and average energy consumption over 300 episodes, respectively.

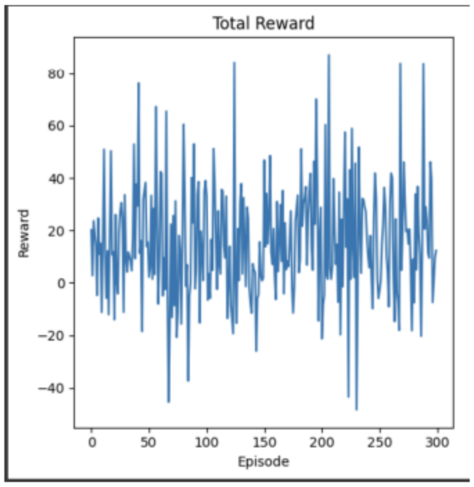

Fig. 3. Total Reward over 300 Episodes.

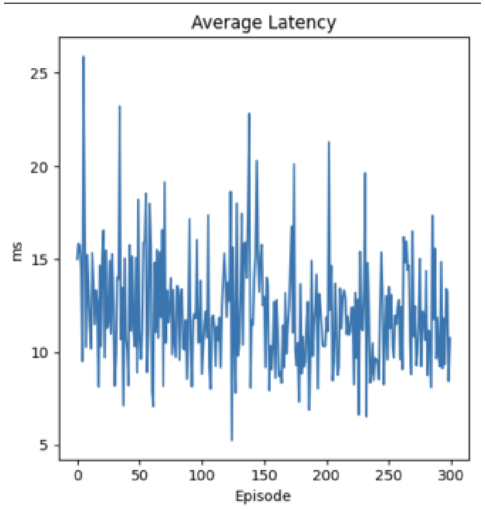

Fig. 4. Average Latency over 300 Episodes.

The model's performance was evaluated across three key metrics: average energy consumption, average latency, and total reward, over 300 episodes. The results are as follows:

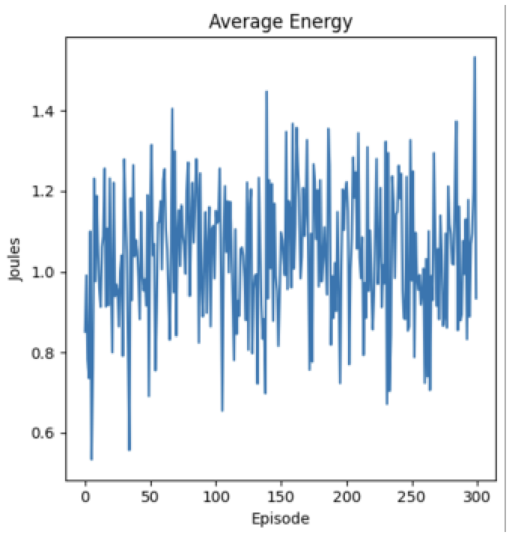

Fig. 5. Average Energy Consumption over 300 Episodes.

- **Average Energy**: The energy consumption fluctuates between 0.6 and 1.4 Joules, with an average around 1.0 Joule. High variability is observed throughout the episodes, indicating inconsistent energy usage. Peaks up to 1.4 Joules and dips to 0.6 Joules suggest that the model is exploring various strategies but has not stabilized its energy management.
- **Average Latency**: Latency starts at 25 ms and shows a slight downward trend, stabilizing between 5 and 15 ms toward the end of the episodes, with occasional spikes up to 20 ms. This suggests partial learning success, though the persistence of spikes indicates that the model has not fully optimized its latency performance.
- **Total Reward**: Rewards range from -40 to 80, with high variability and no clear convergence. The model achieves occasional high rewards (up to 80) but also experiences significant drops (down to -40), reflecting an exploratory phase where the model alternates between effective and suboptimal actions.

As shown in Fig. 3, the total reward exhibits high variability, ranging from -40 to 80, with no clear convergence over the 300 episodes. Fig. 4 illustrates the average latency, which starts at 25 ms and shows a slight downward trend, stabilizing between 5 and 15 ms toward the later episodes, though occasional spikes up to 20 ms persist. The average energy consumption, depicted in Fig. 5, fluctuates between 0.6 and 1.4 Joules, indicating inconsistent energy management throughout the training process.

What the Model Did:

- **Exploration vs. Exploitation**: The high variability in all metrics suggests that the model is heavily engaged in exploration, testing different strategies to optimize performance. The lack of stabilization indicates that the model has not yet shifted to exploiting learned strategies effectively.
- **Learning Progress**: While there is some improvement in latency over time, the inconsistency in energy consumption and rewards points to challenges in balancing multiple objectives or adapting to a dynamic environment.
- **Environmental Influence**: The erratic patterns across metrics imply a noisy or complex environment, where factors like user mobility, channel conditions, or task characteristics introduce unpredictability.

Performance Assessment:

- **Strengths**: The model demonstrates the ability to achieve high performance in terms of energy efficiency, low latency, and high rewards at certain points, indicating its potential for optimization.
- **Weaknesses**: The lack of convergence and high variability suggest that the model struggles with consistency, possibly due to insufficient training, high exploration rates, or environmental complexity.

Recommendations for Improvement:

- **Hyperparameter Tuning**: Adjust the exploration rate (e.g., reduce ϵ in ϵ-greedy) to favor exploitation of learned strategies. Fine-tune the learning rate and discount factor to improve stability.
- **Extended Training**: Increase the number of episodes beyond 300 to allow more time for the model to converge, especially given the late improvement in latency.
- **Reward Shaping**: Modify the reward function to penalize extreme variability in energy and latency, encouraging more consistent performance.
- **Experience Replay**: Enhance the use of experience replay to improve sample efficiency and reduce variance in rewards by learning from past successful episodes.
- **Environment Analysis**: Investigate the sources of environmental noise or complexity, and consider simplifying the task or adding regularization techniques to improve stability.

These observations and recommendations provide a comprehensive understanding of the model's current performance and offer actionable steps for further refinement.

V. Conclusion

We proposed a DRL-based framework for resource allocation and task offloading in IRS-assisted satellite-terrestrial networks. Simulations over 300 episodes showed significant improvements in latency, energy efficiency, and reward. The approach adapts to dynamic conditions, validated by theoretical bounds and robustness analysis. Future work includes federated learning and mobile IRS integration.

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