



DeepISL: Joint Optimization of LEO Inter-Satellite Link Planning and Power Allocation via Parameterized Deep Reinforcement Learning

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Oral Presentation

IEEE GLOBECOM 2023

About my team



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	Dr. Prof. LUO, Jiangtao	Vehicular networks, Satellite Internet (Nankai Univ., CAS, Shanghai Jiao Tong Univ.)
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Background and Motivation



Problem and Approach



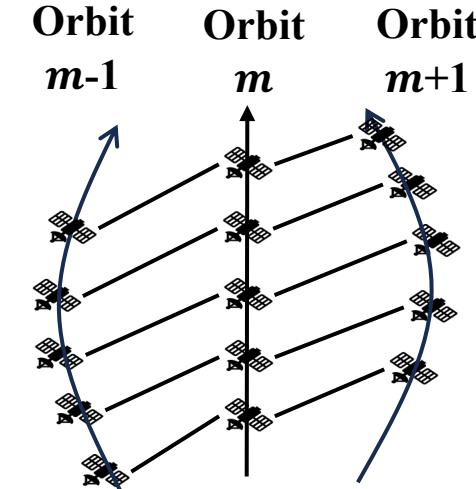
Evaluation and Results



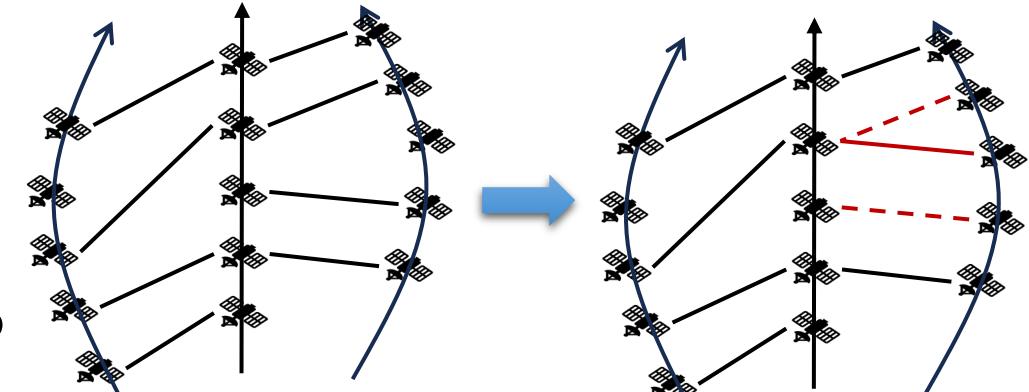
Conclusions

1. Background and Motivation

- Mega LEO Constellations are being built all over the world
- Inter-Satellite Links (**ISLs**) offer **relays, collaboration, path redundancy** and **resilience**.
- Static scheme is simple but **excessively redundant** and needs more energy!



Static Scheme (+Grid)



How to
setup ISLs **on-demand** and **adaptable**?

1. Background and Motivation



□ Challenges

- Beam steering and tracking
- High-speed movement of satellites
- Interference management and channels allocation
- **Power and energy management**
- Limited resources on-board

□ Existing solutions

- Greedy Matching [2]
- ILP [3]
- MA-DRL [4]

[2] I. Leyva-Mayorga, GLOBECOM 2021

[3] Z. Yan, WCL, 2020

[4] J. Pi, ICC 2022 (our previous work)

**Can we combine
dynamic power allocation with dynamic setup of ISLs ?**

Higher trans. rates

Higher energy efficiency

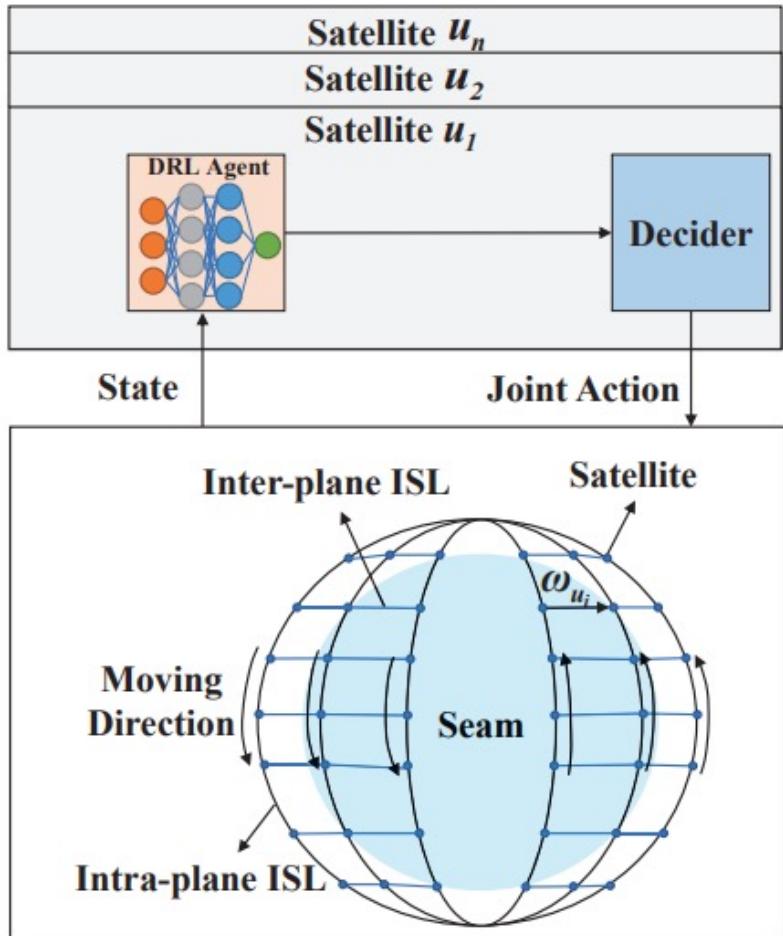
Lowest switching costs



2. Problem and Approach

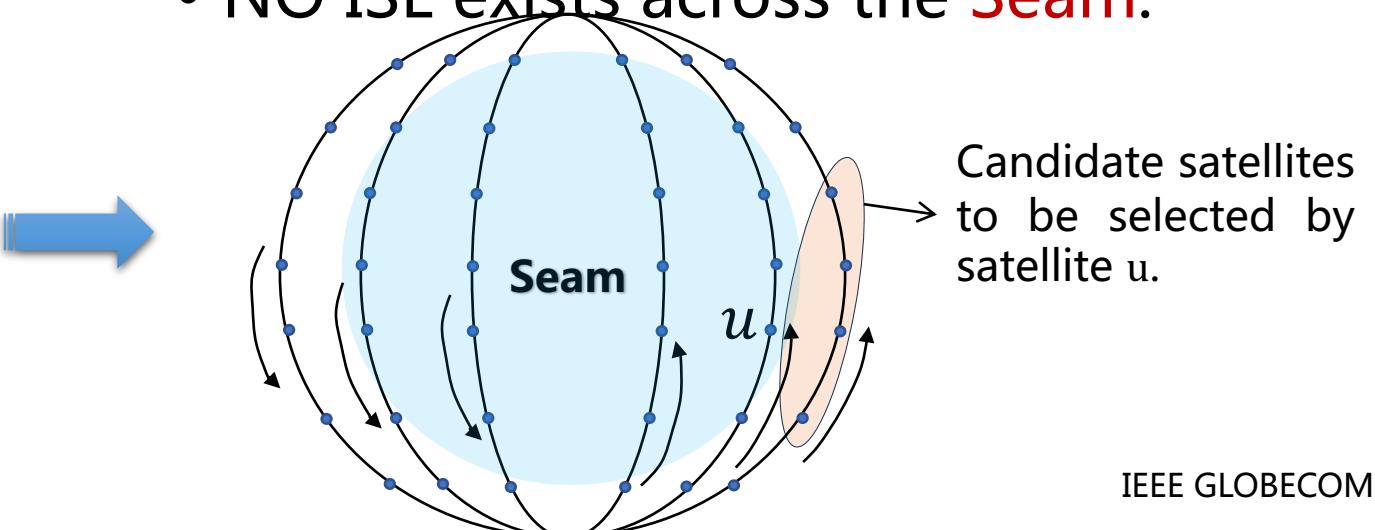


System Model



□ Basic ideas

- Every satellite has an agent.
- Every satellite selects its target peer **on the right orbit** to establish an ISL, based on the observed system states.
- Intra-plane ISLs do not change.
- NO ISL exists across the **Seam**.



2. Problem and Approach



Problem Statement

Normalized Utility function :

$$\varphi(t) = \sum_{e_{uv}} (\alpha_1 E_{eff,t}^{uv} + \alpha_2 R_{e_{uv},t}) - \sum_{e_{uv}} \alpha_3 \theta_{uv,t}$$

Benefits per unit of energy efficiency

energy efficiency

Benefits per unit transmission rate

transmission rate

Steering angle

Cost per unit antenna steering angle

Optimization Problem :

$$\max \sum_{t=1}^{N_d} \varphi(t)$$

$$s.t. \begin{cases} uv \in Y_t \\ e_{uv} \in E_t \\ P_{e_{uv},t} \leq P_{u,t}^{\max} - P_0 \\ \lambda \omega_{u,t} / \delta(t) \leq R_{e_{uv},t} \leq \omega_{u,t} / \delta(t) \end{cases}$$

2. Problem and Approach



Related Models

Energy efficiency model :

$$E_{eff,t}^{uv} = \omega_{e_{uv},t} / E_{e_{uv},t} = R_{e_{uv},t} / P_{e_{uv},t}$$

↓
Data to transmit ↓
 Energy consumed

Doubly constrained of rate :

$$\lambda \omega_{u,t} / \delta(t) \leq R_{e_{uv},t} \leq \omega_{u,t} / \delta(t)$$

Satisfaction factor: minimum ratio of data transmitted

Energy model :

Solar energy harvested :

$$E_{u,t}^{harvest} = P_{u,t}^{harvest} \cdot \delta(t)$$

$$P_{u,t}^{harvest} = \tau \cdot \varphi \cdot \varpi \cdot A_e \cdot \sin \sigma$$

↓
collection constant,
0 or 1 ↓
 Solar irradiance
 per unit area ↓
 Incident angle

Area of the solar panel

Energy consumed :

$$P_{u,t}^{consume} = P_{e_{uv},t} + P_0 \leq P_{u,t}^{max}$$

for Intra-plane ISLs and others
↓
for Inter-plane ISLs

2. Problem and Approach



Related Models

Switching cost model :

The steering angle of satellite u:

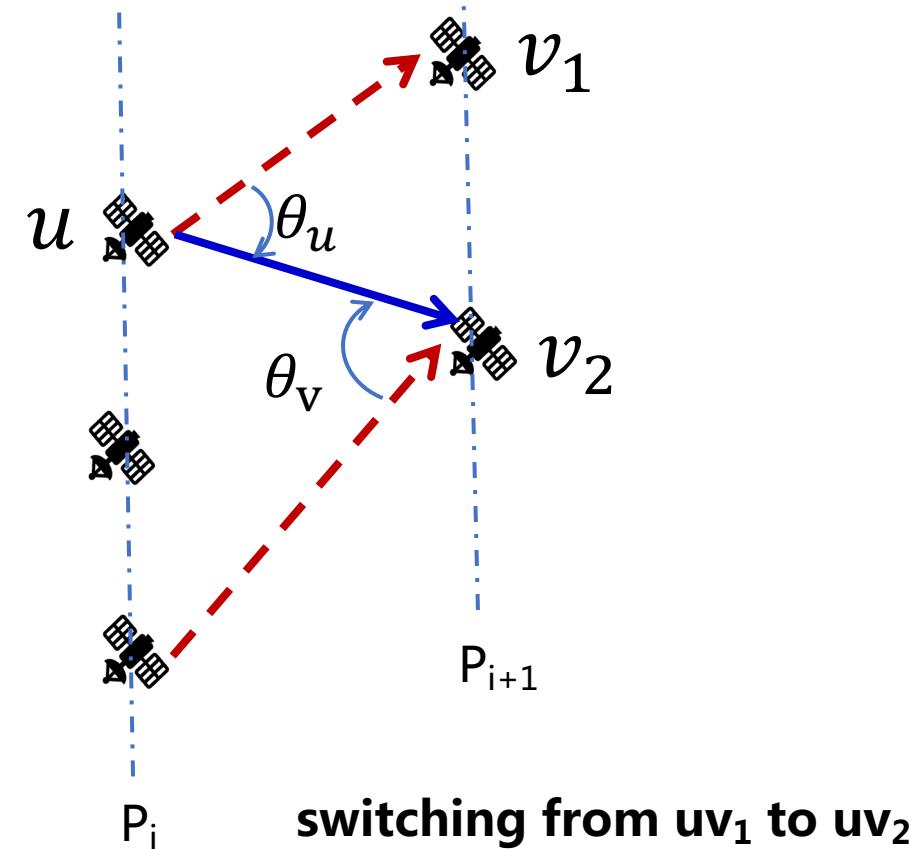
$$\theta_u = \arccos \left(\frac{\left(d_{|uv_1|} \right)^2 + \left(d_{|uv_2|} \right)^2 - \left(d_{|v_1v_2|} \right)^2}{2 \cdot d_{|uv_1|} \cdot d_{|uv_2|}} \right)$$

Average antenna steering angle

$$\hat{\theta}_{u,t} = \frac{\sum_{v_1 \neq v_2 \in Y_{u,t}^+} \theta_u + \sum_{v_1 \neq v_2 \in Y_{u,t}^-} \theta_u}{\binom{N_{u,t}^+}{2} + \binom{N_{u,t}^-}{2}}$$

Mean antenna steering angle

$$\theta_{uv,t} = \begin{cases} 0, & e_{uv} \in E_{t-1} \\ \hat{\theta}_{u,t} + \hat{\theta}_{v,t}, & e_{uv} \notin E_{t-1} \end{cases}$$



The switching costs are assumed proportional to the steering angle,
Switching cost $\propto \theta_{uv}$

2. Problem and Approach



MA-DRL based Approach

State Space :

$$S_i = \{D_{i,t}, C_{i,t}, \omega_{i,t}\}$$

{ Distance to target satellites; Battery capacity; Data bytes to transmit }

Action :

$$a_{i,t} = \{v_{i,t}, p_{i,t}\}$$

{Selected target satellites (**discrete**); Allocated power (**continuous**)}
→

A **hybrid action space** calls for **parameterized DRL approach**.

Reward Function :

$$\text{RWD} = \sum_{i=1}^{N_n} r_{i,t},$$

$$r_{i,t} = \kappa_i \left(\alpha_1 E_{eff,t}^{iv_{i,t}} + \alpha_2 R_{eiv_{i,t},t} \right) - \alpha_3 \theta_{iv_{i,t},t}$$

Conflict factor EE Reward TR reward Switching cost

Procedure of DeepISL algor.

Algorithm 1: Training process of DeepISL

```

1 for agent  $i = 1, N_n$  do
2   Initialize deterministic strategy network  $\mu_{v_i}(\theta_i)$  and
      value network  $Q_i(w_i)$ , learning rate  $\alpha, \beta$  and
      probability  $\xi$ . Initialize the experience pool  $\Gamma$ 
3 end
4 for episode = 1 to  $M'$  do
5   for agent  $i = 1, N_n$  do
6     Observe the state  $s_{i,t}$ 
7     Obtain continuous parameter  $p_{v_{i,t}} \leftarrow \mu_{v_i}(\theta_i)$ .
8     Obtain discrete action by
9        $v_{i,t} = argmax_{v_i \in V_i} Q(s_{i,t}, (V_i, p_{V_i}); w_i)$ 
10    Select action  $a_{i,t}$  according to  $\xi$ -greedy strategy
11    Execute  $a_{i,t}$  and observe  $r_{i,t}$  and  $s_{i,t+1}$ 
12    Store transition  $[s_{i,t}, s_{i,t+1}, a_{i,t}, r_{i,t}]$  into  $\Gamma$ 
13 end
14 end
15 for agent  $i = 1, N_n$  do
16   Randomly draw a batch of  $[s_b, s_{b+1}, a_b, r_b]_{b \in \bar{B}}$  from  $\Gamma$ 
      $y_b = r_b + \gamma \max_{v \in V} Q(s_{b+1}, v, \mu_{v_i}(s_{b+1}; \theta_t); w_t)$ 
     Calculate  $\ell_t(w_i)$  and  $\ell_t(\theta_i)$  according to Equations
     (25) and (26)
17   Update the network parameters  $w_i$  and  $\theta_i$  according to
     Equations (28) and (29)
18 end

```

3. Evaluation and Results



□ Metrics

- Mean energy efficiency:

- ◆ the ratio of the sum of the energy efficiency of each inter-plane ISL to the total number of inter-plane ISLs.

- Mean throughput:

- ◆ the ratio of the sum of the throughput of each inter-plane ISL to the total number of inter-plane ISLs.

- Switching ratio:

- ◆ the ratio of switched inter-plane ISLs to the total inter-plane ISLs.

□ Comparison Algorithms

- a) GIEM: Greedy Independent Experiments Matching [2]

From [2] I. Leyva-Mayorga, TWC, 20(6), 2021.

- b) DY-DQN : relax continuous power allocation to discrete power allocation

- c) FP-DQN : fixed power allocation

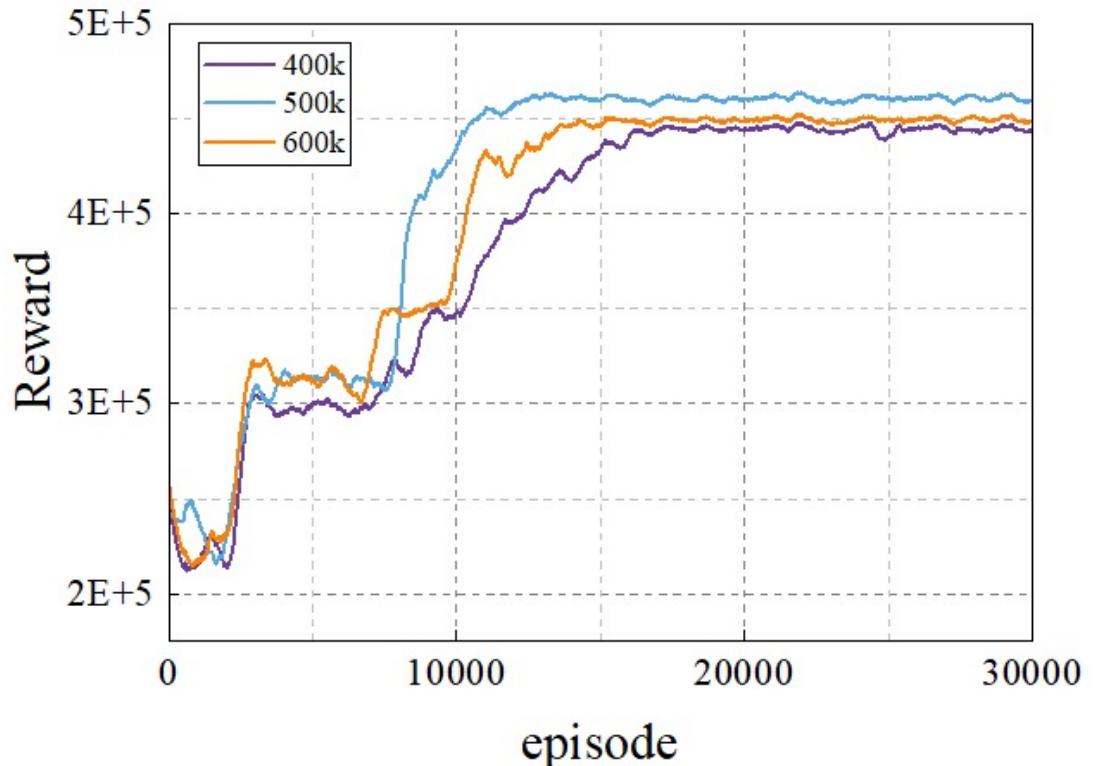
Derived from DeepISL.

3. Evaluation and Results



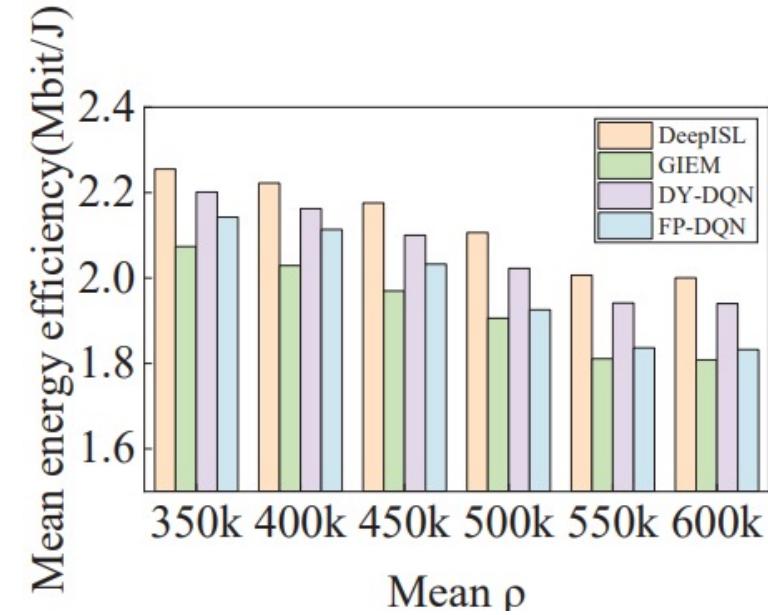
Parameter	Symbol	Value
Number of satellites	N	66
Number of orbital planes	M	6
Altitude of orbital planes	H	780 Km
Inclination of orbital planes	ϵ_m	86.4 deg
Carrier frequency in the Ka-band	f	23.28 GHz
Carrier bandwidth	B	15 MHz
Quality factors	G_{rec}/T_e	8 dB/K
The size of each packet	F_f	$1500B$
The duration of the time slot	$\delta(t)$	300 s
Number of inter-plane transceivers	Q	2
Satisfaction factor	λ	{0.85, 0.9, 0.95}
Probability of greedy strategy	ξ	0.8
Size of the Mini-batch	B	1024
Capacity of the experience memory	Memory	10000
Lerning rate	α, β	0.0095
Discount factor	γ	0.95
Weight factors	$\alpha_1, \alpha_2, \alpha_3$	1, 0.1, 1

Evaluation Parameter Setting



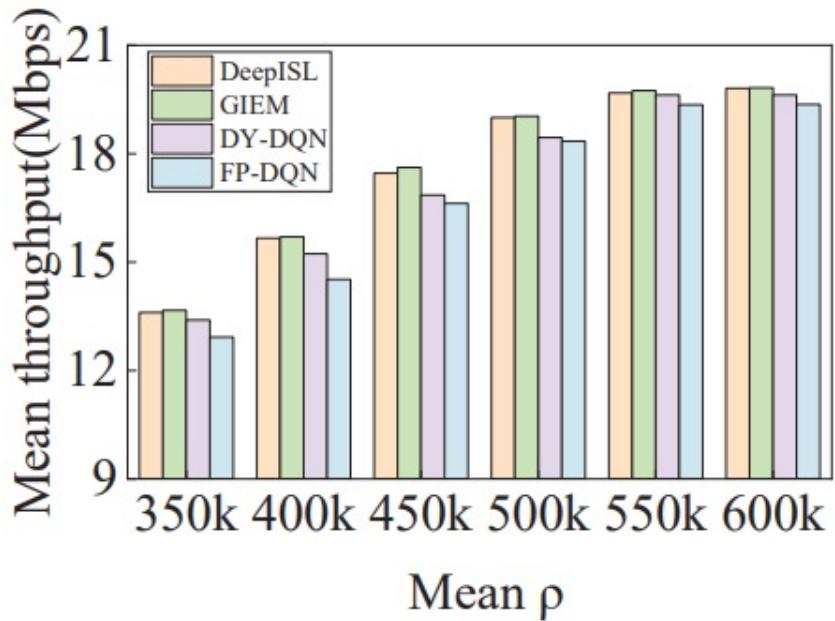
Convergence of DeepISL for training with different amounts of data packets.

3. Evaluation and Results



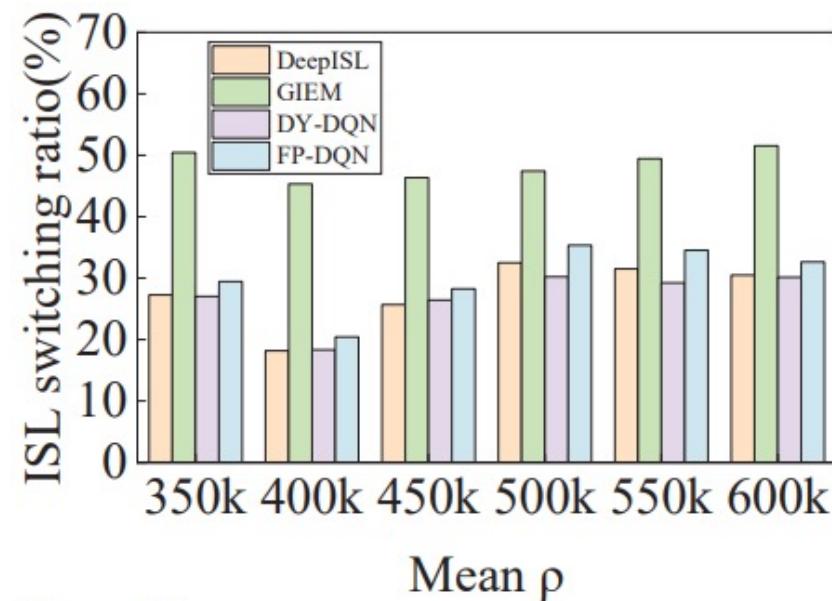
Energy efficiency

1. DeepISL outperforms others in EE.
2. As traffic load increases, EE decreases.
3. DY-DQN performs close to DeepISL.



Throughput

1. Throughput increases as traffic load increases.
2. DeepISL and GIEM performs close, but better than others.



Switching Ratio

1. GIEM needs maximum switching counts.
2. DeepISL and DY-DQN, FP-DQN performs close.

4. Conclusions



- Discussed the joint problem of **dynamic ISL setup with dynamic power allocation**.
- Formulated it into a joint optimization problem about target satellite selection and transmission power allocation to **maximize energy efficiency and transmission rate with minimum switching costs**.
- Solve it using a **parameterized deep reinforcement learning method**, called *DeepISL*.
- In the future, integrate routing with DeepISL to optimize its end-to-end performance.



Thanks for
Your Attention

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Original Paper:

DeepISL: Joint Optimization of LEO Inter-Satellite Link Planning and Power Allocation via Parameterized Deep Reinforcement Learning