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Federated deep reinforcement learning based computation offloading in a low Earth orbit satellite edge computing system

Key words: Federated learning; Low Earth orbit satellite; Mobile edge computing; Deep reinforcement learning; Computation offloading

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Motivation

1. In the traditional cloud computing paradigm, federated learning (FL) servers are placed in remote cloud computing centers that receive massive data for centralized processing, which results in significant communication delay and user privacy problems.
2. Faced with scenarios where FL needs to be performed across multiple geographically separated remote clusters or devices in remote areas that lack communication infrastructure (e.g., rural regions and maritime areas), existing FL techniques primarily use ground networks, and devices in the above scenarios cannot aggregate local model parameters without the help of non-terrestrial networks.
3. Therefore, it is important to combine FL and low Earth orbit (LEO) satellite edge computing system (LSECS) to ensure that base stations (BSs) in different scenarios can obtain the allocation strategies of other BSs and ensure their own privacy security.

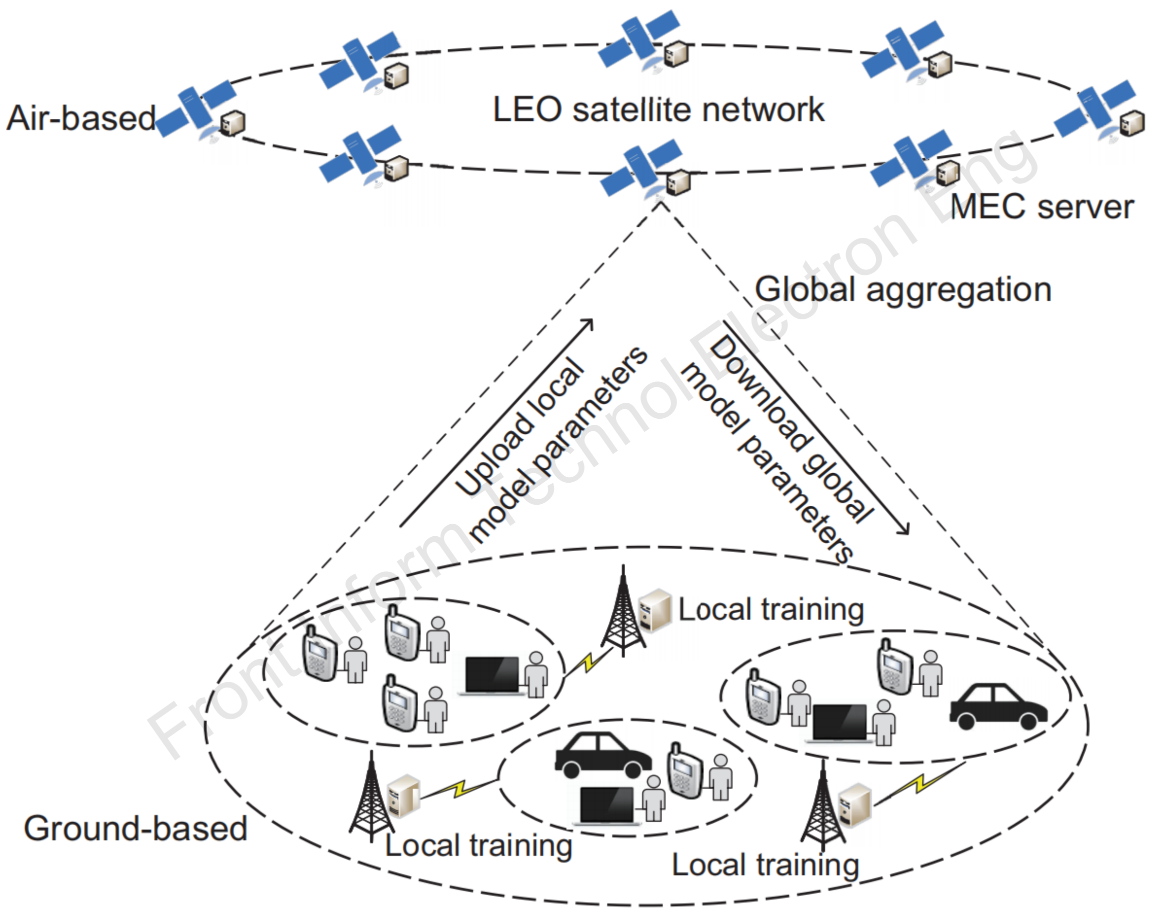
Main idea

1. To ensure that BSs in different scenarios can obtain the allocation strategies of other BSs and ensure their own privacy security, we propose a secure transmission method based on FL for LSECS, realizing secure data transmission.

2. To solve the problems of sub-channel selection and power allocation, a computation offloading algorithm based on a deep Q-network (DQN) is proposed to achieve efficient resource management in cellular networks under the conditions of BS self-interference (SI) and user co-channel interference.

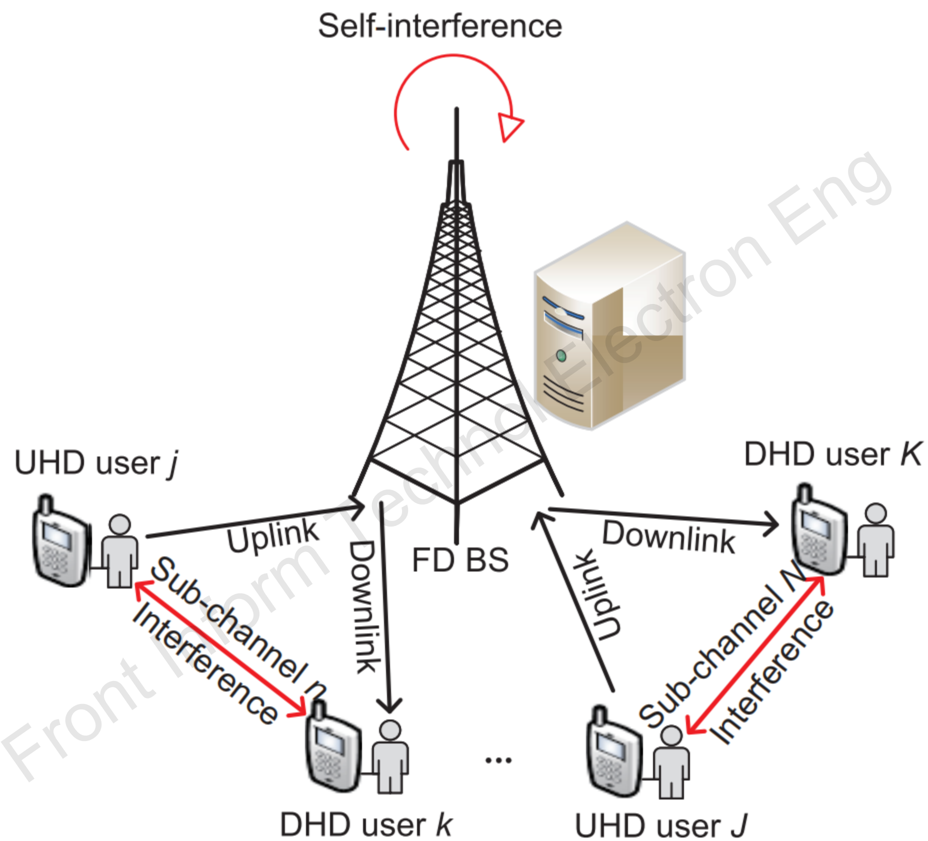
3. The proposed algorithm greatly enhances the weighted sum-rate and achieves excellent convergence performance.

Framework



Low Earth orbit satellite edge computing system model (MEC: mobile edge computing)

Framework



Ground cell model (UHD: uplink half-duplex; DHD: downlink half-duplex; FD: full-duplex; BS: base station)

Problem statements

We define the downlink weighted sum-rate in the i^{th} cell as

$$R_i^{\mathrm{d}} = \sum_{k=1}^{i_K} \sum_{n \in S_{i,k}^{\mathrm{d}}} \eta_{i,k} \log_2 \left(1 + \frac{h_{i,k}(n) p_{i,k}^{\mathrm{d}}(n)}{N_{i,k} + h_{i,k,j_n}(n) p_{i,j_n}^{\mathrm{u}}(n)} \right)$$

We define the uplink weighted sum-rate in the i^{th} cell as

$$R_i^{\mathrm{u}} = \sum_{j=1}^{i_J} \sum_{n \in S_{i,j}^{\mathrm{u}}} \lambda_{i,j} \log_2 \left(1 + \frac{h_{i,j}(n) p_{i,j}^{\mathrm{u}}(n)}{N_{i,0} + \beta_i p_{i,k_n}^{\mathrm{d}}(n)} \right)$$

The proposed optimization problem P1 can be expressed as

$$\mathrm{P1}: \underset{p_{i,k}^{\mathrm{d}}, p_{i,j}^{\mathrm{u}}, S_{i,j}^{\mathrm{u}}, S_{i,k}^{\mathrm{d}}, \forall i,k,j}{\text{maximize}} \quad (R_i^{\mathrm{d}} + R_i^{\mathrm{u}}),$$

$$\text{s.t.} \quad \sum_{k=1}^{i_K} \sum_{n \in S_{i,k}^{\mathrm{d}}} p_{i,k}^{\mathrm{d}}(n) \leq P_{i,0}, \quad \forall i,$$

$$\sum_{n \in S_{i,j}^{\mathrm{u}}} p_{i,j}^{\mathrm{u}}(n) \leq P_{i,j}, \quad \forall i,j,$$

$$p_{i,j}^{\mathrm{u}}(n), p_{i,k}^{\mathrm{d}}(n) \geq 0, \quad \forall i,j,k,n,$$

$$\cup_{j=1}^{J} S_{i,j}^{\mathrm{u}}, \cup_{k=1}^{K} S_{i,k}^{\mathrm{d}} \subseteq \{1, 2, \ldots, S\}, \quad \forall i,$$

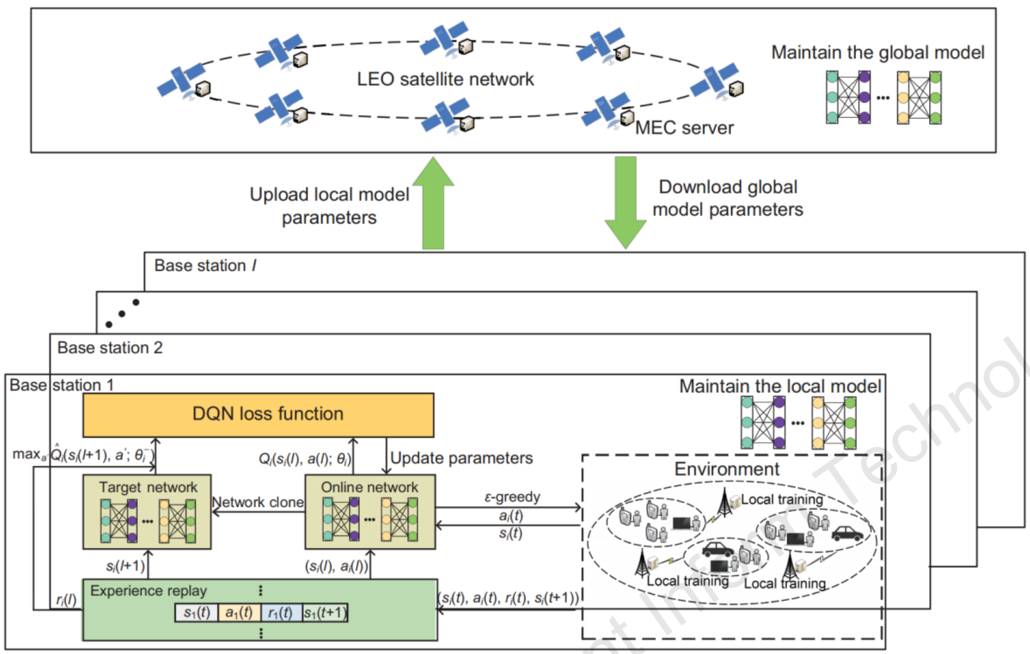
$$S_{i,v}^{\mathrm{d}} \cap S_{i,x}^{\mathrm{d}} = \varnothing, S_{i,v}^{\mathrm{u}} \cap S_{i,x}^{\mathrm{u}} = \varnothing, \quad \forall i, \forall v \neq x,$$

$$S_{i,j}^{\mathrm{u}} \cap S_{i,j}^{\mathrm{d}} = \varnothing, S_{i,k}^{\mathrm{u}} \cap S_{i,k}^{\mathrm{d}} = \varnothing, \quad \forall i,j,k.$$

BS and user transmission power problems

BS and user sub-channel assignment problems

Method



Proposed federated deep Q-network (DQN) based computation offloading architecture

1. State: we define the state space of BS agent *i* as follows:

$$s_i = \{h_{i,k}(n), h_{i,j}(n), h_{i,k,j}(n)\}, \quad \forall j,k,n.$$

2. Action: BS agent *i* performs actions, including allocating BS and user transmission power and setting allocated sub-channels, as follows:

$$a_i = \{p^{\mathrm{d}}_{i,k}(n), p^{\mathrm{u}}_{i,j}(n), S^{\mathrm{d}}_{i,k}, S^{\mathrm{u}}_{i,j}\}, \quad \forall j,k,n.$$

Transmission power

Allocated sub-channels

3. Reward: we define the reward as

$$r_i = R^{\mathrm{d}}_i + R^{\mathrm{u}}_i.$$

The LEO satellite maintains a global DQN model and each BS builds its own local DQN model using the same network structure. Each BS agent has two neural networks (NNs), namely the online network and the target network.

Method

Because the observed state in each cell cannot fully characterize the entire cellular network environment, FL provides an effective way of improving model performance by using decentralized local DRL models. In the e^{th} iteration, each BS agent interacts with a LEO satellite acting as the model aggregator:

1. Local update: Agent *i* first receives the latest global model parameters from the LEO satellite to obtain the local model parameters. Agent *i* then calculates the gradient based on experience and updates the local model parameters:

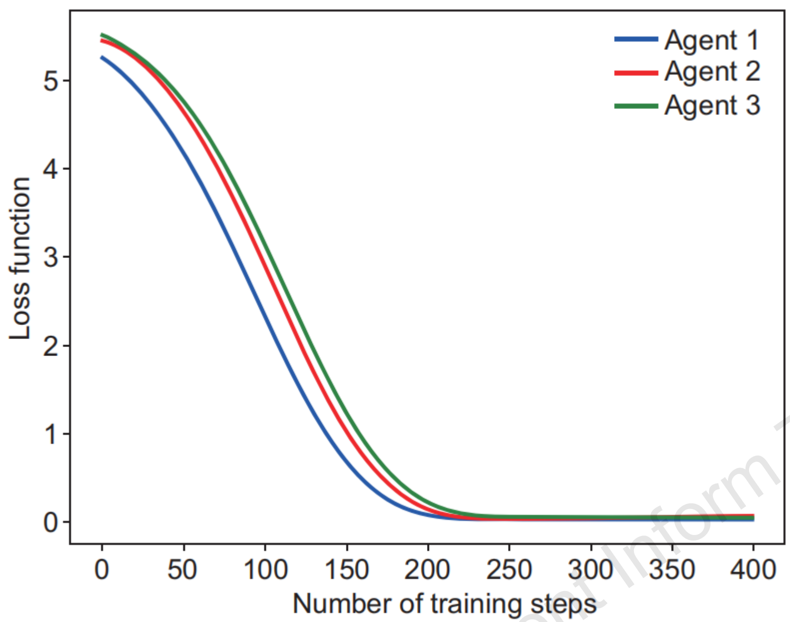
$$\theta_i(e) = \theta(e-1) - \eta \nabla F_i(\theta(e)).$$

2. Upload: After the local update is completed, the i^{th} BS sends the local model parameters to the LEO satellite.

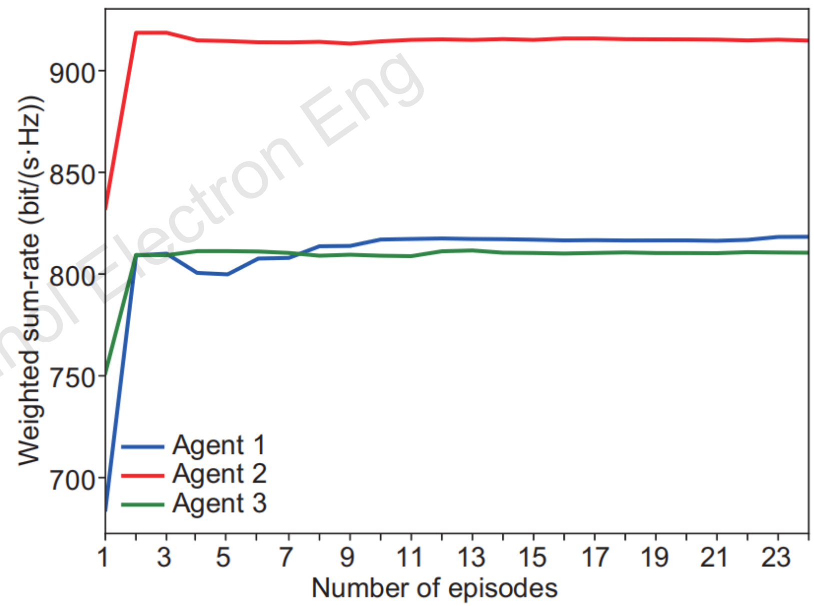
3. Aggregation and feedback: The LEO satellite receives all the uploaded local model parameters and aggregates the models to obtain the updated global model:

$$\theta(e) = \sum_{i=1}^{I} \frac{\rho_i}{\rho} \theta_i(e).$$

Major results

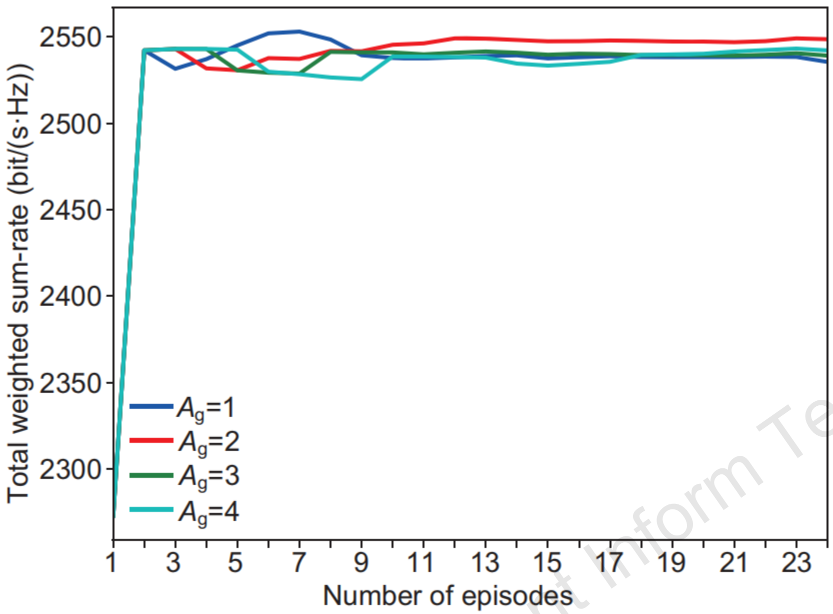


Evaluated loss function for each agent over different numbers of training steps

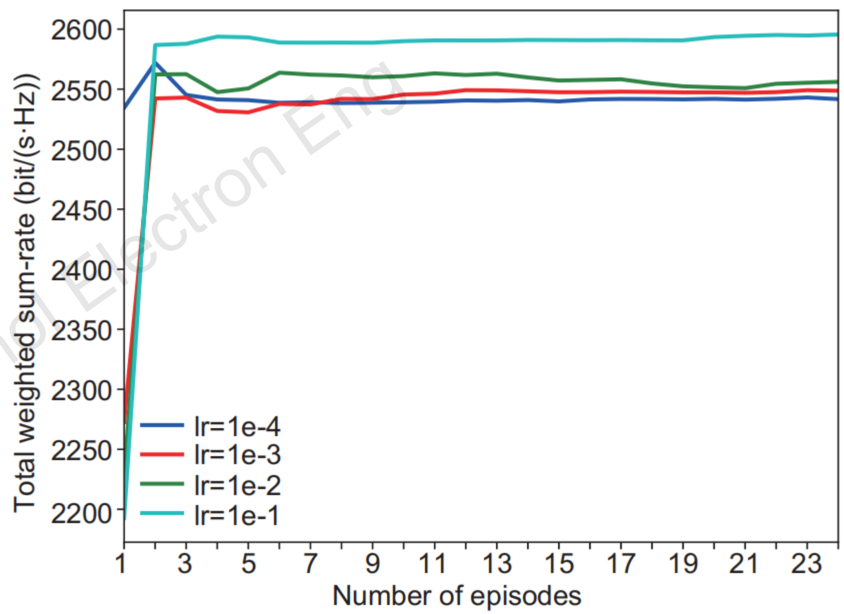


Evaluated weighted sum-rate for each agent over different numbers of episodes

Major results

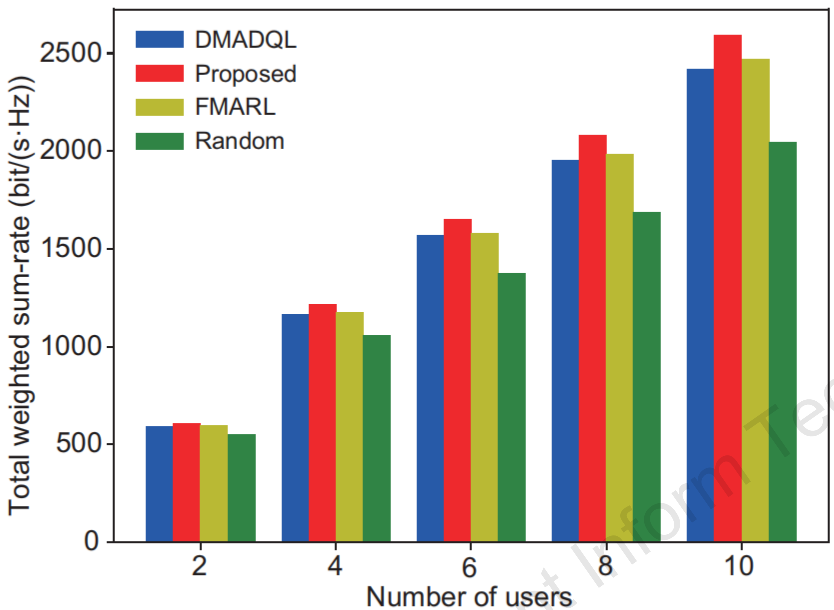


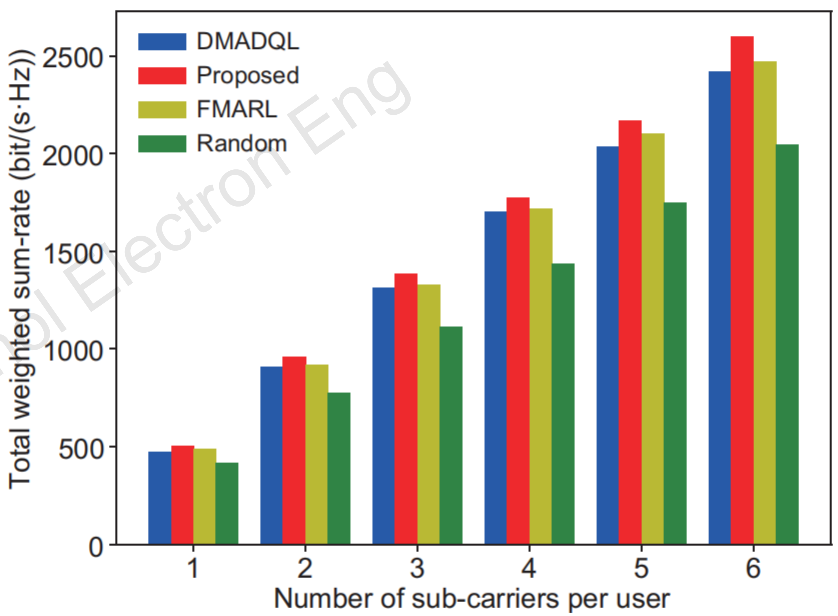
Evaluated total weighted sum-rate for different aggregation frequencies over different numbers of episodes



Evaluated total weighted sum-rate for different learning rates over different numbers of episodes

Major results

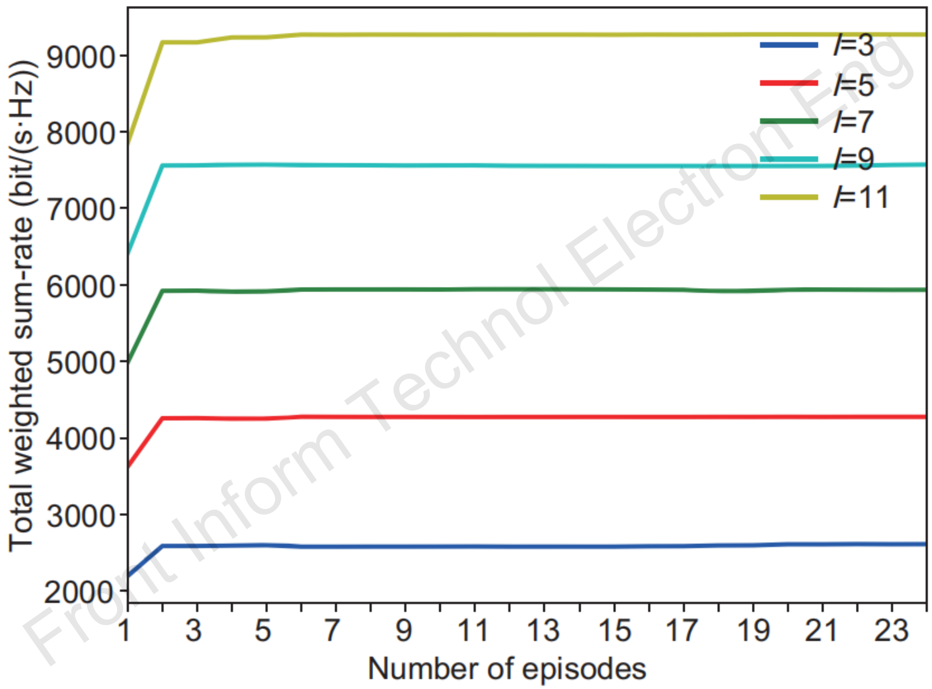




Evaluated total weighted sum-rate of different algorithms for different numbers of users

Evaluated total weighted sum-rate of different algorithms for different numbers of sub-carriers per user

Major results



Evaluated total weighted sum-rate for different numbers of base stations over different numbers of episodes

Conclusions

1. The LSECS model was established, and then the weighted sum-rate maximization problem was modeled.

2. Aiming at the problems of sub-channel allocation and power allocation, we proposed a computation offloading algorithm based on federated DQN.

3. Results showed that the proposed algorithm can significantly improve the weighted sum-rate with excellent convergence performance.

Min JIA received her M.S. degree in information and communication engineering from Harbin Institute of Technology (HIT), Harbin, China, in 2006, and her Ph.D. degree from Sungkyungkwan University, Seoul, South Korea, and HIT, in 2010. She is currently a professor and a Ph.D. supervisor with School of Electronics and Information Engineering, HIT. She has won six best paper awards at several international conferences. She is the General Chair of the IEEE GLOBECOM 2019 Workshop Intelligent and Cognitive Space, Terrestrial and Ocean Internet, Systems and Applications. She is a member of the Steering Committee of the WiSATs international conference. She is also the winner of the Science Fund for Excellent Young Scholars for Heilongjiang Province and elected as a member of the National Major Talent Project. Her research interests focus on advanced mobile communication technology for LTE and 5G, cognitive radios, digital signal processing, and advanced broadband satellite communication systems.

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