Differentiated Federated Reinforcement Learning for Dynamic and Heterogeneous Network

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Abstract—The modern dynamic and heterogeneous network brings differential environments with respective state transition probability to agents, which leads to the local strategy trap problem of traditional federated reinforcement learning (FRL) based network optimization algorithm. To solve this problem, we propose a novel Differentiated Federated Reinforcement Learning (DFRL), which evolves the global policy model integration and local inference with the global policy model in traditional FRL to a collaborative learning process with parallel global trends learning and differential local policy model learning. In the DFRL, the local policy learning model is adaptively updated with the global trends model and local environment and achieves better differentiated adaptation. We evaluate the outperformance of the proposal compared with the state-of-the-art FRL in a classical CartPole game with heterogeneous environments. Furthermore, we implement the proposal in the heterogeneous Space-air-ground Integrated Network (SAGIN) for the classical traffic offloading problem in network. The simulation result shows that the proposal shows better global performance and fairness than baselines in terms of throughput, delay, and packet drop rate.

Index Terms—Federated learning (FL), Reinforcement learning (RL), federated reinforcement learning (FRL), Space-air-ground Integrated Network (SAGIN), heterogeneous network, network optimization, traffic offloading.

I. INTRODUCTION

The optimized decision making is the critical challenge in the Cyber-physical system, especially in the next generation network of 5G/6G with highly dynamic and large-scale environment. Reinforcement learning (RL) is one kind of machine learning technology to optimize decision making by maximizing the cumulative reward with the continuously exploring and exploiting the environment of an agent. Using RL to obtain network optimization strategies is a current research hotspot in the field of modern networks, e.g., network resources allocation [1] and traffic control [2].

However, traditional RL applications still suffer from critical problems in scenarios with complex environment. For example, the local strategy trap problem when the network environment goes into dynamic and heterogeneous. The local strategy trap is the situation ill-informed decision is inferred by incomplete information in local without fully considering the global environment changing. “Carving a boat and seeking a lost sword” is a traditional story in China that insinuating such situation of local strategy trap. Due to the features of high dynamic and heterogeneous of the complex networks, the local strategy trap occurs frequently in network scenarios such as IoT [3], vehicular network [4] and SAGIN [5], [6].

Federated learning (FL) is an advanced learning technology train a shared learning model without raw training data by considering the privacy of distributed devices in complex environment. By combining with both RL and FL, a privacy-preserving multi-agent collaboration approach referred to as Federated Reinforcement Learning (FRL) is proposed. In FRL, each agent trains the data separately, aggregates it into a uniform global policy model, and then distributes it to the agents, ensuring user’s data privacy as much as possible while integrating local learning result from each agent.

The local strategy trap problem is solved to some extent by the shared training manner of FRL as the global information is implicitly shared during the integrated learning process. Naturally, the FRL is widely considered as the potential solution widely used in the network optimization problem and proved to be somehow efficient in the heterogeneous networks. Unfortunately, The global sharing based FRL employing global learning model for local inference may still fall into the local strategy trap. The accuracy of using the global learning model for local inference is ensured by the assumption that the environments of diverse devices are homologous with same state transition probability, which is not practical as the considered state transition probability is always differentiation in the heterogeneous environment.

For example, a dynamic and heterogeneous space-air-
ground integrated network (SAGIN), consisting of satellites, UAVs, ground-based stations in different regions, and user devices. In such a network environment, there is significant dynamism and heterogeneity among regions due to the high-speed movement of nodes, the extensive range of data transmission, and the convergence between different types of networks [7]. The differentiation between regions is generally due to network state differences, sample distribution differences, and dynamic characteristic differences. These discrepancies lead to the global policy model obtained by the aggregation of agents in each region can only be suboptimal compared to the optimal policy in each region. It isn’t easy to obtain a uniform global policy model that performs well in all differentiated regions using the traditional FRL approach.

As shown in Fig. 1, traditional FRL distributes a uniform global learning model to each region. When there are differentiations in the environment of each region, the decisions inferred by the global learning model may be misjudged. Therefore, considering the differentiations between regions in complex network environments, we propose a novel differentiated federated reinforcement learning (DFRL) approach. Instead of seeking a uniform global policy model, DFRL enables agents across regions to cooperate in training their respective policy models.

Precisely, the cooperation among the agents in each region is accomplished through the global trend model. The global trend model is generated by aggregating the trend model developed by all the agents involved in the cooperation, reflecting the state of the environment and its changing trend in each region. Then, under the guidance of the global trend model, the agents in each region get their local policy models by training with local data. The introduction of the global trend model allows agents to consider each region’s differentiations based on the information from multiple regions to obtain local strategies that are more applicable to their regions.

The main contributions of the paper can be summarized as follows:

- We first proposed the concept of Differentiated Federated Reinforcement Learning (DFRL), thus preventing the traditional FRL from falling into the local strategy trap in the differentiated network environment.
- Based on DFRL, we propose a algorithm called DFSAC. The DFSAC algorithm has advantages in learning rate and stability metrics compared to traditional algorithms when dealing with heterogeneous environments.
- We design a Space-Air-Ground Integrated network (SAGIN) structure and propose a dynamic traffic offloading method based on the DFSAC algorithm to solve the traffic control problem under this complex network structure. Simulation results show that our dynamic traffic offloading method achieves better results regarding network throughput, packet loss rate, and delay than other methods.

II. RELATED WORK

A. Federated Learning

Federated learning (FL) is a distributed machine learning approach in privacy-preserving scenarios, where the critical point is that information is passed between collaborators by sharing models rather than data [8]. In recent years, researchers have proposed several solutions to the challenges faced in FL. For example, to obtain higher communication efficiency, McMahan et al. proposed FedAVG [9], which is now widely used as the baseline for FL research. To address the heterogeneity problem in FL, Yuan, Dinh, and Ruan et al. proposed [10], [11], and [12], respectively, to solve data heterogeneity, model heterogeneity, and device heterogeneity. Moreover, the convergence of the FL method is further analyzed by Qu et al. in [13]. They demonstrate the convergence of the FedAVG method in several differentiated scenarios and perform a comprehensive study of its convergence rate. These work provides a solid foundation for federated learning in further research.

B. Federated Reinforcement Learning

Reinforcement learning (RL) is a branch of machine learning (ML). Compared with other machine learning methods such as supervised or unsupervised learning methods, RL generates samples and learns through these samples through constant interaction between the agent and the environment [14]. The RL is widely used for communication and networking optimization in various networks [5], [15]. However, when the environment gets bigger, it becomes difficult for a single agent to complete the complex task in these scenarios due to constraints such as information processing capabilities or learning efficiency. The natural idea is to set up multiple agents in the environment and complete the task by cooperating among them. As a result, researchers have proposed distributed RL and parallel RL [16], but they also bring the risk of agent privacy leakage.

In this context, federated learning (FL), concerned with privacy preservation, has been introduced into RL. Federated reinforcement learning (FRL) is a distributed and collaborative approach that combines FL and RL, where each agent trains...
data locally and builds a shared model, which protects agent privacy and accelerates agent learning efficiency [17].

C. Federated Learning in Heterogeneous Environment

Environmental heterogeneity is a significant challenge for FL in real application scenarios. For this challenge, Yuan et al. proposed an improved FDAM algorithm in [10] to solve the data heterogeneity problem, while Hanzely et al. proposed a hybrid global model and local model to achieve balanced training in [18] to solve the conflicts caused by data heterogeneity. In addition, researchers have also tried to use personalized federated learning methods [19]–[21] to address the challenges caused by environment heterogeneity.

In communication networks, Liu et al. proposed a method for Radio Access Network (RAN) slicing using the FRL approach in [22], which improves the communication efficiency and throughput of the network. Kwon et al. proposed an FRL-based resource allocation method for Internet of Things Underwater (IoUT) devices in [23], which has significant advantages over the single-agent DRL approach.

The above approaches, in dealing with the challenges caused by environmental heterogeneity, usually adopt different aggregation or training methods for local models according to the differentiation of each agent’s local environment but cannot learn dynamically from the environmental differentiation. When the network environment is extended to a more dynamic and heterogeneous large-scale network environment. The above approach does not fully consider the differentiation among regional network environments and network types, which lead to low learning efficiency or even failure to converge. Therefore, a new solution must be proposed for such dynamic heterogeneous networks with differentiation.

III. DIFFERENTIATED FEDERATED REINFORCEMENT LEARNING

Using traditional FRL algorithms in large-scale dynamic heterogeneous networks will face several problems. First, in the real world, the data distribution of different agents in the environment is non-independently and identically distributed (non-IID) due to the existence of implicit unknown parameters. Traditional FRL algorithms use the global model as the center to aggregate information from all agents for learning. However, such a learning approach is designed for IID data, which conflicts with non-IID data in dynamic heterogeneous networks and will leads to the local strategy trap. Second, in the traditional FRL algorithm, agents periodically train models and upload them to the federated center node for aggregation. Although this direct sharing of models with other agents compensates for the lack of efficiency in sampling and learning of a single agent, it faces the risk of stealing key models by malicious nodes. A standard solution is using cryptography to protect the shared models, which introduces additional computational overhead and may reduce model accuracy [24]. Third, each agent in the environment may have different policy preferences caused by the differentiations in network structure or network dynamics in the area where the agent is located. It is difficult for traditional FRL algorithms to combine these differentiations to obtain a global model that satisfies the preferences of all agents.

To address the above issues, we define this large-scale dynamic heterogeneous network as a differentiated environment consisting of a series of dynamically heterogeneous local environments. We propose the novel concept of Differentiated Federated Reinforcement Learning (DFRL) for such differentiated environment as shown in Fig. 2. To conquer the above challenges, the main improvement between DFRL and FRL is that DFRL isolates the local learning from global learning process. We at first divide the local learning model of agent into two parts: the trend model and the policy model. During training, agents only need to share knowledge with other agents by sharing the global trend model. Specifically, the policy model generates policies based on the local environment state which is isolated and never shared with other agents. The trend model is the window to communicate and to be shared with center node during global learning process. The trend model is constructed with local trend model and the global trend model. The local trend model is responsible for describing the local environment state, changing trends, and guiding the update of the policy model. The global trend model is generated by the local trend model and shared among all agents, which is responsible for describing the state of the global environment, changing trends, and transferring the knowledge learned by all the agents. In addition, the global trend model continuously adjusts the local trend model during the interactive updating process. After the interactive, the policy model is jointly updated by both historical local state-policy pairs and the local trend model, which keeps the local variability as well as learning the implicit trend of the global environment.

The introduction of the trend model separates the learning of policy models, thus alleviating the non-IID of data and corresponding local strategy trap problem and avoiding the risk of leakage of key policy models during the communication transfer. Most importantly, this allows agents to cooperate in obtaining policy models that satisfy their preferences. In the next section, we describe the concept of DFRL in the context of specific algorithms.

IV. ALGORITHMS: DIFFERENTIATED FEDERATED SOFT ACTOR-CRITIC

In this section, we propose a novel DFRL algorithm called Differentiated Federated Soft Actor-Critic (DFSA), which introduces the concept of Differentiated Federated Reinforcement Learning (DFRL) based on the Soft Actor-Critic (SAC) algorithm [25]. Compared with the traditional federated reinforcement learning algorithm, this algorithm can better adapt to the variability between the environments in which the agents are located. Then, we construct a set of differentiated OpenAI Gym environments [26] to verify the algorithm’s performance in heterogeneous environments.
A. Description

Due to data heterogeneity and node dynamics, the traditional FRL algorithm is not capable to handle the cooperated learning tasks in differentiated environments. Therefore, we propose the DFSAC which evolve SAC based on the concept of SAC. The SAC algorithm is a DRL method that optimizes random policies in an off-policy manner. Its core feature is entropy regularization, where policy training trades off maximizing expected reward and entropy. Increasing entropy makes the policy explore more, speeding up the subsequent learning process and preventing the policy from prematurely converging to a local optimum. This makes it well-suited for exploring optimal strategies in several differentiated environments. Therefore, we choose this algorithm as our infrastructure.

The DFSAC algorithm is processed by multiple agents and a federated center node, where the agents generate local trend networks and policy networks through the local environment, and the federated center node is responsible for collecting the local trend networks of each agent and aggregating them into a global trend network. The DFSAC algorithm uses an approach like the soft policy iteration [27], that alternately performs the two processes and preventing the policy from prematurely converging to a local optimum. This makes it well-suited for exploring optimal strategies in several differentiated environments. Therefore, we choose this algorithm as our infrastructure.

Fig. 2 shows the whole learning process including global learning, interactive updating and local learning, and the global trend model participates all the process in any agent $k$ as shown in the figure. We define a global environment $E = \{E^1, \ldots, E^k, \ldots, E^n\}$ consisting of a set of $N$ differentiated local environments. A corresponding agent exists for each local environment, i.e. environment $E^k$ corresponds to agent $k$. Unlike the traditional FRL approach, the goal of the DFSAC algorithm is to obtain a set of maximizes the maximum entropy policies $\Pi$ applicable to each local environment $\Pi = \{\bar{\pi}^1, \ldots, \bar{\pi}^k, \ldots, \bar{\pi}^n\}$, and the target policy $\bar{\pi}^i$ in each local environment $E^i$ is:

$$\bar{\pi}^i = \arg\max_{\pi^i} \sum_{t=0}^{T} E(s_t^i, a_t^i) \sim \tau_{\pi^i} \left[ \gamma r(s_t^i, a_t^i) + \alpha^i \mathcal{H}(\pi^i(. \mid s_t^i)) \right]$$

where $\bar{\pi}^i$ is the target policy, $\pi^i$ is a policy of agent $i$ in local environment $E^i$, $\gamma$ is the discount rate and $r$ is reward from environment, $s_t^i \in S$ and $a_t^i \in A$ denote state and action in local environment $E^i$ with timestamp $t$, and $S, A$ are global state space and global action space, respectively. $\tau_{\pi^i}$ is the distribution of trajectories generated from policy $\pi^i$, $\alpha^i$ is temperature parameter to control the positivity of the policy exploration in the local environment and $\mathcal{H}(\cdot)$ indicates the entropy. And, in differentiated environments, the transfer probability varies among local environments, i.e. $P(s_t^{i+1}|s_t^i, a^i) \neq P(s_t^{j+1}|s_t^j, a^j)$, $i \neq j$.

To obtain $\Pi$, the DFSAC algorithm uses an approach like the soft policy iteration [27], that alternately performs the two
Algorithm 1 DFSAC algorithm

1: Initialize $\chi^n_{th_{ik}} : S \rightarrow \mathbb{R}^{|A|}, \chi^{th_{ik}}_{0} : S \rightarrow \mathbb{R}^{|A|}, \pi^{th_{ik}}_{0} : S \rightarrow [0, 1]^{|A|}$ for $n \in \{1, 2, \ldots, N\}$  
2: Initialize $\nabla_{\theta_{ik}} : S \rightarrow \mathbb{R}^{|A|}, \nabla_{\theta_{0}} : S \rightarrow \mathbb{R}^{|A|}$  
3: $\theta^n_{th_{ik}} \leftarrow \theta^n_{th_{ik}} + \theta^n_{th_{ik}}$ for $n \in \{1, 2, \ldots, N\}$  
4: $D^n \leftarrow \emptyset$ for $n \in \{1, 2, \ldots, N\}$
5: while running do
6:   for each agent $n$ do
7:     Get state $s_t$ from the environment $E^n$
8:     $a_t \sim \pi(a_t | s_t)$
9:     $s_{t+1} \sim p(s_{t+1} | s_t, a_t)$
10:    $D^n \leftarrow D^n \cup \{(s_t, a_t, r(s_t, a_t), s_{t+1})\}$
11:    $\theta^n_{th_{ik}} \leftarrow \theta^n_{th_{ik}} - \lambda \nabla_{\theta^n} J \nabla_{\theta^n} J \left(\theta^n_{th_{ik}}\right)$ for $i \in \{1, 2\}$ and $n \in \{1, 2, \ldots, N\}$
12:    $\phi^n \leftarrow \phi^n - \lambda \nabla_{\phi} J (\phi^n)$ for $n \in \{1, 2, \ldots, N\}$
13:    $\alpha^n \leftarrow \alpha^n - \lambda \nabla_{\alpha} J (\alpha^n)$
14:    When running $k$ iterations upload $\theta^n_{th_{ik}}, \theta^n_{th_{ik}}$ to federated center node
15:    end for
16:   if in federated center node then
17:     $\chi_i \leftarrow \epsilon \chi_i + (1 - \epsilon) \bar{\chi}_i$ for $i \in \{1, 2\}$ and $n \in \{1, 2, \ldots, N\}$
18:    end if
19: end while

depth of policy evaluation and policy improvement to converge to the optimal value function and optimal policy. An example is that in agent $k$, the policy network takes the state $s_t^k$ of the local environment $E^k$ at moment $t$ as input to obtain the action $a_t^k$. To evaluate the impact of the policy on the local environment as well as on the global environment, the soft state value is defined as:

$$V(s_t^k) := \pi^k(s_t^k)^T \left[\chi(s_t^k) - \alpha^k \log \left(\pi^k(s_t^k)\right)\right]$$ (2)

among them, $\chi$ denote the trend networks. And, we use the following loss function to update trend networks:

$$J_{\chi^k}(\theta) = \mathbb{E}_{(s_t^k, a_t^k) \sim D} \left[\frac{1}{2} \left(\chi^k(s_t^k, a_t^k) - r(s_t^k, a_t^k)\right)
+ \gamma \mathbb{E}_{s_{t+1} \sim p} \left[V_\theta(s_{t+1}^k)\right]^2\right]$$ (3)

where $D$ denotes a trajectory stored in replay memory and $V_\theta$ denotes use global trend networks to calculate the soft state value. This can be seen as a collaboration learning process using the global information shared by the collaborators. And the global trend networks are obtained by soft update of each agent and then aggregated:

$$\bar{\chi} \leftarrow \epsilon \chi^k + (1 - \epsilon) \bar{\chi}, k \in \{1, 2, \ldots, N\}$$ (4)

where $\bar{\chi}$ is global trend networks. $\chi^k$ is local trend networks in agent $k$, $\epsilon$ is the aggregation factor. Then, the updated trend networks are used to guide the policy improvement:

$$J_{\pi^k}(\phi) = \mathbb{E}_{(s_t^k, a_t^k) \sim D} \left[\pi^k(s_t^k)^T \left[\alpha^k \log \left(\pi^k(s_t^k)\right) - \chi^k(s_t^k)\right]\right]$$ (5)

And $\alpha$ is the temperature parameters, but the appropriate value of $\alpha$ is different at different stages of training. Therefore, the selection of the $\alpha$ is formulated as a constrained optimization problem [28] that maximizing the expected return while keeping the entropy of the policy greater than a threshold as follows:

$$\max_{\pi_0, \ldots, \pi_T} \mathbb{E} \sum_{t=0}^{T} r(s_t, a_t) \quad \text{s.t.} \quad \forall t, \mathcal{H}(\pi_t) \geq \mathcal{H}_0 \quad (6)$$

we also dynamically train with $\alpha$ as a parameter of model, the loss function of $\alpha^k$ in agent $k$ is

$$J(\alpha^k) = \pi_t^k(s_t^k)^T \left[-\alpha^k \log \left(\pi_t^k(s_t^k)\right) + \bar{H}\right]$$ (7)

Through the continuous iteration of the above two steps, agent $K$ is guided by global trend networks to obtain the target policy $\pi^k$ applicable to the local environment $E^k$ by sharing knowledge with other agents eventually.

The complete DFSAC algorithm we proposed is shown in Algorithm 1. Firstly, the algorithm initializes the local network parameters of local networks (two local trend networks and one policy network). Then initialize the global network (two global trend networks), and equalize the global trend networks and local trend networks’ parameters. The agents first each initialize an empty replay memory and store a backup of the global trend networks. And the agent will collect information about the local environment as the input of the policy network and output an action. Then, the agent get the reward value and the next state from the local environment, calculate the cumulative discount function at each moment, and store the transition in the replay memory. When the number of transitions in the replay memory reaches the number set in advance, the algorithm starts training. It updates the local network parameters (two local trend networks and a policy network). Finally, the algorithm updates the temperature parameters. After running a preset training iterations, the agents will upload their local trend network parameters to the federated center node. After receiving the local trend network parameters
of agents, the federated center node integrates these parameters and updates the global trend network parameters. Afterward, the federated center node distributes the global trend network parameters to each agent, and agents update their backup with the latest global trend networks. Through this integrated and distributed processing method, the local network in the agents can reflect the real-time situation of global environment.

B. Experiment

We use CartPole from OpenAI Gym [25] as the experimental environment. CartPole is a cart-pole game with a cart, and a pole erected. The algorithm needs to control the cart to move left or right to keep the pole upright while satisfying the constraints. Whenever an operation is performed without tilting the rod beyond the limit, the environment rewards the agent with a value of 1, otherwise 0. Our goal is to verify the algorithm’s performance in several differentiated environments. Therefore, the transfer probability of the environment is varied by changing the length of the pole to obtain multiple differentiated environments and setting up agents in each of the differentiated environments.

For the DFSAC algorithm, we use the output of the policy network to control the agents. And, an additional node is set as a federated center node for models aggregation and distribution. As described in the previous section, agents in different environments share knowledge by sharing global trend networks. In the actual algorithm implementation, considering the communication overhead between agents, each agent stores a backup copy of global trend networks locally to guide the local data training. After a certain number of training sessions, i.e. soft update, the local trend networks are uploaded to the federal center node for aggregation, and the latest global trend networks are downloaded to update the local backup. This approach can reduce the communication overhead incurred during training.

![Fig. 3. Policy Loss and Reward](image)

(a) Reward (b) Policy Loss

The characteristic between the DFSAC algorithm and the traditional FRL algorithm is that the differentiation between different environments is considered in the learning process. Therefore, we use the SAC algorithm trained by traditional federated learning as our baseline, i.e. FedAVG [9], the agents in each environment share the model including both value parameters and policy model parameters in the SAC algorithm, and the models are aggregated and distributed periodically using averaging model parameters. In addition, we implement a centralized RL algorithm to verify the performance of a non-federated learning algorithm in this scenario. The centralized RL algorithm uses a SAC agent to collect information directly in each environment and then train.

The reward obtained by the different algorithms in each episode is shown in Fig. 3(a) which results from averaging the reward from several differentiated environments. As can be seen, the DFSAC algorithm steadily increases and eventually converges as the training progresses. In contrast, the reward of other algorithms fluctuates significantly during the training process and is lower than that of the DFSAC algorithm. Fig. 3(b) shows the change in the average loss value of each agent’s policy network during the training process. It can be seen from the figure that the DFSAC algorithm has higher learning efficiency than others. This indicates that the DFSAC algorithm can obtain policy models more suitable for agents in differentiated environments than the traditional FRL algorithm. The global policy model obtained by direct aggregation of the traditional FRL algorithm is difficult to adapt to this differentiated environment. Further, the DFSAC algorithm can avoid the additional communication overhead incurred by the centralized RL algorithm when transmitting environmental information.

V. Empirical Study: Traffic Offloading in SAGIN

In this section, we first establish a Space-Air-Ground Integrated Network (SAGIN) environment described in [7], which is a typical dynamic and heterogeneous network. Then, we use the DFSAC-based traffic offloading method to solve the traffic control problem in this scenario. Finally, we compare the performance of the DFSAC-based traffic offloading method with other methods.

A. Settings

We consider traffic offloading in SAGIN like Fig. 4 and establish a multi-dimensional heterogeneous network model.
The ground network is composed of mobile user equipment (UE), base stations (BS), and edge base stations. The air network includes a series of dynamically deployable UAVs as an extension of the ground network. The space network is a double-layer communication satellite composed of low orbit communication satellites (LEO) and geostationary earth orbit communication satellites (GEO).

The SAGIN model as a graph \( G = (V, E) \). Among them, \( V = \{ V^D, V^B, V^U, V^L, V^G \} \) represents different types of nodes in SAGIN. \( V^D = \{ v^D_1, v^D_2, \ldots, v^D_n \} \) is a collection of UE nodes, \( n \) is the number of this type nodes. Similarly, \( V^B \) is the collection of BS nodes, \( V^U \) is the collection of UAV nodes, \( V^L \) and \( V^G \) are collections of LEO nodes and GEO nodes. Each node in \( V \) contains its attribute parameters and network state parameters. When the node encounters buffer overflow or connection breakage during packet transmission, it will discard these packets. And the collection of edges \( E = \{ e^{DB}_{ij}, e^{BB}_{ij}, \ldots, e^{xy}_{ij} \} \) indicates the link between any two nodes in the network. For example, \( e^{xy}_{ij} \) is the link between node \( v^x_i \) and \( v^y_j \), among them \( v^x_i, v^y_j \in V \). The model will dynamically change the value of \( E \) according to the location and connection state of each node in the network. Further, \( V^D \) is divided into two types: source node and target node. The source node is responsible for sending data packets to the target node according to the preset generation mode. Other type nodes in \( V \) are relay nodes used to transfer data packets from the source node to the target node. Among them, some base station nodes will make the offloading decision as the traffic offloading node.

Since SAGIN consists of several different types of nodes, the transmission model between the nodes is not the same. We use the models in [29] and [30] to calculate the transmission rate between the UAV and the BS. The rain attenuation between the satellite and the BS or the UAV is defined using the Weibull distribution [31]. The free space propagation model is used for communication between satellites.

**B. Traffic Offloading Method**

Denoted by \( X_t \), the total amount of data packets in \( t \) th time slot. \( X_t \) follows a normal distribution and these packets are transmitted to node \( v_d \in V \) through the set routing path \( L_t = \{ v_x, v_y, \ldots, v_d \} \). This process can be expressed as \( M_{v_x \rightarrow v_d} = \{ X_t, L_t, T, r \} \), \( X_t \) is the amount of data, \( L_t \) is the defined routing path, \( T \) is the transmission delay of the packet, and \( r \) is the transmission rate of the packet. The system will generate a new routing path when using the traffic offloading algorithm \( A(m) \) during data packet transmission. At this time, there will be UAV or satellite nodes in the path. Our goal is to minimize the packet delay of the entire network over the designed time \( D \) by the usage of the traffic offloading method to generate a new routing path at time \( t \) dependent on specific parameters of:

\[
Z_{\mu}(m, t) = \begin{cases} 
   m_{x,L,v}, & a = 0 \\
   A(m_{x,L,v}), & a \neq 0 
\end{cases}
\]

where \( a = 0 \) means the offloading method is not used, and \( a \neq 0 \) means that the offloading method is used.

\[
\min_{\mu} \sum_{D} \sum_{m} O(Z_{\mu}(m, t))
\]

where \( O(\cdot) \) calculates the delay of all packets in the entire network. We are committed to minimizing the delay of data...
packets by minimizing the parameters of the traffic offloading method.

At time slot $t$, the source node generates a set of packets to be sent to the destination node following a predetermined routing path. However, during the delivery of the packets, the link is broken, or the relay node exceeds the load and other situations that increase the delay of the network. It is necessary to analyze the current network state combined with the historical state and then predict the future network state to make an appropriate offloading strategy. Therefore, we abstract the traffic offloading decision problem as a Markov decision process (MDP).

In large heterogeneous networks such as SAGIN, the cost is unbearable if traffic offloading nodes collect global network information as state space. Therefore, the training node only collects the local network information of its region, not the global network information. For a traffic offloading node, its state space $S$ is defined as the network information in its one-hop neighbor node and two-hop neighbor node, such as node type, node capacity, etc. And we use the method in [5] to collect network information.

$$S = \{\{\theta_i\}, i \in \{N(v_i^B), N(N(v_i^B))\}\}$$  \hspace{1cm} (10)

where $v_i^B$ represents traffic offloading nodes, $\theta$ represents the network information contained in the node and $N(\cdot)$ represents the neighbor nodes.

The action space is defined as follows:

$$a \in \{0, \ldots, v_j^y\}, j \in |N(v_i^B)|, y \in \{U, L, G\}$$  \hspace{1cm} (11)

When a packet arrives at an offloading node $v_i^B$, the node will determine the packet’s destination according to the action value obtained by the traffic offloading algorithm. If the action is 0, the system will still transmit the packet to the next network node according to the original routing path. In addition, each action value represents a neighbor node of the offloading node, and the system will offload the packet to a new routing path according to this action value. The neighbor node can be UAV, or LEO and GEO.

Our optimization goal is to minimize the total delay of the network, so set the reward function to

$$R(s_t, a_t) = \begin{cases} 
\frac{1}{D_t}, & \text{arrive} \\
-(T_{\text{drop}} - T_{\text{born}}), & \text{drop}
\end{cases}$$  \hspace{1cm} (12)

where $D_t$ denotes packet delay, $T_{\text{drop}}$ and $T_{\text{born}}$ are the packet drop time and born time. When the packet arrives at the destination node, a positive reward is given according to the delay, and the lower the delay, the higher the reward value. If the packet is dropped, a negative reward is given according to the difference between the time the packet is dropped and the time of born.

The frame structure of the DFSAC-based traffic offloading method is shown in Fig. [5]. The local base station nodes are training nodes for federated learning to collect the network environment state in replay memory for training. The neural network in each training node can be divided into Actor-network and Critic-network. The Actor-network is responsible for outputting the action of traffic offloading based on the policy network. The Critic-network is responsible for judging the action and the environment trends, which are used to optimize and improve the performance of the policy network. Meanwhile, the edge base station node is used as a federated center node to receive local trend networks uploaded by the local base station nodes, aggregate the parameters and then distribute them to the local base station nodes to update their network parameters to the latest.

### C. Performance Evaluation

| Parameters | Values |
|------------|--------|
| Number of BS nodes | 8 |
| Number of UAV nodes | 6 |
| Number of LEO nodes | 2 |
| Number of GEO nodes | 1 |
| Packet generation rate | $N(1e6, \sigma^2)$ Mbps |
| BS - UAV bandwidth | 20MHz |
| BS - LEO bandwidth | 37.5MHz |
| BS - GEO bandwidth | 25MHz |
| UAV - LEO bandwidth | 10MHz |
| UAV - GEO bandwidth | 5MHz |
| Gamma | 0.99 |
| $\varepsilon$ | 1e-2 |
| Learning rate | 5e-4 |
| Learning rate of $\alpha$ | 1e-3 |
| Target entropy | -4.0 |

In this part, we describe the simulation environment and evaluate our DFSAC-based traffic offloading method. The simulation environment simulates a dynamic and heterogeneous SAGIN environment. The source node device and the destination node device are modeled as user equipment (UE). The source node device generates data using a normally distributed data generation rate. The relay node device transfers data packets based on the Open Shortest Path First (OSPF) traffic routing protocol or the proposed traffic offloading method. The relay nodes are modeled as BS, UAV, LEO, and GEO. Except for BS are static, other devices have their mobile models. The source node and destination node devices use a random-waypoint mobility model [32], which can simply randomize the device’s location. In our simulation, the UEs use the arbitrary movement model to move within a 100km$^2$ two-dimensional plane area. For the mobility model of UAV, we set UAV to fly in a certain direction at a fixed speed in a predefined period. After a while, the UAV’s moving direction will shift arbitrarily and fly at the same moving speed. We consider that LEO periodically covers the considered area as it is moving around the earth. For GEO, due to its high coverage, we consider it to cover the target area all the time and have a stable connection (i.e. the air condition change is not considered). For this area, $(\varphi, \omega_i, \eta, \gamma, h_0)$ is set to (3.04, -3.61, -23.29, 4.14, 20.7) [33]. For the rain attenuation of the
satellite channel model, we set the $F_{\text{rain}}$ to 6dB [33]. The remaining simulation parameters are shown in Table I.

In order to evaluate our proposed traffic offloading method, we run the traditional traffic offloading method used in [34]–[37] in the same environment. The traditional traffic offloading method is a greedy offloading method based on the shortest path. In addition, we simulated the DDQN-based traffic offloading method in [5] for experimental comparison.

Fig. 6(a) and Fig. 6(b) show the change in throughput and packet loss rate as the number of source nodes increases from 200 to 380 for the four different methods. Fig. 6(a) shows that our method improves the throughput as the number of source nodes increases, while the other methods remain unchanged. This indicates that our method increases the network’s maximum capacity compared to the other methods. Fig. 6(b) shows that with the rise of source nodes, the packet loss rate of these methods is rising. But our proposed method has a lower packet loss rate than the other three methods.

Still, as the number of source nodes increased to 380, our proposed method began to show its advantages. And as the number of nodes continues to increase, this advantage becomes more significant. We can see obvious performance differences when the number of source nodes increases to about 480.

Further, to verify the performance of our algorithm in the high mobility environment of SAGIN, we design simulations for packet drop rate and throughput. The movement characteristics of the satellites are already fixed in the environment, so we gradually increase the speed of the UAVs from 5m/s to 30m/s to observe the performance of each method. Fig. 7(a) and Fig. 7(b) shows the packets drop rate increases and throughput decreases with UAVs moving speed increase. However, our method still has a better performance compared with other methods. Combined with the above experimental results, it can be seen that our proposed traffic offloading method has overall advantages over other methods in SAGIN.

VI. CONCLUSION

The dynamic and heterogeneous environment brings differentiated regions and non-IID data, which leads to a local strategy trap for RL. In this paper, we propose a novel concept of Differentiated Federated Reinforcement Learning for the networks with dynamic and heterogeneous environments by isolating the local policy model from the global integration and using the trend model to distinguish differences among regions. Compared with the conventional FRL, the proposal focuses on adjusting differentiated regions’ biases and ensuring the local policy model’s independence. The proposal shows its outperformance with experiments with both classical games and heterogeneous network environments.

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