Multi-Dimensional Resource Optimal Allocation Scheme for Tiansuan Constellation

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***Abstract*—With the advent of the 6G era, the construction of space networks is gradually entering a peak period. Tiansuan constellation came into being in this context, which aims to provide an open research platform for researchers. Tiansuan constellation can be used as the coverage supplement of terrestrial networks and the traffic supplement in hotspot areas, providing flexible, efficient, and seamless coverage of humanized services for global users. Satellite network resource management is more difficult than terrestrial network resource management due to the heterogeneity and difference in characteristics of satellite and terrestrial networks. This paper proposes a multi-dimensional network resource allocation algorithm for the Tiansuan constellation. Considering the limited storage resources and bandwidth resources of the satellite Internet, and taking into account the computing resources of the satellite Internet, the joint optimization of multi-dimensional resources is realized. The policy network-based reinforcement learning model is adopted to independently optimize the decision-making process of satellite Internet resource allocation. Compared with the two baseline algorithms, the proposed algorithm improves the network resource allocation profit and user service rate by 29.9% and 10.7%, respectively. In addition, the effectiveness and flexibility of the proposed scheme are verified by adjusting the storage resource requirements of users.**

***Index Terms*—Tiansuan Constellation, Resource Management, Policy Network, Reinforcement Learning**

I. Introduction

The Russian-Ukrainian conflict that began in February 2022 has attracted worldwide attention. It is worth the attention of academia and industry that satellites are also active in this event. SpaceX provided Ukraine with Starlink services and a batch of Starlink terminals. It can be speculated that Starlink will play an important role in reconnaissance, detection, jamming, and attack. Starlink also restores instant communication capabilities to civilian areas damaged by war. For example, a Starlink terminal can provide communication services for a series of villages on a 10-kilometer road [1]. It cannot be ignored that the construction of satellite Internet has entered the fast lane. Major commercial companies have launched a considerable number of satellites to form their own satellite Internet. Musk's Starlink program has launched more than 2,900 satellites, and the number is expected to reach 12,000 by 2025. The UK's OneWeb programme has launched 428 satellites into low Earth orbit on its 10th anniversary. In addition, Russia, China, and Japan have launched hundreds of satellites for various purposes, ranking among the top in the world.

Researchers investigated the integration and evolution process of 5G and satellite Internet [2]. In the initial and middle stages, the interworking gateway and the satellite network as the access network are used to realize the integration of the two. In the long-term stage, the ultimate goal is to deploy the core network functions on the satellite Internet. Comprehensively improve the performance of satellite Internet from the aspects of business continuity assurance, security, and QoS control. The arrival of the 6G era has opened the prelude to the construction of the space-air-ground integrated network [3]. With its wide coverage, high deployment flexibility, and no geographical restrictions, satellite Internet can be used as a traffic supplement for terrestrial hotspots and as a supplement for coverage in some regions [4]. In order to keep up with the trend of satellite Internet construction, we proposed the Tiansuan constellation, which is an open experimental platform that provides a real satellite environment. Tiansuan constellation supports experiments in multiple fields, including but not limited to the 6G core network, satellite IoT, satellite operating system, AI, and hardware platform. At present, the construction of the Tiansuan constellation is in the first stage, and it is planned to launch 6, 24, and 300 satellites in three stages [5], [6].

A practical problem that needs to be faced is how to allocate satellite network resources efficiently. On the one hand, satellite Internet network resources are limited. Limited computing resources often require satellites to offload computing tasks to other satellites or ground stations, which in turn causes related issues such as channel interference and mobility management. The limited communication resources can significantly increase network latency. This situation will be more serious in an environment with unstable links. On the other hand, the access of a large number of terminals to the satellite Internet will bring about differentiated resource requirements, so it is necessary to improve the rationality of resource allocation. The random allocation of satellite resources will lead to the generation of excessive resource debris. Excessive energy consumption will also reduce satellite life. In the future, the Tiansuan constellation will conduct

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a large-scale network of massive satellites. Therefore, the Tiansuan Constellation will inevitably face urgent resource scheduling needs.

The industry has carried out extensive research in the field of satellite network resource allocation [7]. Referring to the resource management method of the terrestrial Internet, methods such as mathematical programming [8], optimization [9], and machine learning (ML) [10] are usually used to manage satellite Internet resources. Davoli *et al.* [11] optimized the bandwidth resources from the aspects of satellite architecture and algorithms. Combining the advantages of edge computing and cloud computing, Gao *et al.* [8] defined satellite Internet resource allocation as a virtual network function placement problem. Then the distributed algorithm based on integer nonlinear programming is adopted to solve the problem. Zhang *et al.* [12] decomposed the data scheduling and multi-dimensional resource management of satellite Internet into a mixed integer programming problem, and then used matching theory and the simplex method to solve it. Large-scale satellite Internet has more practical application significance. Abe *et al.* [13] defined the optimization of resource allocation for large-scale satellite communication systems as a mixed integer programming problem. Deng *et al.* [14] optimized the problem of hierarchical heterogeneous satellite Internet capacity management by using a genetic algorithm with the goal of user experience quality. With the development and popularization of AI applications, Machine learning has become a reliable solution to the bottleneck problems in real production and life. The same is true in the field of satellite Internet resource allocation. Considering the high computational complexity of the traditional iterative scheme, Wang *et al.* [15] proposed to use a combination of ML and an optimization scheme to solve the problem of satellite task classification and power allocation. With the goal of maximizing the amount of satellite IoT data, Zhou *et al.* [16] used model-free reinforcement learning to uniformly schedule satellite resources and IoT data, which provided a powerful reference for future satellite IoT system design.

In this paper, we propose a policy network-based reinforcement learning scheme to guide and optimize resource management for satellite Internet. The resource allocation efficiency based on machine learning is proved to be superior to traditional optimization schemes, especially in the case of complex network scale and resource conditions [17]. Large-scale satellite networking is an inevitable trend in the future development of satellite Internet. However, the existing research has not done enough work on the resource management of large-scale satellite Internet, ignoring the possible impact of multi-dimensional network resource coordination on the performance of the scheme. In addition, users' demands for satellite network resources are differentiated for massive terminal access. Therefore, it is necessary to make a differentiated arrangement of multi-dimensional satellite Internet resources. To this end, this paper mainly does the following work. The satellite Internet model and user request model are established based on the research background of the Tiansuan constellation. A reinforcement learning model based on the policy network is proposed. By extracting and perceiving the attributes of satellite network resources, the intelligent agent can continuously optimize resource allocation decisions. Finally, the proposed algorithm is tested in terms of network resource allocation profit and the number of service users to verify the effectiveness and flexibility of the algorithm. The proposed scheme will be deployed and verified on satellites launched by Tiansuan constellation, and are expected to provide a reference for other satellite constellation systems.

Section II introduces the system model, including the Tiansuan constellation networking model, the user request model, and related formulas. Section III shows the design and implementation process of the multi-dimensional resource allocation algorithm based on the policy network in detail. In Section IV, the proposed algorithm is tested and the obtained results are analyzed. Finally, the full paper is summarized.

II. System Model

A. Physical Network Model

The physical network model of satellite Internet is established based on the Tiansuan constellation. We only consider satellites with computing power in the Tiansuan constellation. Model the satellite internet as a weighted graph. Each satellite serves as a vertex of the weighted graph, and the channel links between satellites serve as edges. The entire satellite physical network is represented as $\mathcal{SG} = \{N^P, L^P, A^P\}$, where N^P includes all satellite nodes, L^P is the channel link set, and A^P represents the relevant resource attributes of satellite Internet. A specific satellite node is represented by n^p, while the link between two satellite nodes is represented by $l(n_i^p, n_j^p)$, where $n_i^p, n_j^p \in N^P$. The total number of physical nodes is specified as $\mathcal{N}$. The node resource attributes of satellite Internet include computing resource $\mathcal{CPU}(N^P)$ and storage resource $\mathcal{STO}(N^P)$. We assume that the satellite communications of the Tiansuan constellation compete for channel resources within a frequency band. Therefore, the resource attribute of the physical link is the bandwidth resource $\mathcal{BW}(L^P)$. We only consider the operation of the astronomical constellation in a time slot, i.e., the topology of the Tiansuan constellation in this time slot is fixed, and the relative connection relationship between satellites will not change.

B. User Request Model

User requests come in the form of service function chains. User requests also consist of network nodes and links. A complete user request is represented by $\mathcal{G}^U$. The user request node is represented by N^U, and n^u represents a specific virtual network function. The user request link is represented by L^U, and l^u represents the link between virtual network functions. User request node resource requirements include computing resource requirements $\mathcal{CPU}(N^U)$ and storage resource requirements $\mathcal{STO}(N^U)$. The link resource requirement of the user request is the bandwidth resource $\mathcal{BW}(L^P)$. User requests need to occupy a certain type and amount of satellite network resources. Only when the node resource requirements and link

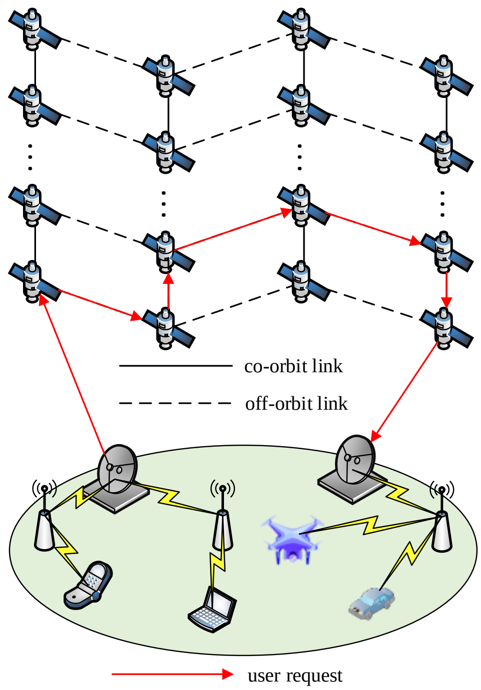

Fig. 1. Satellite Internet architecture.

resource requirements in the user request are satisfied at the same time, the user request can be said to be successful.

The schematic diagram of the satellite Internet physical network model with the Tiansuan constellation as the background and the user request model is shown in Fig. 1. User requests come in the form of service function chains, and each virtual network function may need to be deployed on a different satellite.

C. Problem Formulation

The profit and cost of network resource allocation are common concerns of network providers and users. From the expression of the physical network model, it can be seen that the network resource allocation profit can be defined by defining the consumption of network resources,

$$Pro(\mathcal{G}^U) = \mathcal{CPU}(N^U) + \mathcal{STO}(N^U) + \mathcal{BW}(L^U). \tag{1}$$

Equation (1) represents the profit of the network operator after the user requests $\mathcal{G}^U$ to successfully obtain the satellite Internet resource.

The cost of network resource allocation can be calculated by,

$$Cos(\mathcal{G}^U) = \mathcal{CPU}(N^U) + \mathcal{STO}(N^U) + \mathcal{BW}(L^U) \cdot hops(l_i^u), \tag{2}$$

where $hops(l_i^u)$ represents the number of physical links the user requests the link to pass through, i.e., the bandwidth resources requested by l_i^u are jointly provided by multiple physical links.

User requests need to constantly occupy satellite Internet resources. The number of resources that satellite Internet can provide after a period of resource allocation process may not meet the resource requirements requested by users. Therefore, the following constraints need to be defined,

$$\begin{aligned}
&(a): \ \mathcal{CPU}(n^p) \geq \mathcal{CPU}(n^u), \ n^u \uparrow n^p,\\
&(b): \ \mathcal{STO}(n^p) \geq \mathcal{STO}(n^u), \ n^u \uparrow n^p,\\
&(c): \ \mathcal{BW}(l^p) \geq \mathcal{BW}(l^u), \ l^u \uparrow l^p,\\
&(d): \ \sum_{n_i^u \uparrow n^p} \alpha = 1,\\
&(e): \ \sum_{l_i^u \uparrow l^p} \beta \geq 1,
\end{aligned} \tag{3}$$

where $(3)a$ represents the consumption limit of computing resources. Equation $(3)b$ defines the consumption limit of storage resources. Equation $(3)c$ shows the consumption limit of spectrum resources. Equation $(3)d$ shows that a user request node can only occupy the resources of one satellite node, while $(3)e$ shows that the user request link resource can be provided by multiple satellite links.

Increasing the number of successful services requested by users is an important means to obtain high profits. The calculation method of the user service rate can be given by,

$$\mathcal{A} = \lim_{T} \frac{\sum_{t=0}^{T} suc(\mathcal{G}^U)}{\sum_{t=0}^{T} num(\mathcal{G}^U)}, \tag{4}$$

where $\sum_{t=0}^{T} suc(\mathcal{G}^U)$ represents the number of users requests that successfully obtained the satellite resources, while $\sum_{t=0}^{T} num(\mathcal{G}^U)$ represents the total number of user requests arriving in this time slot.

The overall goal of the satellite Internet resource allocation algorithm is to increase resource profit and the number of service users, so the optimization goal is represented by:

$$\begin{aligned}
maximize \ \mathcal{G} &= \lim_{T}[Pro(\mathcal{G}^U) + \mathcal{A}]\\
&= \lim_{T}[\mathcal{CPU}(N^U) + \mathcal{STO}(N^U) + \mathcal{BW}(L^U)\\
&+ \frac{\sum_{t=0}^{T} suc(\mathcal{G}^U)}{\sum_{t=0}^{T} num(\mathcal{G}^U)}],\\
&s.t. (3)a - (3)e.
\end{aligned} \tag{5}$$

D. Reinforcement Learning Model

The setup of each element of reinforcement learning in the context of satellite Internet is introduced, including environment, state, agent, action, and reward signal.

Environment: The primary source of intelligent agent perception, i.e, the satellite Internet.

State: The environmental state of satellite Internet, including the availability of various network resources, i.e., $S = \{\mathcal{CPU}(N^P), \mathcal{STO}(N^P), \mathcal{BW}(L^P)\}$.

Agent: The main body that interacts with the environment, which is replaced by a self-built policy network model.

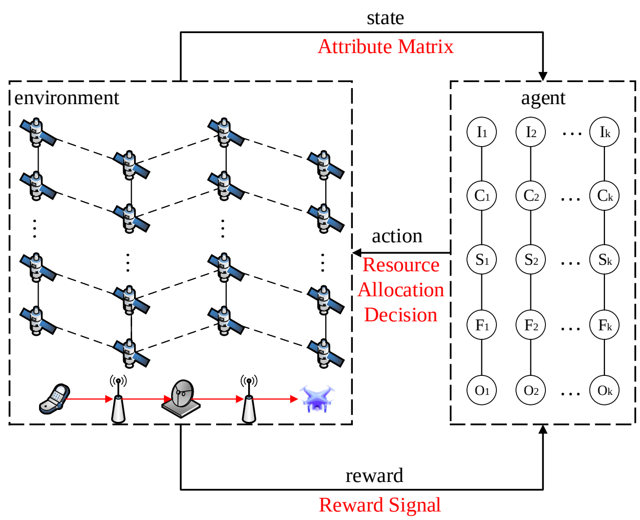

Fig. 2. Algorithm framework of satellite Internet resource allocation based on policy network.

Action: The policy imposed by the agent on the environment, i.e., the specific network resource allocation policy.

Reward: The feedback from the environment to the agent after the agent acts on the environment. Expressed by (5).

III. Resource Allocation Algorithm Based on Policy Network

A. Attribute Matrix

The algorithm framework of the satellite Internet resource allocation based on the policy network is shown in Fig. 2, whose operation process follows the Markov decision process. The intelligent agent perceives state from the environment. In the satellite Internet resource allocation problem, the state refers to the resource state. The state is specified in the form of an attribute matrix, while each element of the attribute matrix is the available resource capacity of the satellite node. Each physical node has four attributes, namely available computing resources, available storage resources, the sum of available spectrum resources of the connected links, and the average distance to other physical nodes. The above four attributes are concatenated into an attribute vector,

$$av_i = (\mathcal{CPU}(n_i^p), \mathcal{STO}(n_i^p), S\_\mathcal{BW}(n_i^p), S\_DIS(l_i^p)). \quad (6)$$

Then, the attribute vectors corresponding to each satellite node are aggregated into an attribute matrix, which is represented by,

$$\mathcal{AM} = \begin{bmatrix} \mathcal{CPU}(n_1^p) & \mathcal{STO}(n_1^p) & S\_\mathcal{BW}(n_1^p) & S\_DIS(l_1^p), \\ \mathcal{CPU}(n_2^p) & \mathcal{STO}(n_2^p) & S\_\mathcal{BW}(n_2^p) & S\_DIS(l_2^p), \\ \cdots & \cdots & \cdots & \cdots \\ \mathcal{CPU}(n_{k-1}^p) & \mathcal{STO}(n_{k-1}^p) & S\_\mathcal{BW}(n_{k-1}^p) & S\_DIS(l_{k-1}^p), \\ \mathcal{CPU}(n_k^p) & \mathcal{STO}(n_k^p) & S\_\mathcal{BW}(n_k^p) & S\_DIS(l_k^p), \end{bmatrix}$$
$$i = 1, 2, \ldots, k. \quad (7)$$

B. Structure and Function of Policy Network

The policy network model based on reinforcement learning is divided into five layers according to functional logic. The basic unit of policy network is neurons. The number of neurons in the input layer is the same as the number of physical nodes in the satellite Internet, whose function is to receive the attribute matrix from the environment. The convolution network is usually used to process images and natural language, which plays the role of sharing parameters and simplification. The convolution layer in the policy network convolutes each attribute vector to obtain the available attribute vector form. The convolution operation method of the attribute vector can be given by,

$$Con_k = \omega \cdot av_k \cdot +b, \quad (8)$$

where Con_k is the convolution output of the k-th physical node, ω is the weight vector, and b is the bias.

The computing layer performs a softmax function operation on each available attribute vector and calculates an available probability for the physical node corresponding to each available attribute vector. And we have,

$$Pro_k = \frac{e^{Con_k}}{\sum_n e^{Con_n}}. \quad (9)$$

The filtering layer filters out satellite nodes that do not have enough resources to ensure that every node resource that is output is available. Finally, a set of satellite nodes are output in the output layer to provide user requests.

C. Model Training and Testing

When a user request reaches the satellite Internet, the intelligent agent senses the state of the physical network environment at this time, i.e., extracting an attribute matrix from the satellite Internet. After a series of operations in the policy network, a resource allocation strategy suitable for the underlying network at this time is obtained, which is applied to the physical network as an action. The satellite Internet will feed back a reward signal to the intelligent agent according to the effect of this resource allocation strategy, and we take (5) as the reward signal. The intelligent agent will adjust the resource allocation strategy according to the situation of the reward signal to obtain a larger cumulative reward. The above process loops until the maximum number of iterations or termination is due to insufficient resources. Each group of physical nodes finally output from the policy network has a probability. The user request will select the physical node providing resources according to the probability.

D. Complexity Analysis

The training process of the algorithm is performed offline. The test process is divided into two stages: satellite node resource allocation and link resource allocation. In the node resource allocation stage, the time complexity is related to factors such as state space, state space, and network model parameters. In the link resource allocation stage, the breadth-first search strategy is adopted and its time complexity is $O(|N^P| + |L^P|)$.

TABLE I
PARAMETER SETTING

Parameter name	Parameter value
number of satellite nodes	100
CPU resource capacity of satellite nodes	U[4,8]TFLOPS
storage resource capacity of satellite nodes	U[1,2]T
bandwidth resource capacity of physical links	U[100,200]Mbs
number of user requests	1000
CPU requirements of user request	U[0,0.5]TFLOPS
storage requirements of user request	U[0,0.1]T
bandwidth requirements of user request	U[0,50]Mbs
learning rate	0.005

IV. PERFORMANCE EVALUATION

A. Parameter Setting

The setting of simulation parameters refers to the actual hardware parameters of the satellites in orbit in the Tiansuan constellation. A series of text files are generated by programming to save the parameters of satellite Internet and user requests, so as to simulate the Tiansuan constellation. The parameters in the text file include network node location, mutual connection relationship, available resource value, and resource demand value, etc. We consider the user request process for one slot. During this period, it can be considered that the connection relationship between satellites is unchanged, i.e., the satellite network topology is fixed. The detailed parameter settings are shown in TABLE I.

B. Results and Analysis

The goal of the satellite network resource allocation algorithm based on the policy network is to allocate network resources reasonably and to increase the allocation profit of network resources and the number of service users. Therefore, the performance of the algorithm is tested from the above two aspects.

The test results of satellite network resource allocation profit are shown in Fig. 3. The proposed algorithm is compared with the NRM algorithm and the RCR algorithm. During a user request process, the resource allocation profit of the proposed algorithm is always relatively high. The advantage of the proposed algorithm is that makes full use of the intelligence of reinforcement learning. The agent can sense the changes in satellite Internet resources in real-time and make reasonable resource allocation decisions for user requests. The NRM algorithm and the RCR algorithm are heuristic resource allocation algorithms, which allocate resources to each user request based on greedy sorting. The former sorts network nodes, while the latter sort network links, which cannot ensure reasonable allocation of resources.

The test results of the number of service users of the satellite Internet resource allocation algorithm are shown in Fig. 4. On the whole, the user service rate of the proposed algorithm is higher than that of the NRM algorithm and the RCR algorithm. The policy network based on reinforcement learning can make more reasonable resource allocation decisions and serve more user requests, so the user service rate is relatively high. In the initial stage, the service success rate of the algorithm has dropped significantly. It means that most user requests cannot obtain sufficient resources. Since the RCR algorithm adopts a greedy strategy to allocate resources for user requests, the resources of physical nodes with larger resource capacity are preferentially allocated to users in the initial stage. The number of user requests that can be satisfied at this time is high. The allocation mode of the NRM algorithm and the RCR algorithm causes more resource fragments and is not conducive to accepting more user requests.

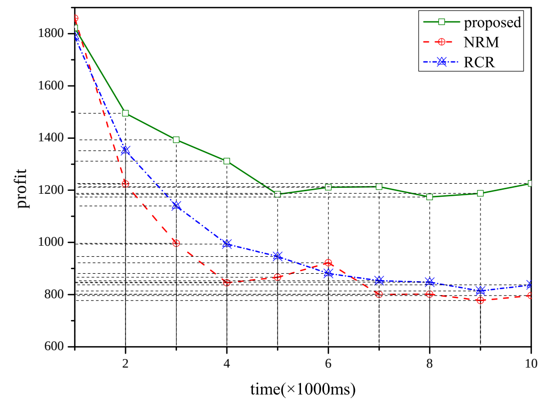

Fig. 3. Test results of resource allocation profit.

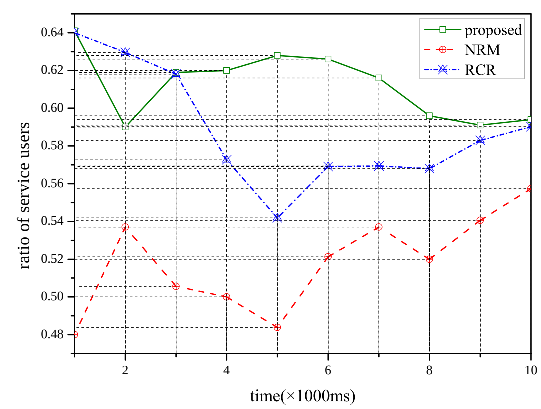

Fig. 4. Test results of ratio of service users.

Besides, we test the flexibility of the algorithm by changing the user's storage resource requirements. The initial storage resource requirement of user requests is [0,0.1]T. We adjust the storage resource requirements of users to [0,0.125]T and [0,0.25]T respectively. The performance of the algorithm in network resource allocation profit and the user service rate is observed. The experimental results are shown in Fig. 5 and Fig. 6.

When the storage resource requirement of users is [0,0.1]T, the resource allocation profit and the number of service users

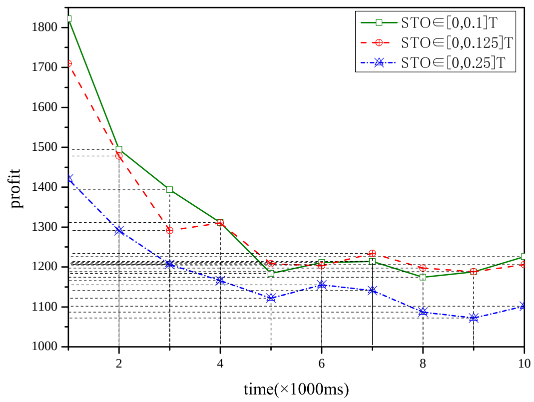

Fig. 5. Resource allocation profit for different storage resource requirements.

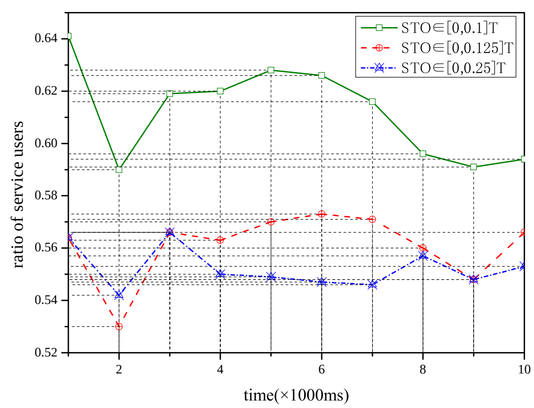

Fig. 6. User service rate for different storage resource requirements.

are highest. Due to the limited amount of satellite Internet resources, when users request fewer network resources, the number of users that can be served will be greatly increased through algorithm scheduling. If a user has a large storage resource requirement, each user request occupies a large number of network resources. Therefore, the number of users that can be served will decrease, and the profit from network resource allocation will also decrease.

V. Conclusion

Facing the deployment and application of the Tiansuan constellation, this paper proposes an optimal allocation scheme for satellite network resources from the theoretical and simulation levels. The proposed multi-dimensional network resource allocation algorithm based on the policy network utilizes reinforcement learning techniques. The key link is that the established policy network can autonomously perceive the state of the underlying physical network environment and formulate resource allocation strategies that meet user requests. Simulation experiments are carried out from the perspective of network resource allocation profit and the number of service users. The results show that the proposed algorithm has better performance than other comparative algorithms. In the future, more types of satellite network resources can be considered. The policy network structure is improved to adapt to the increasingly complex satellite network environment. In addition, it is necessary to deploy this algorithm on the real Tiansuan constellation in the future to verify the actual performance. The proposed scheme is also expected to provide a reference for resource management of other large-scale satellite networks.

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