Dynamic Resource Allocation for Network Slicing in LEO Satellite Networks

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Abstract. Low earth orbit (LEO) satellite networks have advantages such as low latency and wide coverage, which play an increasingly significant role in global connectivity. Satellite network slicing is a technology that enables the partitioning of different resources and capabilities to different service requirements and customers in LEO satellite communication networks. It can guarantee different QoS requirements according to the application scenarios and traffic requirements. However, LEO satellite networks are characterized by uneven traffic distribution and certain periodicity over time, leading to large resource wastage on satellite networks. To address this problem, we study the resource allocation method in satellite network slices, which aims to optimize the utilization of idle communication resources and improve traffic deployment success rate in LEO satellite networks. In specific, we propose a heuristic algorithm named MMAS-RA based on max-min ant system algorithm for resource dynamic allocation. The experimental results in four typical scenarios illustrate that our method improves up to 32.26% traffic deployment success rate and 67.02% resource utilization rate compared with the benchmark algorithm.

Keywords: Satellite Networks · Network Slicing · Resource Allocation · Software Defined Network · Network Functions Virtualization

1 Introduction

Low earth orbit (LEO) satellite networks have wide coverage and powerful broadcasting capabilities, making them a potent communication infrastructure.

This work was supported by Open project of Satellite Internet Key Laboratory in 2022(Research on Elastic Networking Control and Arrangement Technology for Large Scale Satellite Networks).

F. Gao et al. (Eds.): Chinacom 2023, LNICST 590, pp. 112–125, 2024.
https://doi.org/10.1007/978-3-031-67162-3_8

In the information society with exploding data traffic, LEO satellite networks are viewed as a core infrastructure of the next generation of Internet [1], providing low-latency, high-throughput and high-bandwidth global connectivity for terrestrial customers [2]. LEO satellite networks have a wide range of application prospects, such as 6G [3], IoT [4], ground access, and various other services.

Due to the diversity of services in LEO satellite networks, satellite network slicing technology is introduced to guarantee the QoS requirements of different customers. Network slicing refers to the partitioning of multiple logical networks on the same physical network infrastructure. These logical networks are end-to-end and isolated from each other, which all have access, transport and core networks [5]. The isolation between different slices is achieved by resource and security mechanisms, and they are independent of each other with minimal or no interference. Different logical networks can meet different service requirements, thus providing differentiated services for terrestrial customers, such as varying requirements in latency, bandwidth allocation, service reliability, etc. [6]. Therefore, network slicing technology can be applied to different application scenarios, such as video service, gaming service, voice call, etc. Network slicing technology cannot exist independently. Specifically, network slicing can be implemented through Software Defined Network (SDN) and Network Functions Virtualization (NFV) [7]. NFV technology enables the sharing of hardware resources, while SDN technology obtains a centralized and programmable control plane by using the method of control and forwarding separation. As a result, we can dynamically allocate resources on the LEO satellite networks, offering different services for different users.

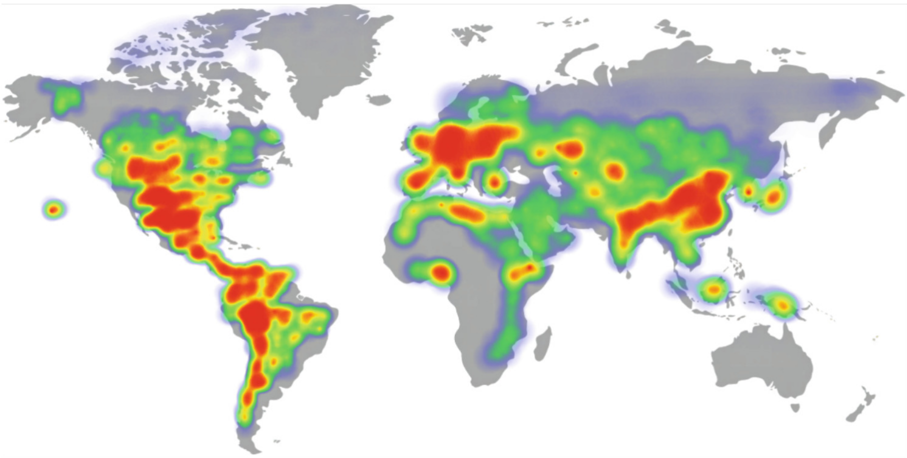

Fig. 1. An example of the traffic dynamics in the satellite network. (Color figure online)

LEO satellite networks face a series of challenges of diversified and differentiated services, as well as the constantly-dynamic topology and terrestrial traffic.

Resources on LEO satellite networks are limited, and traffic intensity demands vary between regions. We give an example in Fig. 1 to illustrate our motivation. Traffic intensive areas are marked in red on the heat map while areas with few terrestrial access are marked in grey. In densely populated urban areas such as large cities, satellite resources experience heavy use to provide diverse services. However, communication and computing capabilities on satellite networks over ocean regions are underutilized. In addition, due to the constant high-speed movement of satellites and the complex space environment, the topology and resource of LEO satellite networks are also dynamically changing [8]. All these dynamic characteristics indicate that traditional resource allocation methods need to be improved to cope with the more stringent requirements. How to reasonably allocate these idle satellite network resources to meet the service quality requirements of various customers and make effective use of various resources on satellite networks is necessary. Therefore, it is essential to allocate the limited satellite network resources effectively, meet the service quality requirements of various customers, and maximize the utilization rate of resources on LEO networks.

In this paper, we propose a heuristic method named MMAS-RA to tackle dynamical resource allocation problem in satellite network slicing. Our objective is to maximize traffic deployment success and resource utilization rate by leveraging the spare resource on satellite networks. MMAS-RA can effectively leverage the bandwidth resource on satellite networks over non-hotspot areas by considering the level of resource shortage as a significant factor of traffic path selection and pheromone updating. In the process of pheromone updating, we adopt the strategy of setting the boundary of pheromone and introduce mutation rate of ant colony for better convergence of the algorithm. Experimental results in four scenarios show that MMAS-RA improves up to 32.26% traffic deployment success rate and 67.02% resource utilization rate compared to the shortest path algorithm for resource allocation (SP-RA).

The main technical contributions of this paper can be summarized as follows:

- We take into account the hotspot areas of traffic and the time periodicity in LEO satellite networks, and formulate the resource allocation problem in satellite network slicing.
- We propose a resource allocation approach based on max-min ant system algorithm to make the effective use of the spare resource on satellite networks.
- We conduct simulations in four typical scenarios of LEO satellite networks. The results show that compared with the previous shortest path for slice resource allocation algorithm, our proposed method can improve up to 32.26% traffic deployment success rate and 67.02% resource utilization rate under the specific scenario.

The rest of this paper is organized as follows. In Sect. 2, the related work is presented. After that, the resource allocation model in LEO satellite networks is formulated in Sect. 3. In Sect. 4, we design a heuristic algorithm to solve the problem, followed by extensive simulations in Sect. 5. At last, we give conclusion in Sect. 6.

2 Related Work

In recent years, research on resource allocation for network slicing has mainly focused on terrestrial wireless access networks and 5G slicing networks, while research on resource allocation for satellite slicing networks is relatively scarce.

Alkhafaji *et al.* [9] proposed a multi-layer network slicing and resource allocation scheme which dynamically adapts the resource allocation and scheduling policies according to the service types and traffic characteristics of different slices. AlQahtani *et al.* [10] designed two operation modes, namely static sharing resource mode and dynamic sharing resource mode, which dynamically adjust the resource allocation according to the demands and states of different slices. Wang *et al.* [11] devised a twin-actor deep deterministic policy gradient algorithm to learn the optimal resource allocation policy for mobile edge network slicing in high-dimensional state space and continuous action space. Azimi *et al.* [12] exploited a collaborative learning framework, which includes deep reinforcement learning and deep learning, to decide on the resource allocation policies on large and small time scales.

Due to the dynamic nature of satellite networks, the resource allocation strategy of satellite network slicing is different from the 5G slicing strategy. Guo *et al.* [13] modeled the network slice allocation problem as a minimum cost flow problem on a time-varying graph, and design an efficient graph algorithm to solve it. Adda *et al.* [14] built a heuristic algorithm based on the Power of Two Choices method, which balances the network load and resource utilization by randomly selecting two candidate nodes and assigning the request to the one with more abundant resources. Suzhi *et al.* [15] designed a network slice allocation algorithm based on greedy algorithm and genetic algorithm to maximize the revenue and utility of satellite networks. Bai *et al.* [16] considered the uncertainty and dynamics of low earth orbit satellite networks, and formulate the network slice admission control and resource allocation problem as a robust integer linear programming problem. Li *et al.* [17] applied an advantage actor-critic (A2C) learning algorithm based on long short-term memory (LSTM) for tracking the user mobility and service demand variations, and dynamically allocate resources to different slices according to the current environment state and reward function. Reinforcement learning-based algorithms require a large amount of training time and data to achieve a certain performance.

However, limited research has examined satellite network slicing in the context of unevenly distributed network hotspots and periodicity over time of LEO satellite networks. In contrast with prior work, we study the problem of resource allocation strategy for satellite network slicing to enhance traffic deployment rates. A heuristic approach based on max-min ant system algorithm is designed to make the effective use of constrained satellite resources.

3 System Model and Problem Formulation

LEO satellite networks are divided into multiple slice networks according to the service type and isolation degree. Resources on the satellite are allocated to each slice network. In this section, we introduce the resource allocation model of the satellite network slicing.

3.1 Network Model

We divide the snapshot time interval according to the satellite orbit period and the aggregation degree of the service requests. The transmission service requests in different slices within this time are based on certain statistical rules when mapped to different satellite nodes within this time. Therefore, for the resource allocation of satellite networks, it can be regarded as the adjustment of satellite resource allocation at each snapshot time point. Assuming that the start time of k-th the time slice of the satellite is t_k, we consider that the resource allocation strategy of the satellite remains unchanged during $[t_k, t_k + 1]$. The satellite network is divided into slices $\{1, \cdots, n\}$. Within the time slice, the resource allocation of satellite node i is expressed as follows:

$$R_i(t_k) = \{s_1(t_k), s_2(t_k), \cdots, s_j(t_k), \cdots, s_n(t_k)\} \tag{1}$$

where $s_j(t_k)$ denotes that the satellite resources allocated to the slice j during $[t_k, t_k + 1]$. The resources dynamically allocated on satellite networks include bandwidth resources. Then the bandwidth resource allocated of each satellite could be calculated as follows:

$$S_i = \sum_{j=1}^{n} s_j(t_k) \tag{2}$$

In addition, the resource utilization rate of satellite i can be calculated by the division of the resource allocated and the total resource of the satellite:

$$E_i(t_k) = \frac{S_i}{S_i^{all}} \tag{3}$$

The inter-satellite links mainly affect the delay of communication, and the bandwidth of the links which constrains the deployment of different traffic. Therefore, we consider two aspects for the inter-satellite links, which are the link distance and link bandwidth.

3.2 Terrestrial Traffic Model

The terrestrial customers in the coverage area of each satellite send resource requests of different service type to the satellite directly connected. If the satellite networks have sufficient resource for the service, the requests are adapted. If not, the requests are refused. For the purpose of better simulating the real traffic requests, the ground traffic requests follow *Poisson Distribution* with different intensities λ, which simulates the situation of uneven service distribution. The intensity of service requests is mainly influenced by two factors: one is the characteristics of the area covered by the satellite, and the other is associated with time. For example, traffic arrival rates are faster in dense urban areas during daytime hours, whereas rates are smaller over areas with sparse services, such as the ocean. Secondly, we also consider the time-periodic characteristics of satellite network services. The request intensity of services change with time and show certain regularity. The traffic arrival rate during $[t_k, t_k + 1]$ of slice i is $\lambda_i(t_k)$.

3.3 Problem Formulation

To make the effective use of the bandwidth resources of LEO satellite networks and improve the traffic deployment success rate, we formulate an optimization model based on this consideration. We aim to maximize the utility function $f(\cdot)$ which is defined as the weighted sum of deployment success rate (DSR), resource utilization rate(RUR), SLA satisfaction ratio (SSR) of different services by dynamically adjusting the allocated resource $w = \{w_1, w_2, \cdots, w_j, \cdots, w_n\}$ to each slice on LEO satellite networks. At the same time, there exist fluctuating terrestrial traffic demands $d = \{d_1, d_2, \cdots, d_j, \cdots, d_n\}$. As is shown in Fig. 2, a resource allocation strategy of satellite slicing must be applied to meet the requirements of different traffic demands. Mathematically, we formulate the optimization objective of resource allocation as:

$$max\ f = \alpha \cdot DSR(d, w) + \beta \cdot RUR(d, w) + \gamma \cdot SSR(d, w), \tag{4}$$

where DSR could be calculated by the ratio of the traffic requests successfully deployed to the total traffic requests, RUR could be calculated by the ratio of the resource leveraged on satellite networks to the total traffic requests while SSR could be computed in terms of the predefined SLAs. α, β and γ denote the relative importance of BGR, RUR and SSR.

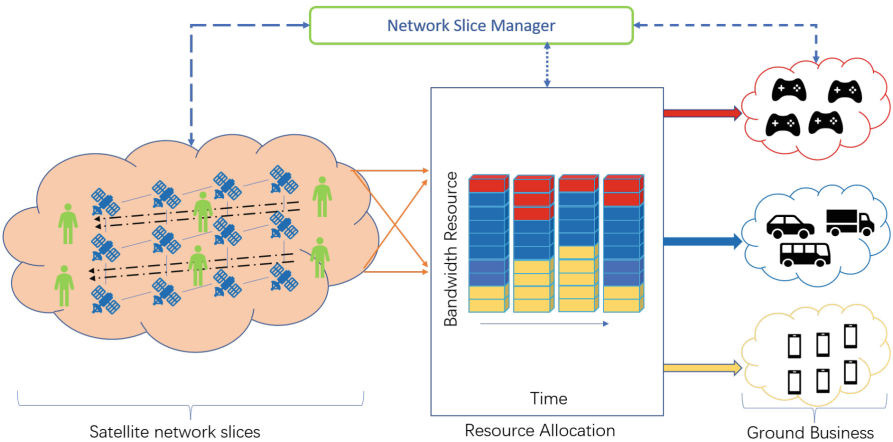

Fig. 2. A specific structure the resource allocation in satellite network slices

Since the traffic demands are uneven among geographical areas and show time periodicity, a heuristic algorithm is adopted to address satellite slice resource allocation problem and find an optimal policy for resource allocation in network slicing.

4 Heuristic Algorithm Design

In this section, we propose a heuristic algorithm based on the max-min ant system algorithm [18,19], which improves the traffic deployment success rate and resource utilization efficiency in satellite network slicing.

The ant colony algorithm is a heuristic algorithm that can solve optimization problems with intuitive logic, multi-objective optimization and low complexity. Specifically, we use the Max-Min Ant System for Resource Allocation (MMAS-RA) to efficiently utilize idle bandwidth resources on LEO satellite networks.

4.1 Structure of MMAS-RA

Algorithm 1 shows the abstract of MMAS-RA algorithm.

In this process, ants act as intermediaries to select suitable resources on satellite nodes for different types of traffic requests. For each traffic request, it would depart from its source satellite and try to allocate bandwidth resources to the corresponding slice along the way, until reaching the target satellite.

For each iterations, ants calculate the pheromone concentration and heuristic information of each inter-satellite link (line 5), and then use this information to calculate the probability of moving to the next hop satellite node (line 6). Ants form a probability set and use the "roulette method" to choose the next hop satellite node. The transfer probability of each node of ant m is defined as follows:

$$p_{ij}^m = \begin{cases} \frac{[\tau_{ij}^\alpha]\cdot[\eta_{ij}^\beta]}{\sum_{j\in set_m}[\tau_{ij}^\alpha]\cdot[\eta_{ij}^\beta]}, & if\ j \in set_m \wedge r < R_{sp}^j \\ 0, & else, \end{cases} \tag{5}$$

where $set_m = \{C - tabu_k\}$, C is the set of all satellite nodes that have inter-satellite links with the satellite i in LEO satellite networks, $tabu_k$ is the taboo list of the ant, which stores the satellite nodes that have already allocated resources to the slice. The parameter α represents the pheromone heuristic factor, while β denotes the expectation heuristic factor, respectively indicating their relative importance. R_{sp}^j denotes the spare bandwidth resources available on satellite j.

The parameter η_{ij} represent the expected degree of using the corresponding satellite, which is determined by factors such as satellite bandwidth availability and inter-satellite link distance. We consider the delay of inter-satellite link and the spare resource proportion of the satellites involved. This way, the network slices aim to maximize the utilization of satellites with more spare resources. The expectation heuristic factor η_{ij} is calculated by the formula below:

$$\eta_{ij} = (\frac{1}{delay_{ij}})^\theta \cdot (\frac{S_j}{S_j^{all}})^{\delta_t}, \tag{6}$$

where θ denotes the importance factor of delay and δ_t denotes the importance factor of the spare resource.

In different time slices, the value of δ_t also changes, which takes into account the periodic variation characteristics of the satellite network hotspot area with time.

After each selection, the ant evaluate whether the selected could meet the requirements of the traffic, and each ant is marked with success or failure (line 7–17). If none of the ants can allocate the resource of satellite nodes for the traffic request, the request is rejected. Then we update pheromone the with *PheromoneUpdating* function (line 23).

Algorithm 1. Algorithm of MMAS-RA

Input: $G(V, E)$: The network topology, where V denotes the set of nodes and E denotes the set of links; R_{sp}: the spare bandwidth resources of satellite nodes; r: the resource required for the terrestrial request.

Output: The slice network resource distribution situation of the satellite nodes *result*

1: Initialize the hyper-parameters of MMAS-RA.
2: **for** t $= 1, 2, \ldots, iterations$ **do**
3:     **for** m $= 1, 2, \ldots, antNum$ **do**
4:         **while** $p_{ij}^{m} \neq \mathbf{0} \wedge set_m \neq \emptyset$ **do**
5:             Calculate the transition probability p_{ij}^{a} according to formula (4)
6:             Select the next satellite node k where the traffic is located according to p_{ij}^{m} by using roulette method
7:             **if** $r < R_{sp}^{j}$ **then**
8:                 Update the path matrix, ant taboo list and the remaining resources of the satellite node
9:                 **if** node j is destination of the traffic **then**
10:                     Mark the current ant with success
11:                     Break
12:                 **end if**
13:             **else**
14:                 Mark the current ant with failure
15:                 Break
16:             **end if**
17:             Mark the current ant with failure
18:         **end while**
19:         **if** The ant is marked with success **then**
20:             Calculate the utility function value of the ant
21:         **end if**
22:     **end for**
23:     Run PheromoneUpdating()
24: **end for**
25: **return** *result*

4.2 PheromoneUpdating Function

Pheromone concentration update is a key step of MMAS-RA algorithm. The dynamic change of pheromone concentration enables the positive feedback mechanism of the ant system algorithm and accelerates its convergence to the optimal solution. For each iteration, the updating of pheromone must be calculated according to Algorithm 2. In each iteration, multiple ants find the resource allocation scheme independently. We then calculate the utility function of each ant (line 1) according to the formula bellow,

$$cost_m = \frac{E_{avg}^{\chi}}{||path_m||^{\kappa}}, \tag{7}$$

where E_{avg} denotes the average resource utilization rate of the satellites passed through by the ant and $||path_m||$ denotes the number of satellites passed along the path. Then update the global pheromone with the pheromone of the best ant (line 2–11) and the pheromone update formula is defined as follows:

$$\tau_{ij} = (1 - \rho_t) \cdot \tau_{ij} + \Delta\tau, \tag{8}$$

where $\Delta\tau$ represents the concentrations released by the ant obtaining the best utility value during the iteration process.

$$\Delta\tau = \sum_{path_{ij} \in paths} \frac{Q}{delay_{ij}^{\theta} \cdot \frac{S_j}{S_j^{all}}^{\delta_t}}, \tag{9}$$

In order to avoid search stagnation, the pheromone is limited to the range of $[\tau_{min}, \tau_{max}]$(line 4–9). When the pheromone exceeds the maximum or minimum value, the pheromone is initialized. According to the defined maximum and minimum intervals, the pheromone that exceeds the boundary is modified to the boundary value, which increases the global search ability. In the initial phase of the algorithm, to prevent the large-scale satellite network from causing difficulties in searching for feasible solutions, we first use the shortest path algorithm to find the path traversed by the source and destination satellites of traffic request, and then set the pheromone value of the inter-satellite links on this path to the maximum value τ_{max}, while initializing all other values in the pheromone matrix to $\tau_{max}/2$. By such initialization processing, we can enhance the search ability of the algorithm. the algorithm can prevent the stagnation caused by the excessive difference of pheromone concentration among different paths to some extent.

To improve the performance of the algorithm, after each iteration of global pheromone update, a mutation operation is performed on the pheromone concentration. The mutation operation is determined by a mutation rate ρ_m (line 12). If the mutation rate is satisfied, a solution path is randomly selected from the current solution set, and a randomly generated pheromone concentration value within the range is used as the pheromone concentration on this path (line 14–17).

Algorithm 2. PheromoneUpdating Function

Select the *path* of the best ant of the iteration from ant solutions *paths*
for each $path_{ij} \in path$ **do**
  Calculate the pheromone concentration τ_{ij} according to formula (7)
  if $\tau_{ij} < \tau_{min}$ **then**
    τ_{ij} is set to τ_{min}
  end if
  if $\tau_{ij} > \tau_{max}$ **then**
    τ_{ij} is set to τ_{max}
  end if
  Update the pheromone matrix according to formula (8)
end for
if $random() < \rho_m$ **then**
  Select a solution $path_r$ from *paths* randomly
  for $path_{ij}$ in *path* **do**
    The value of concentration pheromone τ_{ij} is randomly taken between $[\tau_{min}, \tau_{max}]$
  end for
end if
return The pheromone matrix updated

In the initial iterations, the pheromone evaporation rate ρ_t is kept very low to enhance the search ability of the algorithm. Consequently, during early iterations, pheromone evaporation has a negligible impact on the pheromone outcomes of ant colony movements, thereby facilitating the rapid discovery of optimal solutions in the search process. After reaching a certain number of iterations, ρ_t would gradually increase up to a fixed value, and then remain unchanged for the remaining iterations. The evaporation of pheromone is constrained to prevent local optimum and converges to the global optimum result. As such, the pheromone evaporation rate ρ_t is defined as:

$$\rho_t = \begin{cases} 0.01, & if\ t \leq 20, \\ 0.0032 \cdot t + 0.01, & else\ \ if\ 20 < t \leq 80, \\ 0.2, & else\ \ if\ 80 < t \end{cases} \tag{10}$$

Finally, the pheromone updating function returns an updated pheromone matrix, terminating one iteration of the algorithm.

5 Simulation

5.1 Simulation Settings

In our simulation, we model a LEO satellite network. We assume there are three types of network slices to be deployed in the LEO satellite network. The hyper-parameter settings of MMAS-RA are shown in Table 1. The traffic requests are distributed among all satellites. The hotspot area and traffic requests on each satellite change during the simulation time. We assume that the amount of bandwidth resource of satellites above hot areas is less than other areas. The simulation sustains 24 h which is divided into 96 time slices, and the simulation results are calculated the average value of ten simulations.

Scenarios: In our study, we test our algorithm in four typical scenarios. *1)* hotspot area distribution concentrated; *2)* hotspot area distribution dispersed; *3)* network slices passing through few hotspot areas; *4)* network slices passing through multiple hotspot areas.

Table 1. Hyper-parameters settings of MMAS-RA

Parameters	Description	value
$iterations$	The iteration time of the algorithm	50
$antNum$	The number time of the ant colony	100
α	Pheromone heuristic factor	1.2
β	Expectation heuristic factor	2
Q	Pheromone constant for updating	0.5
ρ_m	Mutation rate	0.1
θ	Distance importance factor	2
δ_t	Bandwidth importance rate	2.5
τ_{max}	The maximum value of pheromone	1.5
τ_{min}	The minimum value of pheromone	0.5

Performance Metrics: We use the following three performance metrics to evaluate our proposed algorithm: *1)* deployment success rate: the ratio of the traffic requests which is successfully deployed to the total traffic requests of satellite networks; *2)* effective throughput: the bandwidth of successfully deployed traffic flows; *3)* average traffic hops: the average hop number of traffic path; *4)* resource utilization rate: the ratio of the bandwidth resource of successfully leveraged to the total bandwidth resource on satellite networks.

Comparisons: We compare our proposed algorithm with the commonly used the shortest path algorithm for resource allocation (SP-RA). SP-RA uses the resource of satellites along the shortest path between the source and the destination of the traffic requests. If any satellite on the path lacks sufficient spare bandwidth capacity, the request will be rejected.

5.2 Simulation Results

Figure 3(a) shows the deployment success rate for three types of slices applying the two algorithms, which is conducted in *scenario1*. We can see that the MMAS-RA algorithm has superior deployment success rates in all three slices. In detail, compared with SP-RA, the MMAS-RA algorithm increases the deployment success rate up to 17.02% in total.

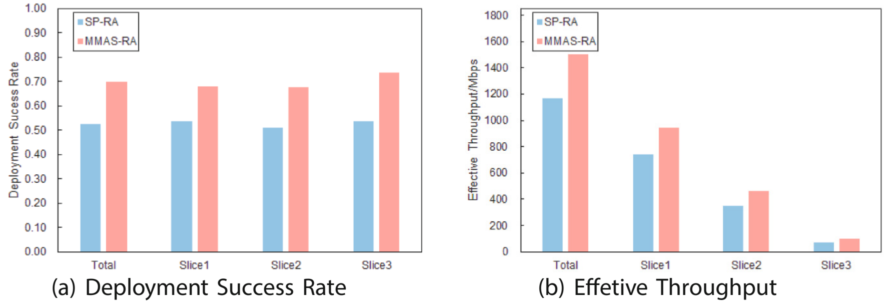

Fig. 3. Simulation results of three types of slices for resource allocation

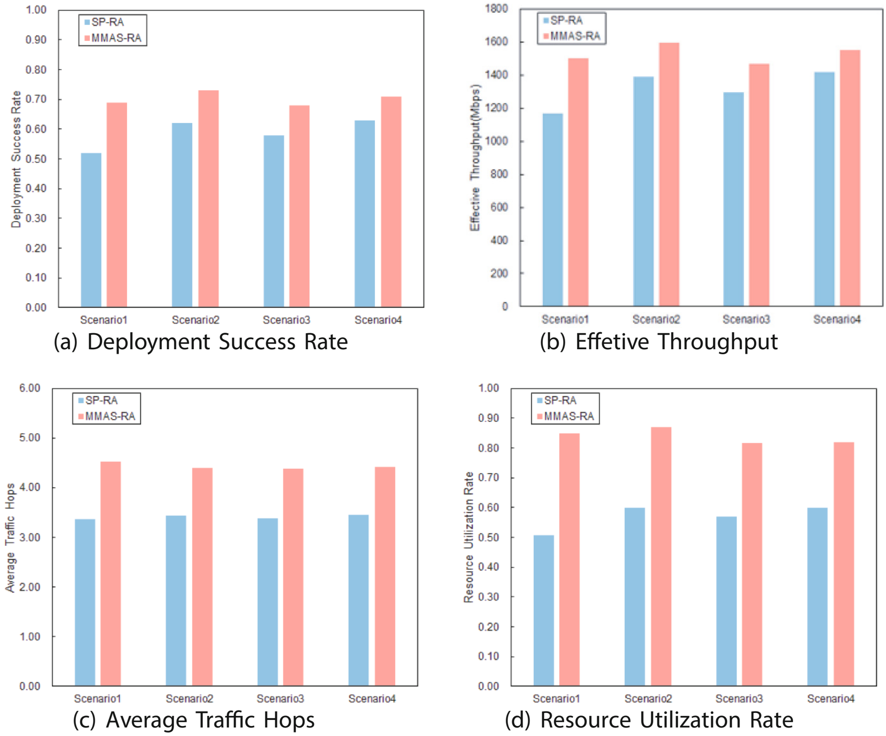

Fig. 4. Simulation results in four scenarios for resource allocation

In addition, the deployment success rate of slice 3 increases up to 32.26%. The reason is that the MMAS-RA algorithm, to improve the utilization of resources on satellites with more spare bandwidth resource, may forward the service along a long path rather than the shortest one. Figure 3(b) shows that the effective throughput of three types of slices. Compared with SP-RA, the MMAS-RA algorithm improves up to 28.92% effective throughput in total. In detail, the effective throughput of slice3 increases up to 37.67%, which gains the best results among three types of slices. Figure 4 shows simulation results of the algorithm we proposed and the shortest path algorithm for resource allocation, including deployment success rate (see in Fig. 4(a)), effective throughput (see in Fig. 4(b)), average traffic hops (see in Fig. 4(c)), resource utilization rate (see in Fig. 4(d)). We can see that the MMAS-RA achieves better deployment success rate, effective throughput and resource utilization rate in the four scenarios. In scenario1 whose hotspot area distribution is concentrated our algorithm achieves the best performance among all scenarios. The resource utilization rate increased 67.02%. However, in scenario4 where network slices pass through multiple hotspot areas, our algorithm improves the deployment success rate by only up to 12.70%, the effective throughput by 9.34%, and the resource utilization rate by 36.51%. The reason is that if satellite networks exist too many hot areas it is difficult to find satellites with sufficient resource for the traffic requests. As is shown in Fig. 4(c), we can see that the average traffic hops of MMAS-RA is bigger than SP-RA. In detail, the average traffic hops increase 30.03% in average than the shortest traffic hops adopted by SP-RA, which is regarded as necessary cost for other higher performance. In scenario1, the average traffic hops increase up to 34.52%. The reason is that network slices may need to take longer paths to avoid hotspot areas with fewer bandwidth resources when those hotspots are concentrated.

6 Conclusion

In this paper, we consider the spare bandwidth resource caused by uneven distribution of terrestrial traffic and study the resource allocation method for LEO satellite network slices. We propose a heuristic algorithm named MMAS-RA to leverage spare bandwidth resources on LEO satellite networks which mainly includes ant colony searching and pheromone updating. Simulation results show that the proposed algorithm can improve the traffic deployment success rate by up to 32.26% and resource utilization rate by up to 67.02% under specific network conditions.

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