Resource allocation algorithm for space-based LEO satellite network based on satellite association

Baochao Liu[1], and Lina Wang[1*]
[1] School of Computer and Communication Engineering, University of Science and Technology Beijing
Beijing, 100083 China
[e-mail: Liubaochao1997@163.com, wln_ustb@126.com]
[*]Corresponding author: Lina Wang

Received February 20, 2024; revised May 14, 2024; accepted June 9, 2024; published June 30, 2024

Abstract

As a crucial development direction for the sixth generation of mobile communication networks (6G), Low Earth Orbit (LEO) satellite networks exhibit characteristics such as low latency, seamless coverage, and high bandwidth. However, the frequent changes in the topology of LEO satellite networks complicate communication between satellites, and satellite power resources are limited. To fully utilize resources on satellites, it is essential to determine the association between satellites before power allocation. To effectively address the satellite association problem in LEO satellite networks, this paper proposes a satellite association-based resource allocation algorithm. The algorithm comprehensively considers the throughput of the satellite network and the fairness associated with satellite correlation. It formulates an objective function with logarithmic utility by taking the logarithm and summing the satellite channel capacities. This aims to maximize the sum of logarithmic utility while promoting the selection of fewer associated satellites for forwarding satellites, thereby enhancing the fairness of satellite association. The problems of satellite association and power allocation are solved under constraints on resources and transmission rates, maximizing the logarithmic utility function. The paper employs an improved Kuhn-Munkres (KM) algorithm to solve the satellite association problem and determine the correlation between satellites. Based on the satellite association results, the paper uses the Lagrangian dual method to solve the power allocation problem. Simulation results demonstrate that the proposed algorithm enhances the fairness of satellite association, optimizes resource utilization, and effectively improves the throughput of LEO satellite networks.

Keywords: Low Earth Orbit (LEO), satellite association, throughput, resource allocation, Kuhn-Munkres algorithm

This paper is supported by the National Natural Science Foundation of China under Grants No. 61701020.

http://doi.org/10.3837/tiis.2024.06.012 **ISSN : 1976-7277**

1. Introduction

In the upcoming era of 6G communication, satellite internet based on LEO networks will become an indispensable extension of ground communication networks. Due to the proximity of LEO satellite networks to the Earth's surface, they can provide ground users with low-latency, low-loss, and globally covered communication services. Additionally, LEO satellites have lower maintenance costs and shorter research cycles compared to other types of satellites in the 6G network. As a result, research on satellite communication focusing on LEO satellites has been widely recognized [1] . Many countries have successively proposed their plans to build LEO satellite internet constellations. Typical large constellations include the Starlink constellation in the United States, the OneWeb constellation in the United Kingdom, and the GW-2 constellation in China[2].

Despite this, the deployment speed of LEO satellites still struggles to meet the growing wireless service demands of ground users. In satellite networks, the discontinuity of inter-satellite links, limitations in the number of transceivers, and power resources further challenge the performance of satellite network resources[3]. To fully utilize resources in LEO satellite networks, it is essential to implement satellite association using reasonable association algorithms before resource allocation. Satellite association, as a critical technology in resource management, can achieve load balancing and interference management, aiming to enhance user throughput.

In the context of the complex topology of LEO satellite networks, although traditional Maximum Signal-to-Interference-plus-Noise Ratio (SINR) algorithms can enhance the throughput of individual satellites, they may lead to overload on accessing satellites with favorable channel conditions, while satellites with poor channel conditions may experience underutilization[4]. This results in suboptimal utilization of satellite network resources and a decrease in overall network throughput. Therefore, addressing how to establish reasonable associations to achieve load balancing in satellite networks and thereby enhance overall network performance is a pressing issue.

This paper effectively addresses the satellite association problem using an improved Kuhn-Munkres (KM) algorithm. Subsequently, based on the obtained association solution, a power allocation algorithm is employed to optimize power distribution, effectively improving the throughput of the satellite network and enhancing fairness in satellite associations. The contributions of this paper are summarized as follows.

1) We establish a resource allocation model for LEO satellite networks based on the actual communication scenarios of accessing satellites and forwarding satellites. To enhance the fairness of associations, we take the logarithm of satellite channel capacities and sum them to obtain an objective function with logarithmic utility.
2) To address the satellite association problem, we utilize an improved KM algorithm. By extending the virtual satellites, we ensure that the number of nodes on the left and right sides of the bipartite graph are equal, transforming the original many-to-one matching problem into a one-to-one matching problem. Ultimately, we determine the association between accessing satellites and forwarding satellites by solving the maximum weighted matching in the bipartite graph.
3) After obtaining the results of satellite association, we obtain the mathematical model of power allocation between accessing satellites and relay satellites and prove that it is a convex optimization problem by mathematical derivation. The constraints are integrated into the objective function using the Lagrangian dual method, and the optimal power solution is obtained through iterative refinement.

The remaining sections of this paper are organized as follows. In Section II, we present related work. Section III introduces the transmission model for communication among LEO satellites and establishes a resource allocation model based on this transmission model. In Section IV, we utilize an improved KM algorithm to address the satellite association problem in resource allocation. Based on the results of the satellite association, we employ the Lagrangian dual algorithm to solve the optimal power allocation. In Section V, we conduct simulation experiments and analyze the simulation results. Finally, in Section VI, we draw conclusions based on the findings.

2. Related Work

In some existing research on inter-satellite resource allocation, Panayiotou et al [5] propose a multi-objective optimization function that simultaneously optimizes QOS fairness and network efficiency to obtain the fairest possible distribution without reducing network utilization. However, the sensitivity of the approximated function has limitations Wang et al [6] use the successive approximation method to solve time and power allocation in cellular networks in order to maximize the minimum value of energy harvest and allocates spectrum resources by constructing a fair allocation mechanism. However, the comparative experiment only considered the simplest genetic algorithm and Average time algorithm, with no comparison with the machine learning algorithm. Bandopadhyay et al [7] propose a distributed resource allocation strategy for multi-star collaboration networks, which reduces the matching error between business requests and achievable throughput. Zhao et al [8] first use deep reinforcement learning to solve task offloading and channel allocation sub-problems, and then use convex optimization algorithms to solve the calculation allocation problem. Zhao et al [9] proposed an adaptive joint resource allocation scheme based on deep reinforcement learning, including the allocation of uplink, computing, and downlink resources, which effectively improved the performance of the system while meeting the constraints of task delays and system resources.

A reasonable association strategy not only achieves load balancing in satellite networks but also significantly enhances the utilization efficiency of on-board resources. Huang et al [10] proposed a dynamic hierarchical game method to study user association and resource allocation in heterogeneous networks. The user layer uses an evolutionary game method to model user base stations. At the resource layer, a resource allocation mechanism based on Stackeberg differential game is proposed. Zhou et al [11] jointly perform the switching operation of the base station and user association to obtain better association effects. Jiang et al [12] proposed a dynamic user association strategy, which reduced excessive iteration consumption and unexpected group switching during continuous service, and improved the overall utility of the network. Mahmoudi et al [13] are based on an efficient user clustering algorithm to establish fairness among all users based on user success probability, thereby improving system throughput. Khoshkbari et al. [14] proposed a deep recursive Q network method to solve the associated solution, but it requires powerful computing power to train the neural network. Xue et al [15] consider a hybrid association under a user-centric architecture, which minimizes the blocking effect and thus optimizes the power allocation problem. Xia et al [16] proposed a joint user association and bandwidth allocation algorithm to maximize system message throughput but did not consider user fairness in semantic meaning. Zhang et al [17] proposed an adaptive joint resource allocation scheme based on deep reinforcement learning, including the allocation of uplink, computing, and downlink resources, which effectively improved the performance of the system while meeting the constraints of task delays and system resources.

This article proposes a satellite-associated LEO satellite network resource allocation algorithm, addressing the complex topology of LEO satellite networks and limited onboard resources. An optimization model is established from the perspectives of network throughput and fairness. Since this optimization problem is a Mixed-Integer Nonlinear Programming (MINLP) problem, it cannot be directly solved. The article decomposes it into satellite association subproblems and power allocation subproblems for resolution.

In the satellite association subproblem, the Kuhn-Munkres (KM) algorithm is introduced to determine the satellite associations. The article addresses this by extending virtual satellites, making the number of nodes on both sides equal. The number of virtual satellites is determined based on the visibility of each access satellite to the forwarding satellites. This transforms the original many-to-one matching problem into a one-to-one matching problem, obtaining the satellite matching results. Based on the matching results, the optimal power solution for associated forwarding satellites is obtained for each access satellite using the Lagrangian dual method.

3. Satellite constellation model

3.1 LEO Satellite Constellations

The LEO satellite network studied in this article adopts the Walker constellation, which is composed of orbiting satellites with the same altitude and inclination. On each orbit plane in the constellation, all satellites are symmetrically and uniformly distributed. Three parameters mainly represent the satellite orbits of the Walker constellation (N,P,F), N represents the total number of satellites P Represents the number of orbits, and F represents the phase factor. The relationship between the right ascension of the ascending node and the angular distance of the ascending node of any satellite numbered in the Walker constellation is as follows:

$$\begin{cases} W=\dfrac{360}{P}(P_i-1),\ (P_i=1,2,...,P) \\ u_i=\dfrac{360}{s}(N_i-1)+\dfrac{360}{N}F(P_i-1),\ (N_i=1,2,...,S-1) \end{cases} \tag{1}$$

Among them, S represents the number of satellites on each orbital plane, P_i is the number of satellites in the orbital plane, and is the number of satellites in the orbital plane. The basic constellation configuration of the LEO satellite network set in this article is walker(60/10/1), with an orbital altitude of 800km and an orbital inclination angle of 68.5° The constellation diagram of this configuration was obtained through simulation using Satellite ToolKit software, as shown in **Fig. 1**.

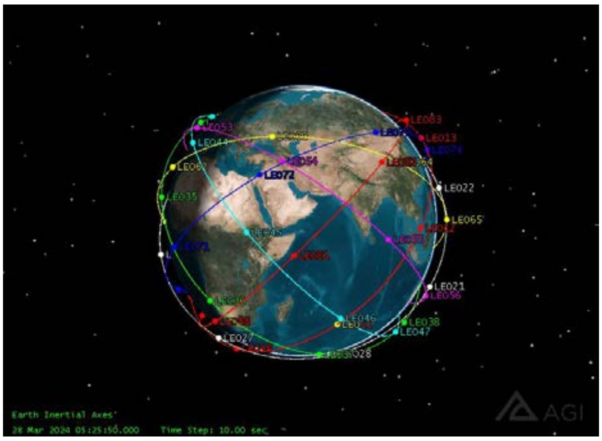

Fig. 1. Walker constellation diagram

3.2 Satellite Visibility Analysis

In LEO satellite constellations, the relative position of satellites and the establishment of links are constantly changing dynamically. For the problem of resource allocation in LEO satellite networks, it is necessary to first determine whether the two satellites are visible before resource allocation can be carried out. Generally speaking, satellite visibility generally needs to meet the following two conditions: inter-satellite geometric constraints and satellite antenna constraints.

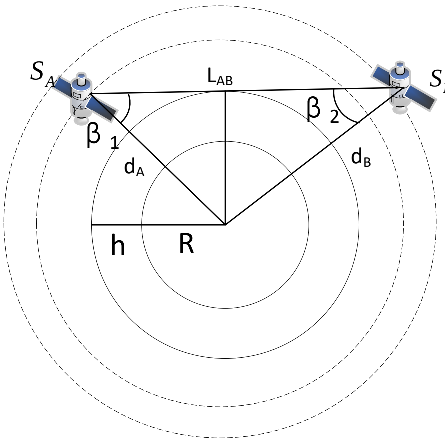

Fig. 2. Interstellar geometric visual constraints

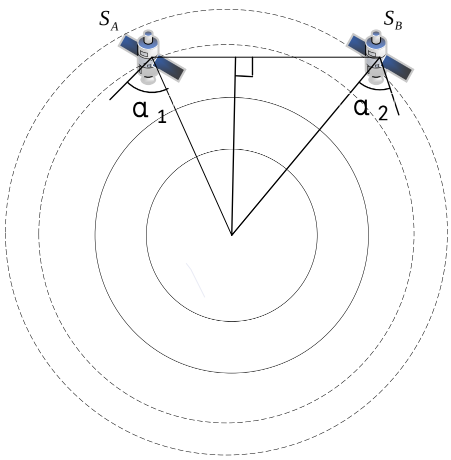

Fig. 3. Intersatellite antenna visual constraints

3.2.1 Interstellar geometric constraints

Fig. 2 shows the critical state in which S_A and S_B can establish an inter-satellite link, and the geometric relationship should satisfy

$$\begin{cases} \theta_1 > \beta_1 = \arcsin((R+h)/(R+h+d_A)) \\ \theta_2 > \beta_2 = \arcsin((R+h)/(R+h+d_B)) \end{cases} \tag{2}$$

Therefore, the inter-satellite distance constraint between satellite S_A and satellite S_B can be expressed as:

$$L_{AB} < \sqrt{(R+h+d_A)^2-(R+h)^2} + \sqrt{(R+h+d_B)^2-(R+h)^2} \tag{3}$$

Among them, the orbital heights of satellite S_A and satellite S_B are d_A and d_B, respectively. The distance between the two satellites is L_{AB}, the radius of the Earth is R, and the thickness of the atmosphere is h, θ_1 denotes the pitch angle of satellite S_B relative to satellite $\boldsymbol{S_A}$ and θ_2 denotes the pitch angle of satellite $\boldsymbol{S_A}$ relative to satellite $\boldsymbol{S_B}$.

3.2.2 Visible constraints on interstellar antennas

Fig. 3 shows the critical state where both satellite S_A and satellite S_B antennas are within each other's scanning range, and at this point, they should meet the following conditions

$$\begin{cases} \theta_1 < \alpha_1 \\ \theta_2 < \alpha_2 \end{cases} \tag{4}$$

Therefore, the inter satellite distance constraint between satellite S_A and satellite S_B can be expressed as

$$L_{AB} > (R+h+d_A)\cos\alpha_1 + (R+h+d_B)\cos\alpha_2 \tag{5}$$

Among them, α_1 and α_2 are the maximum scanning angles of the two satellites. After comprehensively analyzing the visibility constraints between satellites, it is concluded that the conditions under which any two satellites can establish an inter-satellite link are

$$(d_A+R)\cos\alpha_1 + (d_B+R)\cos\alpha_2 < L_{AB} < \sqrt{(R+d_A)^2-R^2} + \sqrt{(R+d_B)^2-R^2} \tag{6}$$

4. System model and problem formulation

4.1 System model

The setting of this paper is an LEO satellite network as depicted in **Fig. 1**. Within the LEO network, there are two sets of satellite nodes. The first is the accessing satellite Node Set, and the second is the Forwarding Satellite Node Set. In the LEO satellite network, accessing satellites receive data transmitted from ground stations and transfer the data to the associated forwarding satellites through inter-satellite links. The forwarding satellites then forward the data to ground users or other satellites, thereby providing communication services to remote areas. In the LEO satellite network, each satellite has the potential to access data, but for a specific region's ground station, the accessing satellite that receives data is determined by certain standards[18]. For forwarding satellites, not all accessing satellites are visible. Each forwarding satellite can only be associated with one access satellite, while an access satellite can transmit data to multiple forwarding satellites[19].

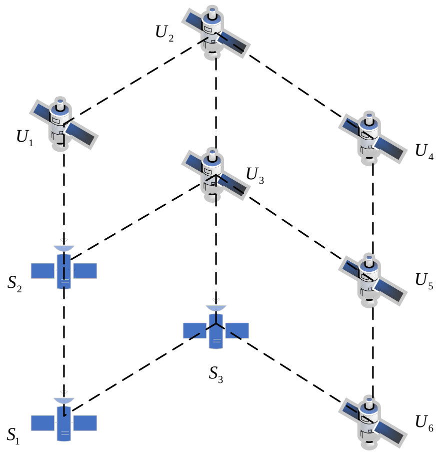

Fig. 4. System model

In the LEO satellite network, for each forwarding satellite U_i, if U_i is associated with S_j, the received SINR for forwarding satellite U_i can be expressed as

$$SINR_{ji} = \frac{P_{ji}\left|h_{ji}\right|^2}{\sum_{k \neq j}^{N} P_{ki}\left|h_{ki}\right|^2 + \sigma}, i \in [1, M], j \in [1, N], k \in [1, N] \text{且} \mathrm{k} \neq j \tag{7}$$

P_{ji} represents the transmission power from access satellite S_j to the forwarding satellite U_i. $\sum_{k \neq j}^{N} P_{ki}\left|h_{ki}\right|^2$ denotes the interference received by forwarding satellite U_i from other accessing satellites. σ represents the power of Gaussian white noise. In the equations, h_{ji} signifies the channel state factor between the accessing satellite S_j and the forwarding satellite U_i, expressed as the following expression

$$h_{ji} = \frac{\sqrt{G_R G_T}}{4\pi \dfrac{d_{ji}}{\lambda}} \tag{8}$$

We define variable x_{ji} as the associated variable of the forwarding satellite indicating whether the accessing satellite S_j is accessed. If $x_{ji} = 1$, it indicates the association between the forwarding satellite U_i and the accessing satellite S_j, otherwise, $x_{ji} = 0$. The number of forwarding satellites associated with the accessing satellite S_j is defined as A_j. Therefore, the channel capacity that forwarding satellite U_i can obtain is

$$R_{ji} = x_{ji} \frac{B_j}{A_j} \log_2(1 + SINR_{ji}) \tag{9}$$

Where B_j represents the available bandwidth for the accessing satellite S_j, and the available bandwidth for the accessing satellite S_j is evenly distributed among the associated forwarding satellites. The channel capacity of the entire network can be expressed as

$$R = \sum_{j=1}^{N}\sum_{i=1}^{M} x_{ji} B_{ji} \log_2(1+SINR_{ji}) \tag{10}$$

4.2 Problem formulation

In order to enhance the throughput of the entire satellite network during the actual transmission process, this paper sets the objective function to maximize the channel capacity of the entire network. In this paper, the relationship between accessing satellites and forwarding satellites is represented by the correlation variable x_{ji} and satisfies the condition

$$\begin{cases} x_{ji} = \{0,1\} \\ \sum_{j=1}^{N} x_{ji} = 1 \end{cases} ,1 \le \mathrm{i} \le \mathrm{M}, 1 \le \mathrm{j} \le \mathrm{N} \tag{11}$$

In the formula(11), $x_{ji} = \{0,1\}$ represents the associated variable as a binary variable. $x_{ji} = 1$ indicates the association between the accessing satellite S_j and the forwarding satellite U_i. $x_{ji} = 0$ signifies the lack of association between the accessing satellite S_j and the forwarding satellite U_i. $\sum_{j=1}^{N} x_{ji} = 1$ implies that, for the forwarding satellite U_i, there is one and only one access satellite associated with it. Combining these conditions with constraints on satellite power resources and channel capacity, we can obtain the following mathematical model

$$\begin{aligned} & \max \sum_{j=1}^{N}\sum_{i=1}^{M} x_{ji} \frac{B_j}{A_j} \log_2(1+SINR_{ji}) \\ & a(1): x_{ji} = \{0,1\} \ ,1 \le i \le M, 1 \le j \le N \\ & a(2): \sum_{i=1}^{M} x_{ji} P_{ji} + P_c \le P_{jt} \ ,1 \le j \le N \\ & a(3): \sum_{j=1}^{N} x_{ji} = 1 \ ,1 \le i \le M \\ & a(4): R_{\min} \le \sum_{j=1}^{N} x_{ji} \frac{B_j}{A_j} \log_2(1+SINR_{ji}) \le R_{\max} \ ,1 \le i \le M \end{aligned} \tag{12}$$

Where $a(1)$ represents that the associated variable is a binary variable. $a(2)$ represents power constraints, where P_{ji} is the transmission power from the accessing satellite S_j to the forwarding satellite, P_c represents static circuit power, and P_{jt} represents the total available power of the accessing satellite. $a(3)$ indicates that the forwarding satellite can only be associated with one access satellite. $a(4)$ represents channel capacity with maximum and minimum constraints.

5. Resource allocation algorithm based on satellite association

Due to the binary integer constraints in the constraint conditions of Formula (12), the resource allocation problem in this article can be regarded as a MINLP problem and cannot be directly solved. To solve this problem, we decompose it into satellite association subproblems and power allocation subproblems. Firstly, the association algorithm is used to determine the association relationship between satellites, and then the optimal power solution between the accessing satellite and the forwarding satellite is solved under resource constraints based on the association relationship.

For the satellite association subproblem, this paper employs an improved KM algorithm to solve it. The traditional KM algorithm can only solve one-to-one matching problems when determining matching relationships, while the satellite association subproblem in this paper is a many-to-one matching problem. Therefore, by introducing virtual satellites, this paper equalizes the number of matching sides, transforming the original many-to-one matching problem into a one-to-one matching problem. Subsequently, the KM algorithm is utilized to solve the maximum weight matching in the bipartite graph, ultimately determining the association between accessing satellites and forwarding satellites. As for the power allocation subproblem, after establishing the association relationships between satellites, power allocation is conducted for each access satellite and its associated forwarding satellite. Since power allocation is a convex optimization problem, this paper employs the Lagrangian dual method to integrate the constraints into the objective function, thus transforming the original problem into its dual problem for solving.

5.1 Satellite association algorithm based on improved KM

Before allocating resources to the LEO satellite network, it is essential to address the association problem between accessing satellites and forwarding satellites. A reasonable satellite association strategy can effectively enhance the overall system performance of the network. To effectively address the satellite association problem in LEO satellite networks and improve the rationality of resource allocation, this paper proposes a satellite association algorithm based on an improved KM algorithm. This algorithm not only enhances the throughput of the entire network but also ensures load balancing for accessing satellites, thereby improving the fairness of satellite associations.

In order to better solve the associated solution between accessing satellites and forwarding satellites, we assume that the power allocated by the accessing satellite to each forwarding satellite is the same, and bandwidth resources are evenly distributed. The mathematical model can be represented as follows

$$\begin{aligned}
&\max \sum_{j=1}^{N}\sum_{i=1}^{M} x_{ji}\frac{B_j}{A_j}\log_2(1+SINR_{ji}) \\
&b(1): x_{ji}=\{0,1\}\ ,1\le i\le M,1\le j\le N \\
&b(2): \sum_{j=1}^{N} x_{ji}=1\ ,1\le \mathrm{i}\le \mathrm{M}
\end{aligned} \tag{13}$$

We assume that during the determination of the association relationship, the transmit power for each forwarding satellite accessing the satellite is fixed, and the SINR received by the forwarding satellite is constant, neglecting changes in channel conditions[20]. According to reference [21], the traditional association strategy is based on the maximum SINR received by the user to determine the association relationship. When certain forwarding satellites are relatively close to a specific access satellite, it may lead to too many forwarding satellites accessing that access satellite, causing an imbalance in the load between accessing satellites and wasting a significant amount of network resources [22]. To ensure load balance between accessing satellites, considering both the number of associated forwarding satellites and network throughput, the logarithm of the objective function is taken [23]. The mathematical model of the association subproblem can be transformed as follows

$$\begin{aligned}
&\max \sum_{j=1}^{N}\sum_{i=1}^{M}\log_2(x_{ji}\frac{B_j}{A_j}\log_2(1+SINR_{ji}))\\
&b(1): x_{ji}=\{0,1\}\ ,1\le i\le M,1\le j\le N\\
&b(2): \sum_{j=1}^{N}x_{ji}=1\ ,1\le \mathrm{i}\le \mathrm{M}
\end{aligned}\tag{14}$$

The paper discusses the application of the KM algorithm to solve the above-mentioned model. The traditional KM algorithm is used to solve one-to-one matching relationship problems. In **Fig. 5**, the nodes on the left represent forwarding satellites, and the nodes on the right represent accessing satellites. Dashed connections between the nodes on the left and right represent visual relationships, and The weight numbers on the dashed line represent correlation metrics, indicating the benefits brought about by the association. Finally, by solving the maximum weight matching problem under the optimal matching, the associated relationship is determined. From **Fig. 5**, it can be seen that in this paper, the matching relationship between accessing satellites and forwarding satellites is a many-to-one matching. Therefore, the traditional KM algorithm cannot directly solve this, and it is necessary to transform the many-to-one matching problem into a one-to-one matching problem.

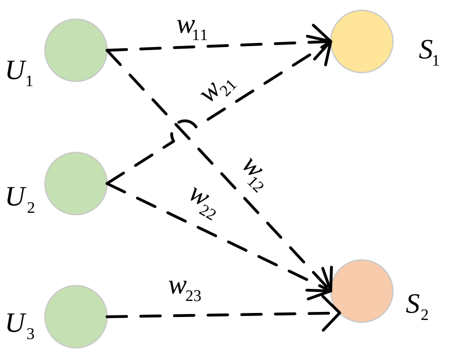

Fig. 5. Bipartite graph model between satellites based on traditional KM algorithm

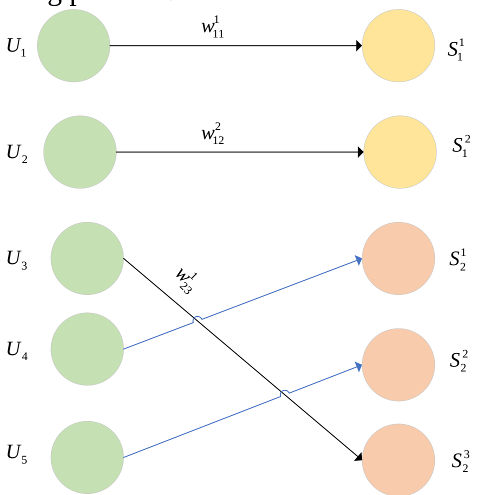

Fig. 6. Matching results between satellites based on improved KM algorithm

In this paper, virtual satellites are added to the accessing satellites S_j and forwarding satellites U_i in a bipartite graph. The number of visual forwarding satellites for each access satellite S_j is defined as L_j and for each access satellite S_j, the quantity is increased to L_j by adding virtual accessing satellites. The virtual vertex set of accessing satellites S_j is defined as F_j, which includes L_j virtual access satellite nodes. These virtual access satellite nodes are numbered as $S_j^1, S_j^2, S_j^3 ... S_j^{L_j}$ for the L_j virtual access satellite nodes. Therefore, the total number of accessing satellites is $\sum_{j=1}^{N} L_j$. Adding virtual forwarding satellites increases the forwarding satellites from the original M to $\sum_{j=1}^{N} L_j$, so the quantities of accessing satellites and forwarding satellites are the same, and can be solved using the KM algorithm. However, to ensure that the final solution is not affected by virtual forwarding satellites, the weight of the added virtual forwarding satellites on the matching edges should be set to zero. Count the forwarding satellite $S_j^l, 1 \le l \le L_j$ matched with $U_i, 1 \le i \le M$,which is the actual forwarding satellite associated with the accessing satellite S_j . The counted forwarding satellites matched with the accessing satellites do not include virtual forwarding satellites with matching edge weights of 0. **Fig. 6** shows the matching results obtained based on the improved KM algorithm. The nodes on the left represent forwarding satellite nodes, U_3 and U_4 are the added virtual forwarding satellites with matching edge weights of 0. The final matching results are: the accessing satellite S_1 is associated with the forwarding satellites U_1 and U_2 ,and the accessing satellite S_2 is associated with the forwarding satellite S_3 .

We assume that A_j accessing satellites are matched with the first A_j virtual forwarding satellites. If forwarding satellite U_i is associated with virtual access satellite S_j^f , $S_j^f \in F_j$, where $1 \le f \le A_j$, we define the weight of the matching edge as w_{ji}^f . Based on the objective function in formula (8) and the properties of the logarithmic function, the weight is defined as follows

$$w_{ji}^f = \log_2\left[B_j \log_2(1+SINR_{ji})\right], \quad \mathrm{A}_j = 1 \tag{15}$$

$$w_{ji}^f = \log_2\left[B_j \log_2(1+SINR_{ji})\right] + (A_j - 1)\log_2(A_j - 1) - A_j \log_2 A_j, \quad 2 \le \mathrm{A}_j \le M \tag{16}$$

Therefore, when A_j forwarding satellites are associated with access satellite S_j , the sum of their weights is equivalent to the sum of weights of the first A_j virtual accessing satellites and A_j forwarding satellites, where the sum is $\sum_{i=1}^{M}\sum_{f=1}^{A_j} w_{ji}^f x_{ji}^f$, and x_{ji}^f is a binary association variable. When $x_{ji}^f = 1$, it indicates that the fth virtual access satellite node of access satellite S_j is associated with forwarding satellite U_i ; otherwise, it is not associated. Thus, the original problem is transformed into the optimal matching problem between virtual accessing satellites and virtual forwarding satellites.

$$\begin{aligned} &\max \sum_{j=1}^{N}\sum_{i=1}^{M}\sum_{f=1}^{A_j} w_{ji}^f x_{ji}^f \\ &c(1): \sum_{j=1}^{N}\sum_{f=1}^{A_j} x_{ji}^f = 1 \\ &c(2): x_{ji}^f \in \{0,1\} \end{aligned} \tag{17}$$

where $c(1)$ represents virtual forwarding satellite U_i will be associated only with one virtual access satellite. $c(2)$ represents x_{ji}^f as a binary correlation variable. Since the original problem has been transformed into a one-to-one matching problem, it can be solved using the KM algorithm.

The time complexity of using the KM algorithm to solve satellite-related optimization problems is related to the number of forwarding satellites that have a visual relationship with the access satellite. Its time complexity is $O(L^3)$, which is much smaller than the time complexity $O(N^L)$ of the exhaustive algorithm. Moreover, in this article, the number of visible satellites with the access satellite in the low-orbit satellite network is much smaller than the total number of forwarding satellites M. Therefore, this article solves the satellite correlation problem with less algorithm complexity, thereby making the use of satellite network resources more fully.

5.2 Power Allocation Algorithm

Once the relationship between the forwarding satellite and the accessing satellite is determined, we can obtain the mathematical model for the power allocation subproblem

$$\begin{gathered} max\sum_{i=1}^{A_j} R_{ji} = \sum_{i=1}^{A_j} B \cdot log_2\left(1 + SINR_{ji}\right) \\ c(1): \sum_{i=1}^{A_j} P_{ji} + P_c \le P_{jt} \\ c(2): R_{min} \le B \cdot log_2(1 + SINR_{ji}) \le R_{max} \end{gathered} \tag{18}$$

The following demonstrates that Formula (18) is a convex optimization problem:
In formula (18), the constraints are all linear constraints. Therefore, for any power solution, the variables P_{ji_1} and P_{ji_2} satisfy

$$A \cdot P_{ji_1} \le b, A \cdot P_{ji_2} \le b \tag{19}$$

If $0 \le \theta \le 1$, then

$$A(\theta P_{ji_1} + (1-\theta)P_{ji_2}) = \theta A P_{ji_1} + (1-\theta)AP_{ji_2} \le \theta b + (1-\theta)b = b \tag{20}$$

Therefore, the feasible domain of Formula (18) is a convex set. It is only necessary to prove that the objective function is a concave function. Due to $\frac{\partial^2 R_{ji}}{\partial P_{ji}^2} = -\frac{B\ln 2\left|h_{ji}\right|^4}{(\sum_{k\ne j}^{N} P_{ji}\left|h_{ki}\right|^2 + \sigma)^2} < 0$, the objective function is concave, making Formula (18) a convex optimization problem. Utilizing the Lagrangian dual method to transform it into a dual problem for further solution, the Lagrangian function can be expressed as follows

$$L(P_{ji}) = \sum_{i=1}^{A_j} R_{ji} - \beta_1(\sum_{i=1}^{A_j} P_{ji} + P_0 - P_{total}) + \beta_2(R_{ji} - R_{\min}) + \beta_3(R_{\max} - R_{ji}) \tag{21}$$

The problem can be further reformulated as the Lagrangian dual problem, expressed as follows

$$\begin{gathered} \min_{\beta_1,\beta_2} \max_{P_i} L(P_{ji}, \beta_1, \beta_2, \beta_3) \\ s.t. \beta_1 \ge 0, \beta_2 \ge 0, \beta_3 \ge 0 \end{gathered} \tag{22}$$

The optimization problem modeled in Equation (22) consists of two sub-problems, namely, the internal maximization sub-problem and the external minimization sub-problem, which can be iteratively solved. Given a set of Lagrange multipliers, the internal maximization sub-problem can be solved to obtain a locally optimal power solution, which is then used to solve the external minimization sub-problem to obtain updated Lagrange multipliers.

By calculating the derivative of the Lagrangian function with respect to P_{ji} , we obtain the local optimal power allocation strategy

$$\frac{\partial L}{\partial P_{ji}}=\frac{B\left|h_{ji}\right|^{2}}{\ln 2(\sum_{k\neq j}^{N}P_{ji}\left|h_{ki}\right|^{2}+\sigma)}-\beta_{1}+\frac{\beta_{2}B\left|h_{ji}\right|^{2}}{\ln 2(\sum_{k\neq j}^{N}P_{ji}\left|h_{ki}\right|^{2}+\sigma))}-\frac{\beta_{3}B\left|h_{ji}\right|^{2}}{\ln 2(\sum_{k\neq j}^{N}P_{ji}\left|h_{ki}\right|^{2}+\sigma))} \tag{23}$$

$$P_{ji}(k+1)=\left[P_{ji}(k)+m\frac{\partial L}{\partial P_{ji}}\right]^{+} \tag{24}$$

In the formula, m represents the iteration step size, $z^{+}=\max\{z,0\}$, The iterative formulas for the corresponding Lagrange multipliers are as follows

$$\beta_{1}^{k+1}=[\beta_{1}^{k}-q_{1}(P_{tatal}-\sum_{i=1}^{M}P_{ji})]^{+} \tag{25}$$

$$\beta_{2}^{k+1}=\left[\beta_{2}^{k}-q_{2}(R_{ji}-R_{\min})\right]^{+} \tag{26}$$

$$\beta_{3}^{k+1}=\left[\beta_{3}^{k}-q_{3}(R_{\max}-R_{ji})\right]^{+} \tag{27}$$

In the formula, q_1, q_2 and q_3 are all iteration step sizes.

6. Simulation results and analyses

6.1 LEO Satellite Network Parameters

In order to better reflect the advantages of the algorithm, the comparison experiment here uses the maximum SINR correlation algorithm in the literature [4] and the K-means algorithm proposed in the literature [24] for comparison. In this study, a new scenario was created using the Satellite Tool Kit (STK), with the scenario time set from 14 Jun 2023 04:00:00.000 to 14 Jun 2023 05:00:00.000. Reference [25] was consulted to generate a walker satellite constellation by creating seed satellites with specific parameters as outlined in **Table 1**.

Table 1. Walker constellation parameter settings

Parameter name	Parameter value
Type	Delta
Number of satellites per satellite plane	10
Number of planes	6
Inter plane spacing	1
RAAN spread	360 deg
Inclination	86.4 deg
Altitude	780 Km

This article assigns numbers 1 to 6 to six orbital planes, and accessing satellites are randomly distributed along the satellite orbits. The forwarding satellites are set to be in the line of sight with the accessing satellites. According to references [18] and [26], the parameters of the satellite network are set as shown in **Table 2**. Using STK (Systems Tool Kit) to analyze the visibility constraints between satellites, the connectivity status between satellites at any given time can be determined. Subsequently, utilizing the interface between MATLAB and STK, the information of the link visibility matrix in the report and the distance matrix between satellites are passed to MATLAB. MATLAB is then used to model the channels based on this information.

Table 2. Satellite network parameter settings

Parameter	Value
Total transmit power of the host satellites	100W
Free space loss	209.54dB
Avaiable bandwidth of each host satellite	[20,40,30,25,30]MHz
Noise power spectral density	-174dBm/Hz
Minimum Channel capacity of R_{ji}	100kbps
Maximum Channel capacity of R_{ji}	20Mbps
Length of time slot	1min
Number of time slots for simulation	60
Average data stream size of each host satellite	20Mbps

6.2 The simulation results and analysis of the algorithm

The changes in the network throughput with an increasing number of forwarding satellites are shown in **Fig. 7** and **Fig. 8** for access satellite numbers 3 and 5, respectively. Initially, with a small number of forwarding satellites, access satellite resources are relatively abundant, allowing the channel capacity between access and forwarding satellites to reach the maximum channel capacity. As a result, the throughput increases as the number of forwarding satellites increases. However, as the number of forwarding satellites reaches a certain point, resources become scarce. In order to guarantee the minimum channel capacity, more and more resources are transferred from forwarding satellites with good channel conditions to those with poor channel conditions. This leads to a gradual decrease in the overall system capacity, resulting in a gradual decline in network throughput. We can see that in the graphs with satellite access of 3 and 5, the throughput obtained by improving the KM algorithm is always greater than that of the maximum SINR algorithm and K-means algorithm. The maximum SINR only focuses on the signal-to-noise ratio received by the access satellite. Although it can improve the throughput of individual satellites, it reduces the throughput of the entire satellite network. The K-means algorithm utilizes satellite spatial position to balance the access satellite load, but does not consider interference between satellites, so the throughput is always between the other two algorithms.

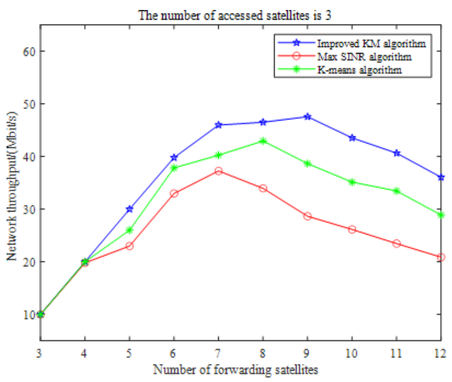

Fig. 7. The impact of the number of forwarding satellites on network throughput when accessing 3 satellites

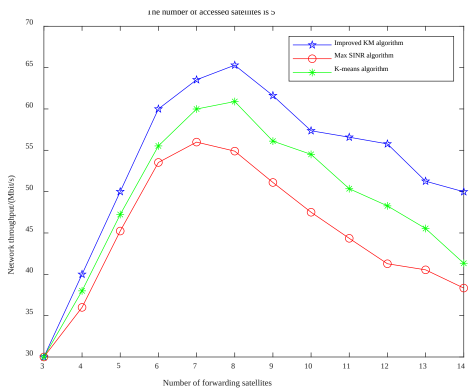

Fig. 8. The impact of the number of forwarding satellites on network throughput when accessing 5 satellites

Fig. 9 shows the situation of forwarding satellites associated with each access satellite when there are 5 accessing satellites and 18 forwarding satellites. We can see that the maximum SINR algorithm only considers SINR, resulting in a large number of forwarding satellites only being associated with the accessing satellites with the best channel conditions, resulting in a particularly uneven load on each access satellite. The accessing satellites with good channel conditions are associated with more satellites, while the accessing satellites with poor channel conditions are associated with fewer satellites. Among them, the access satellite S_2 is not associated with forwarding satellites due to poor channel conditions, leading to insufficient utilization of satellite network resources. Although the K-means algorithm also makes the forwarding satellite association more uniform, it relies too much on the spatial position of the satellite, while the improved KM algorithm has the most balanced access to satellite-associated satellites, with a relatively close number of connected satellites, and resources can be fully utilized.

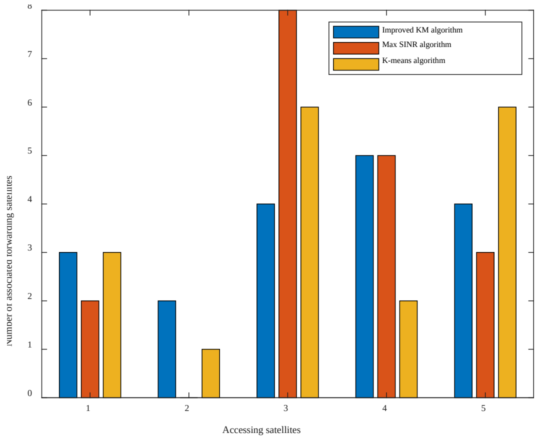

Fig. 9. Differences in the number of satellites associated with different accessing satellites

Fig. 10 illustrates the variation in channel capacity between accessing satellites and forwarding satellites as the number of associated forwarding satellites increases. This variation is observed under three different power allocation algorithms, with the accessing satellite bandwidth set at 100MHz. PA represents the power allocation algorithm for average bandwidth allocation, while JA represents the joint power and bandwidth allocation algorithm. LA is the Lagrangian algorithm in this article, and PSOA is the PSO algorithm in reference [27]. AA is a power average allocation algorithm. From the graph, it can be seen that the channel capacities of all three algorithms increase initially and then decrease as the number of forwarding satellites grows. This is because, in the beginning, with a small number of satellites, power resources are relatively abundant, leading to an increase in channel capacity with an increasing number of forwarding satellites. However, as the number of satellites continues to increase, power resources become insufficient, requiring more power to be allocated to forwarding satellites with poor channel conditions to meet the minimum channel capacity constraint.

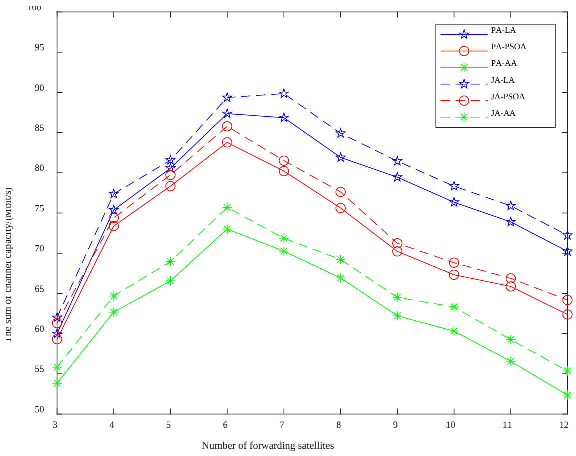

Fig. 10. Comparison of Three Power Allocation Algorithms

Notably, the power average allocation algorithm, due to its neglect of differences between channels, results in significantly lower channel capacities compared to the other two algorithms. The PSO algorithm, while initially close to the Lagrangian algorithm in terms of channel capacity with a small number of forwarding satellites, exhibits a decreasing channel capacity compared to the Lagrangian algorithm as the number of relays increases. This is attributed to the PSO algorithm's tendency to converge to local optimal points as the number of satellites grows, resulting in decreased search efficiency and requiring longer search times and more computational resources. The joint power and bandwidth allocation algorithm, due to its more flexible resource allocation, enables the JA algorithm to achieve greater channel capacity than the PA algorithm.

In order to demonstrate the fairness of satellite association relative to the total number of forwarding satellites, the fairness index from reference [28] is adopted here to measure fairness. The fairness index is defined as $f = \dfrac{(\sum_{j=1}^{N} NU_j)^2}{N(\sum_{j=1}^{N} NU_j^{\,2})}$, where NU_j is the number of associated forwarding satellites for access satellite s_j, and N is the total number of accessing satellites. The parameter f ranges from 0 to 1, with the fairness index being highest when f is 1, representing an equal number of associated users for all accessing satellites and the best fairness in satellite association. The rationality of the fairness index f will be proven as follows

In this paper, the fairness index f is defined as follows

$$f = \frac{(\sum_{j=1}^{N} NU_j)^2}{N(\sum_{j=1}^{N} NU_j^{\,2})} \tag{28}$$

In Formula (28), NU_j represents the number of associated forwarding satellites for the accessing satellite s_j, and N is the total number of accessing satellites. First, we derive the range of values for f :

By applying the Cauchy inequality, we obtain:

$$\sum_{j=1}^{N} NU_j^2 \cdot \sum_{j=1}^{N} b_j^2 \geq (\sum_{j=1}^{N} NU_j \cdot b_j)^2 \tag{29}$$

When $\frac{NU_1}{b_1} = \frac{NU_2}{b_2} = ...\frac{NU_N}{b_N}$ is satisfied, both sides of Formula (29) are equal. Let's set $b_1 = b_2 = ...b_N = 1$; then, the Cauchy inequality becomes

$$\sum_{j=1}^{N} NU_j^2 \cdot N \geq (\sum_{j=1}^{N} NU_j)^2 \tag{30}$$

Dividing both sides by the left side, we get

$$1 \geq \frac{(\sum_{j=1}^{N} NU_j)^2}{N \sum_{j=1}^{N} NU_j^2} = f \tag{31}$$

N and NU_j are clearly greater than or equal to 0, therefore $f \in [0,1]$.

The following provides a detailed analysis of why Formula (28) can measure the fairness of satellite association.

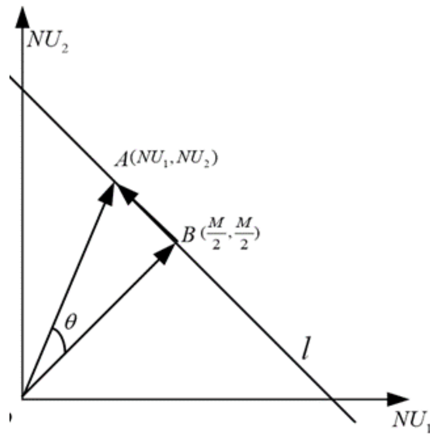

Fig. 11. Geometric relationship diagram of the number of satellites associated with access satellites

Assuming there are only 2 accessing satellites at present, and they are associated with forwarding satellites denoted as NU_1 and NU_2, the total number of forwarding satellites is represented by m. Therefore, the equation for the number of forwarding satellites can be expressed as:

$$l : NU_1 + NU_2 = M \tag{32}$$

To achieve fairness in the association of accessing satellites with forwarding satellites, the fairness equation should be satisfied:

$$NU_1 = NU_2 \tag{33}$$

In **Fig. 11**, the horizontal axis NU_1 represents the number of forwarding satellites associated with access satellite S_1, and the vertical axis NU_2 represents the number of forwarding satellites associated with access satellite S_2.Therefore, the equations of the two straight lines represented by formulas (32) and (33) in the coordinate system are shown in **Fig.**

8, with their intersection denoted as point $B(\frac{M}{2},\frac{M}{2})$. Here, $A(NU_1, NU_2)$ represents the actual number of associated forwarding satellites for two accessing satellites, satisfying formula (32) and lying on the line l. Thus, vectors $\overrightarrow{OA}$ and $\overrightarrow{OB}$ can be expressed as

$$\overrightarrow{OA} = (NU_1, NU_2), \overrightarrow{OB} = (\frac{M}{2}, \frac{M}{2}) \tag{34}$$

According to the Law of Cosines, we can obtain

$$cos\theta = \frac{\overrightarrow{OA}\cdot\overrightarrow{OB}}{|\overrightarrow{OA}|\cdot|\overrightarrow{OB}|} = \frac{NU_1+NU_2}{\sqrt{2}\cdot\sqrt{NU_1^2+NU_2^2}} \tag{35}$$

Squaring both sides, we get

$$\cos^2\theta = \frac{(NU_1+NU_2)^2}{2(NU_1^2+NU_2^2)} = f \tag{36}$$

In formula (36), as f increases, and θ decreases, A approaches B, and the correlation becomes more equitable. Similarly, we can derive the cases with N accessing satellites, where the equations for the number of forwarding satellites and fairness are, respectively

$$\begin{aligned} &NU_1 + NU_2 + \ldots + NU_N = M \\ &NU_1 = NU_2 = \ldots = NU_N \end{aligned} \tag{37}$$

Therefore, we can obtain

$$\cos^2\theta = \frac{(\sum_{j=1}^{N} NU_j)^2}{N(\sum_{j=1}^{N} NU_j^{\,2})} = f \tag{38}$$

Therefore, Formula (28) represents the fairness of satellite correlation, where $f \in [0,1]$, and a larger f indicates a fairer satellite correlation.

Fig. 12 shows the changes in fairness indices of the three algorithms as the number of forwarding satellites increases. We can see that the fairness of the improved KM algorithm remains stable at a relatively large value as the number of users increases, while the maximum SINR algorithm and K-means algorithm gradually decrease with the increase of users. Among them, the K-means algorithm has higher fairness than the maximum SINR algorithm because it considers linking satellites with similar spatial positions to the same access satellite.

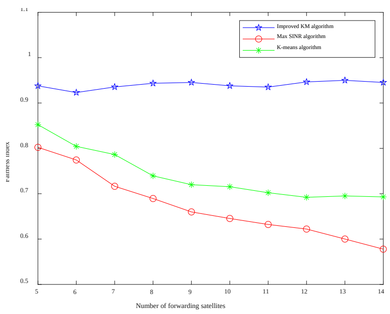

Fig. 12. Fairness Differences under Different Number of Forwarding Satellites

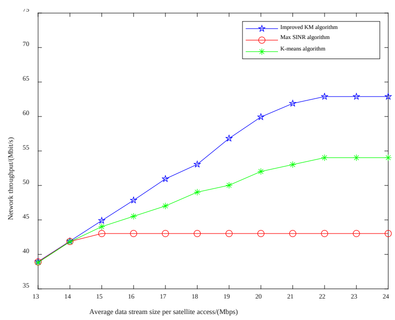

Fig. 13. The impact of data stream size on network throughput

Fig. 13 shows the changes in network throughput of the three algorithms as the average data flow of the connected satellites increases, with the number of connected satellites being 3 and the number of forwarding satellites being 5. We can see that at the beginning, as the data flow increases, all three algorithms increase accordingly. However, the maximum SINR algorithm quickly reaches the maximum network transmission rate, resulting in a stable throughput of 43Mbps. The K-means algorithm also stabilizes at 54Mbps, while the improved KM algorithm stabilizes until the network throughput approaches 63Mbps. Therefore, the improved KM algorithm can achieve a larger network throughput compared to the maximum SINR algorithm and K-means algorithm.

7. Conclusion

This paper proposes a satellite-based LEO satellite resource allocation algorithm that comprehensively considers the throughput and fairness of LEO satellite networks. The resource allocation problem is decomposed into satellite association subproblems and power allocation subproblems. For the satellite association subproblem, virtual satellites are introduced to ensure that the number of accessing satellites matches the number of forwarding satellites. This transforms the original many-to-one matching problem into a one-to-one matching problem. The KM algorithm is then employed to find the maximum weighted matching under perfect matching conditions, determining the association relationships between accessing satellites and forwarding satellites. Based on these associations, the Lagrange dual method is utilized to obtain the optimal power solution for each forwarding satellite.

Simulation results indicate that, under the same data flow conditions, the improved KM algorithm can achieve a higher network throughput compared to traditional algorithms. Additionally, in similar scenarios, the improved KM algorithm exhibits a more balanced association of satellites with accessing satellites, demonstrating increased fairness in associations and more efficient resource utilization . In future research, we will consider how to improve the real-time decision-making capabilities of satellites based on the research work of this article. Based on this article, we will use machine learning to train neural networks to solve real-time low-orbit satellite network resource allocation problems, and can use digital Twin technology-assisted resource optimization[29].

References

[1] D. Deng, C. Wang, M. Pang and W. Wang, "Dynamic Resource Allocation With Deep Reinforcement Learning in Multibeam Satellite Communication," *IEEE Wireless Communications Letters*, vol. 12, no. 1, pp. 75-79, Jan. 2023. Article (CrossRef Link)

[2] G. Liu, X. Jiang, H. Li, Z. Zhang, S. Sun and G. Liang, "Last-Hop Scheduling Strategy for Large-Scale LEO Constellation Data Download Based on Bidirectional Dynamic Domains," in *Proc. of 2023 IEEE 98th Vehicular Technology Conference (VTC2023-Fall)*, Hong Kong, Hong Kong, pp. 1-6, 2023. Article (CrossRef Link)

[3] D. Zhao, H. Qin, N. Xin and B. Song, "Flexible Resource Management in High-Throughput Satellite Communication Systems: A Two-Stage Machine Learning Framework," *IEEE Transactions on Communications*, vol. 71, no. 5, pp. 2724-2739, 2023. Article (CrossRef Link)

[4] N. Hassan and X. Fernando, "Interference Mitigation and Dynamic User Association for Load Balancing in Heterogeneous Networks," *IEEE Transactions on Vehicular Technology*, vol. 68, no. 8, pp. 7578-7592, Aug. 2019. Article (CrossRef Link)

[5] T. Panayiotou and G. Ellinas, "Balancing Efficiency and Fairness in Resource Allocation for Optical Networks," *IEEE Transactions on Network and Service Management*, vol. 21, no. 1, pp. 389-401, Feb. 2024. Article (CrossRef Link)
[6] P. Wang, K. Yang and H. Mei, "Joint Resource Allocation Algorithm for Energy Harvest-Based D2D Communication Underlaying Cellular Networks Considering Fairness," *IEEE Communications Letters*, vol. 27, no. 4, pp. 1200-1204, April 2023. Article (CrossRef Link)
[7] A. Bandopadhyay, S. Swain, R. Singh, P. Sarkar, S. Bhattacharyya and L. Mrsic, "Game-Theoretic Resource Allocation and Dynamic Pricing Mechanism in Fog Computing," *IEEE Access*, vol. 12, pp. 51704-51718, 2024. Article (CrossRef Link)
[8] M. Zhao, H. Yu, J. Pan, Y. Jin, G. Lv and Y. Jin, "Dynamic Resource Allocation for Multi-Satellite Cooperation Networks: A Decentralized Scheme Under Statistical CSI," *IEEE Access*, vol. 12, pp. 15419-15437, 2024. Article (CrossRef Link)
[9] J. Zhao, H. Quan, M. Xia and D. Wang, "Adaptive Resource Allocation for Mobile Edge Computing in Internet of Vehicles: A Deep Reinforcement Learning Approach," *IEEE Transactions on Vehicular Technology*, vol. 73, no. 4, pp. 5834-5848, April 2024. Article (CrossRef Link)
[10] B. Huang and A. Guo, "A Dynamic Hierarchical Game Approach for User Association and Resource Allocation in HetNets With Wireless Backhaul," *IEEE Wireless Communications Letters*, vol. 13, no. 1, pp. 59-63, Jan. 2024. Article (CrossRef Link)
[11] T. Zhou, Y. Fu, D. Qin, X. Li and C. Li, "Joint User Association and BS Operation for Green Communications in Ultra-Dense Heterogeneous Networks," *IEEE Transactions on Vehicular Technology*, vol. 73, no. 2, pp. 2305-2319, Feb. 2024. Article (CrossRef Link)
[12] H. Jiang, H. Wang, Y. Hu and J. Wu, "Dynamic User Association in Scalable Ultra-Dense LEO Satellite Networks," *IEEE Transactions on Vehicular Technology*, vol. 71, no. 8, pp. 8891-8905, Aug. 2022. Article (CrossRef Link)
[13] A. Mahmoudi, B. Abolhassani, S. M. Razavizadeh and H. H. Nguyen, "User Clustering and Resource Allocation in Hybrid NOMA-OMA Systems Under Nakagami-m Fading," *IEEE Access*, vol. 10, pp. 38709-38728, 2022. Article (CrossRef Link)
[14] H. Khoshkbari and G. Kaddoum, "Deep Recurrent Reinforcement Learning for Partially Observable User Association in a Vertical Heterogenous Network," *IEEE Communications Letters*, vol. 27, no. 12, pp. 3235-3239, Dec. 2023. Article (CrossRef Link)
[15] Q. Xue, H. Xia, J. Mu, Y. Xu, L. Yan and S. Ma, "User-Centric Association for Dense mmWave Communication Systems With Multi-Connectivity," *IEEE Transactions on Green Communications and Networking*, vol. 8, no. 1, pp. 177-189, March 2024. Article (CrossRef Link)
[16] L. Xia, Y. Sun, D. Niyato, X. Li and M. A. Imran, "Joint User Association and Bandwidth Allocation in Semantic Communication Networks," *IEEE Transactions on Vehicular Technology*, vol. 73, no. 2, pp. 2699-2711, Feb. 2024. Article (CrossRef Link)
[17] L. Zhang, H. Zhang, L. Yu, H. Xu, L. Song and Z. Han, "Virtual Resource Allocation for Mobile Edge Computing: A Hypergraph Matching Approach," in *Proc. of 2019 IEEE Global Communications Conference (GLOBECOM)*, Waikoloa, HI, USA, pp. 1-6, 2019. Article (CrossRef Link)
[18] C. Dong, X. Xu, A. Liu and X. Liang, "Load balancing routing algorithm based on extended link states in LEO constellation network," *China Communications*, vol. 19, no. 2, pp. 247-260, Feb. 2022. Article (CrossRef Link)
[19] X. Fan, J. Hu, Y. Cui, P. He, D. Wu and R. Wang, "Channel-Aware Gradient Fair Association for LEO Inter-Satellite Links," in *Proc. of 2022 IEEE 96th Vehicular Technology Conference (VTC2022-Fall)*, London, United Kingdom, pp. 1-5, 2022. Article (CrossRef Link)
[20] Q. Ye, B. Rong, Y. Chen, M. Al-Shalash, C. Caramanis and J. G. Andrews, "User Association for Load Balancing in Heterogeneous Cellular Networks," *IEEE Transactions on Wireless Communications*, vol. 12, no. 6, pp. 2706-2716, June 2013. Article (CrossRef Link)
[21] T. Zhou, Z. Liu, J. Zhao, C. Li and L. Yang, "Joint User Association and Power Control for Load Balancing in Downlink Heterogeneous Cellular Networks," *IEEE Transactions on Vehicular Technology*, vol. 67, no. 3, pp. 2582-2593, March 2018. Article (CrossRef Link)

[22] P. Han, Z. Zhou and Z. Wang, "User Association for Load Balance in Heterogeneous Networks With Limited CSI Feedback," *IEEE Communications Letters*, vol. 24, no. 5, pp. 1095-1099, May 2020. Article (CrossRef Link)
[23] Q. Ye, B. Rong, Y. Chen, M. Al-Shalash, C. Caramanis and J. G. Andrews, "User Associat-ion for Load Balancing in Heterogeneous Cellular Networks," *IEEE Transactions on Wireless Communications*, vol. 12, no. 6, pp. 2706-2716, June 2013. Article (CrossRef Link)
[24] M. Liu, J. Zhang, K. Xiong, M. Zhang, P. Fan and K. B. Letaief, "Effective User Clustering and Power Control for Multiantenna Uplink NOMA Transmission," *IEEE Transactions on Wireless Communications*, vol. 21, no. 11, pp. 8995-9009, Nov. 2022. Article (CrossRef Link)
[25] J. Shuai, Y. Liu and Y. Wang, "Energy Efficient Maximal Throughput Resource Scheduling Strategy in Satellite Networks," *IEEE Wireless Communications Letters*, vol. 12, no. 2, pp. 312-316, Feb. 2023. Article (CrossRef Link)
[26] Z. Han, C. Xu, G. Zhao, S. Wang, K. Cheng and S. Yu, "Time-Varying Topology Model for Dynamic Routing in LEO Satellite Constellation Networks," *IEEE Transactions on Vehicular Technology*, vol. 72, no. 3, pp. 3440-3454, March 2023. Article (CrossRef Link)
[27] Z. Chen, D. Guo, K. An, B. Zhang, X. Zhang and B. Zhao, "Efficient and Fair Resource Allocation Scheme for Cognitive Satellite-Terrestrial Networks," *IEEE Access*, vol. 7, pp. 145124-145133, 2019. Article (CrossRef Link)
[28] T. -d. Nguyen and Y. Han, "A Proportional Fairness Algorithm with QoS Provision in Downlink OFDMA Systems," *IEEE Communications Letters*, vol. 10, no. 11, pp. 760-762, November 2006. Article (CrossRef Link)
[29] L. Zhang et al., "Digital Twin-Assisted Edge Computation Offloading in Industrial Internet of Things With NOMA," *IEEE Transactions on Vehicular Technology*, vol. 72, no. 9, pp. 11935-11950, Sept. 2023. Article (CrossRef Link)

Baochao Liu received a bachelor's degree. He graduated from North China University of Science and Technology in 2020 with a bachelor's degree in electronic information engineering. Later, he is currently pursuing a master's degree in electronic and communication engineering at the School of Computer and Communication Engineering at University of Science and Technology Beijing. His research interests include deep space communication and resource allocation algorithms.

Lina Wang received the M.S. and Ph.D. degrees in communication and information systems from the Harbin Institute of Technology in 2001 and 2004, respectively. She is currently a Professor with the Department of Communication Engineering, School of Computer and Communication Engineering, University of Science and Technology Beijing. Her research interests include space communications, cognitive radio technologies, resource allocation algorithms, satellite positioning algorithms, and rateless codes.