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Joint optimization of user association and resource allocation in cache-enabled terrestrial-satellite integrating network

Shuang NI, Junyu LIU*, Min SHENG, Jiandong LI & Xiaona ZHAO

State Key Laboratory of Integrated Service Networks, Xidian University, Xi'an 710071*, China*

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Abstract Although low earth orbit (LEO) satellites can provide high-capacity backhaul to serve the terrestrial network, the performance of terrestrial-satellite communication systems is critically influenced by the coupling of user association and resource allocation in this integrating system, where user association includes small-cell base station (SBS)-user association and SBS-satellite association. In this work, we consider a cache-enabled terrestrial-satellite integrating network, in which LEO satellites provide backhaul for cache-enabled SBSs to serve ground users. Targeting at maximizing the downlink sum rate of the system and the number of accessed ground users, we formulate an optimization problem where user association and resource allocation of both terrestrial and satellite networks are joint optimized. Owing to the coupling relationship and integer programming nature of this optimization problem, we use Lagrangian relaxation to decouple and decompose it into two subproblems. We propose a user-division matching (UDM) algorithm by dividing all users into multiple user groups, which skillfully solves the first subproblem with multi-objectives. Afterward, to depict the nature of multi-connectivity sufficiently, the second subproblem is converted into a many-to-one matching game and solved by a modified Gale-Shapely (MGS) algorithm, which is highly efficient for different satellite constellations. Simulation results demonstrate the proposed algorithms can significantly improve the downlink sum rate of the system by 28.5–120.7 compared to the benchmark algorithms in the typical settings and balance the tradeoff between the downlink sum rate of the system and the number of accessed ground users. Moreover, it also shows that <1% system performance loss can be obtained by the proposed method compared to the optimal solution.

Keywords terrestrial-satellite integrating network, content caching, user association, resource allocation, satellite backhaul

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1 Introduction

In the past decades, the advance in low earth orbit (LEO) satellite networks have aroused extensive research attention from both industry and academia. It has been foreseen as an effective method to support seamless global coverage and high-quality stable connectivity. In particular, an integrated terrestrial-satellite communication network is developed in [1–5], where satellites are incorporated into terrestrial networks to provide services to the ground users. Zhang et al. [3] proposed a cloud-based terrestrial-satellite network in which the satellites and base stations are connected with a cloud-computing based centralized processor, where joint optimization of multicast beamforming and user scheduling is performed to provide high-speed multimedia services. Jiang et al. [4, 5] focused on the serious interference exists in the integrated terrestrial-satellite network, where multigroup precoding, resource allocation, and cooperative transmission are jointly optimized to significantly improve the performance of the network. Hu et al. [1] studied user association and resource allocation in an integrated satellite-drone network, where

* Corresponding author (email: junyuliu@xidian.edu.cn)

the satellites and the macrocell base stations (MBSs) are integrated to provide backhaul resources for base stations. Di et al. [2] designed an offload scheme in terrestrial-satellite integrating architecture where the LEO backhaul link is combined with the traditional backhaul link for each user to upload its data, and algorithms to effectively solve the joint optimization problem of the user scheduling in this architecture. It is shown that the satellite backhaul could efficiently improve the user coverage and capacity of the communication network. Although the backhaul capacity could be improved with the adoption of higher frequency, e.g., Ka/Ku bands, it still serves as a limiting factor, which bottlenecks the performance of the terrestrial network. For example, the capacity of satellite backhaul on each terrestrial-satellite terminal (TST) calculated in [2] is around 150 Mbps, while at least 3 Mbps transmission rate is required by a single user to watch HD 1080p videos smoothly [6]. With the rapidly increasing number of ground users, congestions are more likely to occur in terrestrial networks with restricted backhaul resources.

To improve the performance of the system with limited backhaul capacity, caching popular files on local devices, e.g., base stations (BSs) and unmanned aerial vehicles (UAVs) is a promising solution, which could significantly relieve the backhaul pressure. The user requesting popular files can be served directly by their associated local caching devices without fetching content with backhaul resources. In a cache-enabled system, user association and resource allocation are of great importance in the backhaul saving which can give prominence to its advantage. Therefore, many efforts have been devoted to design efficient scheduling schemes in cache-enabled networks [7–10]. Yu et al. [7] studied the joint user-BS association and data caching problem to maximize the network throughput with the constraint of backhaul traffic of the network. In contrast to caching files at the terrestrial static ground base stations, which fails to meet high-quality demand and the mobility patterns of the users, Chen et al. [8, 10] investigated a network of cache-enabled unmanned aerial vehicles to provide reliable communication links to the users. They focused on improving the system performance by jointly optimizing user association, resource allocation, the UAVs' locations, and the cache deployment with machine learning. Moreover, Chen et al. [9] also studied the backhaul loads and the content caching of the integrated satellite-drone network where the popular contents are cached separately at the remote radio heads and the baseband units.

Recently, the architecture, which integrates the conventional terrestrial cache and the satellite communication, has been proposed to support massive stable connectivity [11–14]. An et al. [11] combined the terrestrial cache with satellite-terrestrial relay network to improve spectral efficiency and proved the benefit of proposed schemes in reducing the system outage probability. The content cache was incorporated into satellite-terrestrial network by Wu et al. [13] with a multi-layer caching model which consists of the ground stations caching and the satellite caching. Nevertheless, assuming either ideal or fixed backhaul capacity, most of the available researches failed to characterize the correlation between user association and resource allocation in this integrated architecture. On the one hand, the dynamically varying satellite backhaul capacity is determined by small-cell base station (SBS)-satellite association, which is coupled with SBS-user association via backhaul traffic constraint. On the other hand, the high-capacity satellite backhaul links suffer long propagation delays resulting in higher overall delay. Furthermore, the influence of the angular separation and the multi-connectivity should be carefully considered as well. Therefore, the design of scheduling schemes becomes very challenging in cache-enabled terrestrial-satellite communication network. It is crucial to jointly consider SBS-user association, SBS-satellite association, resource allocation and characteristics of satellite communications.

In this paper, we jointly investigate user association and resource allocation in a cache-enabled terrestrial-satellite integrating network, where LEO satellites provide backhaul for cache-enabled SBSs to serve the ground users. Specifically, we formulate a joint optimization problem to maximize the downlink sum rate of the system and the number of accessed ground users. Since the optimization problem is shown to be non-convex and an integer programming problem which is computationally intractable because of the complicated coupling constraint between the satellite and terrestrial network, a user-division matching (UDM) algorithm and a modified Gale-Shapely (MGS) matching algorithm are proposed to solve it. The main contributions of our paper are summarized below.

- We use Lagrangian relaxation to solve the coupling constraint and decompose the original problem into two subproblems: the terrestrial transmission optimization problem and the satellite backhaul capacity optimization problem. Considering the multi-objective nature of the first subproblem, we propose a UDM algorithm to solve it by dividing all users into multiple user groups, which transforms the original problem into multiple single-objective problems. Then, owing to the multi-connectivity of the terrestrial-satellite integrating network, we convert the second subproblem into a many-to-one matching game and propose an MGS matching algorithm to improve satellite backhaul capacity effectively.

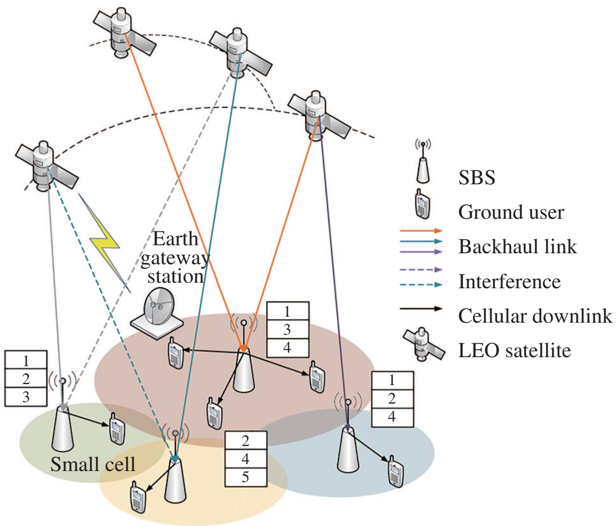

Figure 1 (Color online) Illustration of the system model of cache-enabled terrestrial-satellite integrating network.

• Simulation results show that the performance of our proposed algorithms outperforms the greedy algorithm and random algorithm especially in the case of limited cache capacity. Specifically, the proposed UDM algorithm can obtain the gain of the system sum rate from 28.5% to 120.7% compared to other algorithms in the typical settings. We also show that the proposed algorithms can balance the tradeoff between the downlink sum rate of the system and the number of accessed ground users with a varying conversion factor. Furthermore, the system performance achieved by our method is shown to obtain <1% loss and simultaneously save the computation time, compared to the ES algorithm in small-scale testing. The results in this work could provide helpful guidelines for the design of user association and resource allocation in cache-enabled terrestrial-satellite integrating network.

The remainder of this paper is organized as follows. In Section 2, we introduce the model of cache-enabled terrestrial-satellite integrating network. The optimization problem is formulated and decomposed in Section 3. Then, two subproblems are converted into the matching game and solved in Section 4. In Section 5, the simulation results are given. At last, we conclude the paper in Section 6.

2 System model

2.1 Network model

We consider a downlink of cache-enabled terrestrial-satellite integrating network in Figure 1, which consists of LEO satellites[1)], small cells and downlink ground users. Each SBS is equipped with a single antenna to communicate with ground users in its coverage, and multiple independent antenna apertures to obtain LEO backhaul over the Ka-band [15]. For LEO backhaul, each user will access the requested files from the satellites via the associated SBS rather than directly communicate with the satellites[2)]. Note that each SBS can simultaneously connect to multiple satellites, which further improves the capacity of LEO backhaul.

2.2 Caching and request mechanism

Suppose that there are N files of identical size in $\mathcal{F} = \{f_n \mid n = 1, 2, \ldots, N\}$, where f_n is the n-th most popular file. Each user independently requests file in a probabilistic manner. Without loss of generality, the request probability follows Zipf distribution [16]. Specifically, the request probability of f_n is

1) The proposed network model is independent of the satellite altitude and constellation, and thus, can be directly extended to the MEO and GEO satellite systems.

2) Each satellite gets files from an earth gateway station (connected to the core network) or a macro BS. We ignore this process owing to its high-speed transmission. Meanwhile, the satellite operator and the traditional terrestrial operator cooperate for inter-cell interference management.

given by

$$q_n = \frac{n^{-\gamma}}{\Omega}, \qquad \forall f_n \in \mathcal{F}, \tag{1}$$

where $\Omega = \sum_{n=1}^{N} n^{-\gamma}$, γ is the decay constant describing the skewness coefficient of the file popularity distribution. For instance, a large γ indicates that file popularity is unevenly distributed. In other words, it indicates that the files with high popularity are more likely to be requested by users.

Let $\mathcal{M}=\{\mathrm{SBS}_m \mid m=1,2,\ldots,N_{\mathrm{SBS}}\}$ denote the set of SBSs and $\mathcal{J}=\{\mathrm{user}_j \mid j=1,2,\ldots,N_{\mathrm{user}}\}$ denote the set of users, where N_{SBS} and N_{user} are the numbers of the SBSs and users, respectively. Moreover, equipped with a cache memory, each SBS can cache at most $N_{\max}$ files. Let $\boldsymbol{y}_m = [y_{m,f_1}, y_{m,f_2}, \ldots, y_{m,f_n}]$ denote the indicator array of caching files at SBS_m, where

$$y_{m,f_n} = \begin{cases} 1, & \text{if } f_n \text{ is cached in } \mathrm{SBS}_m, \\ 0, & \text{otherwise.} \end{cases} \tag{2}$$

Let $\boldsymbol{q}_j = [q_{j,f_1}, q_{j,f_2}, \ldots, q_{j,f_n}]$ denote the indicator array of the user_j's request, where

$$q_{j,f_n} = \begin{cases} 1, & \text{if } f_n \text{ is requested by } \mathrm{user}_j, \\ 0, & \text{otherwise.} \end{cases} \tag{3}$$

Aided by (2) and (3), $\boldsymbol{q}_j \boldsymbol{y}_m^{\mathrm{T}}$ denotes whether the file requested by user_j is cached by SBS_m, where

$$\boldsymbol{q}_j \boldsymbol{y}_m^{\mathrm{T}} = \begin{cases} 1, & \text{if requested file is cached on } \mathrm{SBS}_m, \\ 0, & \text{otherwise.} \end{cases} \tag{4}$$

Note that $\sum_{n=1}^{N} \boldsymbol{q}_j \boldsymbol{y}_m^{\mathrm{T}} = 1$, which indicates that at most one file can be requested by one user at each time. Accordingly, the requested file can be delivered to the user in the following cases:

- **Local-cache case.** The associated SBS has cached the requested file and transmits it to the user directly, i.e., $\boldsymbol{q}_j \boldsymbol{y}_m^{\mathrm{T}} = 1$.
- **Backhaul-retrieving case.** The requested file is not available in the associated SBS and the file will be delivered to the user through backhaul, i.e., $\boldsymbol{q}_j \boldsymbol{y}_m^{\mathrm{T}} = 0$.

2.3 Transmission model for terrestrial communications

Each user is associated with the geometrically nearest SBS. We define a binary matrix $\boldsymbol{A}$ for user association where $a_{m,j} = 1$ represents that the user_j is associated with SBS_m, otherwise $a_{m,j} = 0$. Consider that there are N_{sub} available subchannels on C-band spectrum which are reused by each SBS. Especially, each subchannel can be occupied by at most one user in a time slot. Accordingly, a matrix $\boldsymbol{X}$ of size $N_{\mathrm{SBS}} \times N_{\mathrm{user}} \times N_{\mathrm{sub}}$ is introduced to represent the relationship between SBS-user association and subchannel allocation. If $x_{m,j,k} = 1$, it indicates the k-th subchannel of SBS_m is assigned to user_j, otherwise $x_{m,j,k} = 0$. Then, the achievable rate of user_j from SBS_m over the k-th subchannel can be written as

$$R_{m,j,k} = B_{\mathrm{C}} \log_2 \left(1 + \frac{p_{m,k} \mid h_{m,j,k} \mid^2}{I_{m,j} + \sigma^2} \right), \tag{5}$$

where $I_{m,j} = \sum_{m_i \neq m} \sum_{j_i \neq j} x_{m_i,j_i,k} p_{m_i,k} |h_{m_i,j,k}|^2$ is the co-channel interference, B_{C} is the bandwidth of one subchannel over C-band, $p_{m,k}$ (or $p_{m_i,k}$) is the transmit power allocated by SBS_m (or SBS_{m_i}) to the k-th subchannel, $h_{m,j,k}$ (or $h_{m_i,j,k}$) means the channel gain between user_j and SBS_m (or SBS_{m_i}) over the k-th subchannel. The additive white Gaussian noise (AWGN) is considered with σ^2 denoting the noise power.

Note that the data rate of users in the local-cache case is affected by both wireless channel and backhaul traffic. In particular, we assume that each user requesting files from the satellites will generate the same backhaul traffic U_{back}, and thus, the achievable rate of these users could be rewritten as

$$\underset{(\boldsymbol{z}_j \boldsymbol{y}_m^{\mathrm{T}}=0)}{R'_{m,j,k}} = \min\left(R_{m,j,k}, U_{\mathrm{back}}\right). \tag{6}$$

According to (5) and (6), we can obtain the date rate of SBS_m by

$$R_m = \sum_{j=1}^{J} \sum_{k=1}^{K} x_{m,j,k} R_{m,j,k}. \tag{7}$$

2.4 Transmission model for satellite-terrestrial communications

We consider that there are N_S satellites with different altitudes flying over the area with demand. The satellite set is denoted as $\mathcal{S} = \{\mathrm{SAT}_s \mid s = 1, 2, \ldots, N_\mathrm{S}\}$. For simplicity, the locations of satellites are fixed during each time slot separated from a time period. Dividing the available bandwidth on Ka-band spectrum into a set of subchannels $\mathcal{C} = \{1, 2, \ldots, N_\mathrm{C}\}$, we use a binary matrix $\boldsymbol{B}$ to represent the SAT-SBS association and subchannel allocation. If $b_{m,s,c} = 1$, it indicates that SBS_m is associated with the SAT_s over the c-th subchannel and $b_{m,s,c} = 0$ otherwise. Accordingly, the achievable rate between SAT_s-SBS_m link over the c-th subchannel is given by

$$R_{m,s,c} = B_\mathrm{Ka} \log_2 \left(1 + \frac{b_{m,s,c} p_{m,s,c} h_{m,s,c}}{I_{m,s} + \sigma^2} \right), \tag{8}$$

where $I_{m,s} = \sum_{s_i \neq s} \sum_{m_i \neq m} b_{m_i,s_i,c} p_{m_i,s_i,c} h_{m,s_i,c}$ is the co-channel interference, B_Ka is the bandwidth of one subchannel over Ka-band, $p_{m,s,c}$ (or $p_{m_i,s_i,c}$) is the transmitting power of SAT_s to SBS_m (or SAT_{s_i} to SBS_{m_i}) over the c-th subchannel. Considering both large-scale fading and shadowed-Rician fading, let $h_{m,s,c}$ denote the channel gain of the mmWave link between SAT_s and its associated SBS_m over the c-th subchannel, which is given by [1]

$$h_{m,s,c} = \begin{cases} L_1 10^{\frac{-L_2(d_{m,s})}{10}} G_M(\kappa_{m,s}) G_R(\kappa_{m,s}), & \bar{\omega}_{m,s} = 1, \\ 0, & \bar{\omega}_{m,s} = 0, \end{cases} \tag{9}$$

where L_1 is the Rician fading channel coefficient and $L_2(d_{m,s}) = \beta + \alpha 10 \log_{10}(d_\mathrm{m,s}) + \chi$ captures the large-scale channel effects over the mmW link between SAT_s and SBS_m. Note that α is the slope of the fit and the intercept parameter β is the path loss (dB) for 1 meter of distance. In addition, χ models the deviation in fitting (dB) for 1 meter of distance, $d_{m,s}$ is the distance between SAT_s and SBS_m, and $G_M(\kappa_{m,s})$ and $G_R(\kappa_{m,s})$ denote the transmit gain and the receive gain of an antenna at an offset angle $\kappa_{m,s}$, respectively [1].

Note that each satellite-terrestrial link is also influenced by the propagation delay owing to the long-distance transmission. Thus, the equivalent LEO backhaul capacity of SBS_m is given by (10) which depicts the impact of high propagation delay and the multi-connectivity on LEO backhaul capacity simultaneously [2]:

$$C_m = \sum_{s=1}^{N_S} \frac{1}{1/C_{m,s} + T_{\mathrm{prop},s}/d_{m,s}}, \tag{10}$$

where $C_{m,s} = \sum_{c=1}^{N_\mathrm{C}} R_{m,s,c}^\mathrm{T} b_{m,s,c}$ is the capacity of SAT_s-SBS_m link, $T_{\mathrm{prop},s}$ is the propagation delay dependent on the altitude of SAT_s and the speed of light, and $d_{m,s}$ is the data traffic of SAT_s-SBS_m link. The equations calculating the values of $d_{m,s}$ could refer to [2].

3 Problem formulation

We concentrate on the target of maximizing the downlink sum rate of the system and the number of accessed ground users by jointly optimizing SBS-user association, SAT-SBS association, and subchannel allocation. In this section, we first formulate the optimization problem in the following.

3.1 Utility based problem formulation

In this work, we define a utility function that takes into account both the downlink sum rate of the system and the number of accessed ground users for the performance evaluation. The optimization problem is formulated as follows:

$$\max_{\{x_{m,j,k}, b_{m,s,c}\}} \sum_{m=1}^{N_\mathrm{SBS}} R_m + \mu \sum_{m=1}^{N_\mathrm{SBS}} \sum_{j=1}^{N_\mathrm{user}} \sum_{k=1}^{N_\mathrm{sub}} x_{m,j,k} \tag{11}$$

$$\text{s.t.} \quad x_{m,j,k} \leqslant a_{m,j}, \tag{11a}$$

$$\sum_j x_{m,j,k} \left(1 - \boldsymbol{q}_j \boldsymbol{y}_m^{\mathrm{T}}\right) U_{\text{back}} \leqslant C_m, \ \forall m \in \mathcal{M}, \tag{11b}$$

$$\sum_{m=1}^{N_{\text{SBS}}} \sum_{k=1}^{N_{\text{sub}}} x_{m,j,k} \leqslant 1, \ \forall j \in \mathcal{J}, \tag{11c}$$

$$\sum_{j=1}^{N_{\text{user}}} x_{m,j,k} \leqslant 1, \ \forall m \in \mathcal{M}, \forall k \in \mathcal{K}, \tag{11d}$$

$$\sum_{s=1}^{N_{\text{S}}} \sum_{c=1}^{N_{\text{C}}} b_{m,s,c} \leqslant N_r, \ \forall m \in \mathcal{M}, \tag{11e}$$

$$\sum_{m=1}^{N_{\text{SBS}}} b_{m,s,c} \leqslant 1, \ \forall s \in \mathcal{S}, \forall c \in \mathcal{C}, \tag{11f}$$

$$x_{m,j,k}, b_{m,s,c} \in \{0,1\}, \tag{11g}$$

where μ is the conversion factor. A large μ indicates that the optimization problem prefers to pursue a greater number of accessed ground users. The constraint (11a) indicates that each user has access to the SBS in its reach and the constraint (11b) is the constraint of the backhaul traffic on each SBS. The constraints (11c) and (11d) ensure that the relationship between users and SBS-subchannel units is one-to-one matching. Without loss of generality, at most one SBS can occupy each subchannel over Ka-band and each SBS can simultaneously be associated with N_r satellites, which are indicated by constraints (11e) and (11f), respectively. Note that the constraint (11b) establishes the coupling relationship between the terrestrial and satellite network, which is considered in the following.

3.2 Lagrangian relaxation method

According to (11), we formulate a non-convex integer programming (IP) problem which cannot be solved by the traditional convex optimization methods. Moreover, it is also mathematically hard to deal with (11) owing to the coupling between the terrestrial user association and the satellite selection via the backhaul capacity constraint in (11b). Therefore, we in this work intend to use the Lagrangian relaxation method to solve the non-convex integer programming problem with the mathematically complicated constraint.

We first introduce a Lagrangian multiplier vector $\boldsymbol{\lambda} = (\lambda_1, \lambda_2, \ldots, \lambda_{N_{\text{SBS}}}) \geqslant 0$ incorporating the constraint (11b) into the objective function. Then, the original problem (IP) is transformed into the Lagrangian relaxation (LR) problem and the dual optimum of problem (11) can be defined as

$$g^* = \min_{\lambda \geqslant 0} g(\boldsymbol{\lambda}) \triangleq \min_{\lambda \geqslant 0} \max_{\{\boldsymbol{X}, \boldsymbol{B}\}} \mathcal{L}(\boldsymbol{X}, \boldsymbol{B}, \boldsymbol{\lambda}), \tag{12}$$

where the Lagrangian is

$$\begin{aligned} \mathcal{L}(\boldsymbol{X}, \boldsymbol{B}, \boldsymbol{\lambda}) &= \sum_{m=1}^{N_{\text{SBS}}} R_m + \mu \sum_{m=1}^{N_{\text{SBS}}} \sum_{j=1}^{N_{\text{user}}} \sum_{k=1}^{N_{\text{sub}}} x_{m,j,k} + \sum_{m=1}^{N_{\text{SBS}}} \lambda_m \left(C_m - \sum_j x_{m,j,k} \left(1 - \boldsymbol{q}_j \boldsymbol{y}_m^{\mathrm{T}}\right) U_{\text{back}} \right) \\ &= \sum_{m=1}^{N_{\text{SBS}}} R_m + \mu \sum_{m=1}^{N_{\text{SBS}}} \sum_{j=1}^{N_{\text{user}}} \sum_{k=1}^{N_{\text{sub}}} x_{m,j,k} - \sum_{m=1}^{N_{\text{SBS}}} \sum_j x_{m,j,k} \left(1 - \boldsymbol{q}_j \boldsymbol{y}_m^{\mathrm{T}}\right) U_{\text{back}} + \sum_{m=1}^{N_{\text{SBS}}} \lambda_m C_m. \end{aligned} \tag{13}$$

Note that for the given dual vector $\boldsymbol{\lambda}$, Eq. (13) consists of two segments where the first segment only depends on $\boldsymbol{X}$ while the second segment is determined by $\boldsymbol{B}$. Consequently, the Lagrangian relaxation problem is divided into two subproblems [17], i.e., the terrestrial transmission optimization problem

$$\max_{\{x_{m,j,k}\}} \sum_{m=1}^{N_{\text{SBS}}} R_m + \mu \sum_{m=1}^{N_{\text{SBS}}} \sum_{j=1}^{N_{\text{user}}} \sum_{k=1}^{N_{\text{sub}}} x_{m,j,k} - \sum_{m=1}^{N_{\text{SBS}}} \lambda_m \left(\sum_j x_{m,j,k} \left(1 - \boldsymbol{q}_j \boldsymbol{y}_m^{\mathrm{T}}\right) U_{\text{back}} \right) \tag{14}$$

and the satellite backhaul capacity optimization problem

$$\max_{\{b_{m,s,c}\}} \sum_{m=1}^{N_{\rm SBS}} \lambda_m C_m. \tag{15}$$

The computation of the dual function in (12) requires the optimal $\{\boldsymbol{X}^*, \boldsymbol{B}^*\}$ for given $\boldsymbol{\lambda}$. Therefore, the optimization process involves multiple iterations, during each of which three steps are performed. (1) Given $\boldsymbol{\lambda}^{(t)}$, two subproblems are solved. (2) For each SBS, if the constraint (11b) is violated, the associating users in the Backhaul-retrieving case should be removed one by one ascendingly according to the user rate until the constraint is satisfied[3)]. (3) According to the results from (1) and (2), the dual vector $\boldsymbol{\lambda}$ is updated by gradient descent method, where $\lambda_m^{(t+1)} = \lambda_m^{(t)} - \eta^{(t)}(C_m - \sum_j x_{m,j,k}\left(1 - \boldsymbol{q}_j \boldsymbol{y}_m^{\rm T}\right) U_{\rm back})$, and $\eta^{(t)}$ denotes the learning rate function which is a monotonically decreasing exponential function of iteration t. The optimization process will continue until $|\mu^{(t+1)} - \mu^{(t)}| \leqslant \varepsilon$, where ε is the Lagrangian iteration parameter.

It should be noted that the strong duality cannot hold owing to the non-convex nature of the problem in (11) [19]. The dual optimum obtained by the above steps is the upper bound that is as close as possible to the optimal solution (see Appendix A). Therefore, we discuss the relationship between the optimal solution and dual optimum in the following.

4 Algorithm design

In this section, we adopt the matching theory and transfer the original optimization problem into a matching game with externalities. In particular, we use the idea of Gale-Shapely (GS) matching algorithm with modified two-sided preferences [20].

4.1 Matching game for terrestrial transmission

Note that the terrestrial transmission optimization problem consists of SBS-user association and subchannel allocation which is a three-dimensional matching problem. Consequently, the matching game for terrestrial transmission has three sets of players: users, SBSs and subchannels. Especially, the interdependency exiting among three sets allows us to adopt matching theory to find a solution to the problem. The matching game is defined as follows.

(1) Definitions. Three players sets are denoted as $\mathcal{J}$, $\mathcal{M}$ and $\mathcal{K}$. With joint considering the SBSs and the subchannels, we construct the SBS-subchannel set as $\mathcal{D} = \mathcal{M} \times \mathcal{K}$, where the element (m,k) represents one SBS-subchannel unit. For $j \in \mathcal{J}$ and $(m,k) \in \mathcal{D}$, a matching game η is $\{\mathcal{J} \cup \mathcal{D}\} \rightarrow \{\mathcal{J} \cup \mathcal{D}\}$, which satisfies

- $\eta\,(j) \in \mathcal{D}$ and $|\,\eta\,(j)\,| \leqslant 1$;
- $\eta\,(m,k) \in \mathcal{J}$ and $|\,\eta\,(m,k)\,| \leqslant 1$;
- if and only if $j \in \eta\,(m,k)$, $\eta\,(j) \in (m,k)$.

We transfer the terrestrial transmission optimization problem into a one-to-one matching game meeting (11c) and (11d).

(2) Preference relation [21]. As the users are unaware of the caching files in each SBS, their preference is exclusively concentrated on the transmission data rate. Thus, each user will select a SBS-subchannel unit from $\mathcal{D} \cup \emptyset$ to match with the best channel condition, i.e.,

$$(j,(m_1,k_1)) \succ_j (j,(m_2,k_2)) \Leftrightarrow h_{m_1,j,k_1} > h_{m_2,j,k_2}. \tag{16}$$

At the SBS-subchannel side, the externalities exist in this matching game owing to the co-channel interference, which means the utility of (m,k) may be influenced by other matched SBS-subchannel units (t,k) [22]. Therefore, each SBS-subchannel unit actually has a preference relation over other co-channel units. For a matched pair $(j,(m,k))$, it prefers to match with a new pair $(i,(t,k))$ with high quality SBS$_t$-user$_i$ link and poor quality SBS$_t$-user$_j$ link according to (5). Therefore, we define a preference matrix

3) Note that the outcome obtained from our method cannot be guaranteed to always satisfy the constraints owing to the discreteness of the binary variables in our formulated problem. Therefore, we adjust the aforementioned strategy to ensure the constraints are satisfied [18].

$\mathbf{\Gamma}_{j,(m,k)}$ to represent the impact of all possible pairs to the matched pair $(j,(m,k))$ in the following:

$$\Gamma_{j,(m,k)}^{i,(t,k)} = (h_{t,i,k})^{\lambda_t} / (h_{t,j,k}). \tag{17}$$

Then, if $\Gamma_{j,(m,k)}^{j_1,(m_1,k)} > \Gamma_{j,(m,k)}^{j_2,(m_2,k)}$, the matched pair (m,k) is preferred to match with $(j_1,(m_1,k))$ as compared to $(j_2,(m_2,k))$.

Moreover, we define the preference of each subchannel over different matching pairs. For convenience, let $\sum_{m=1}^{N_{\rm SBS}}\sum_{j=1}^{N_{\rm user}}(R_{m,j,k}+\mu x_{m,j,k})$ denote the utility of the k-th subchannel. Accordingly, the preference relation of the k-th subchannel over different matching pairs is given by

$$\eta_1 \succ_k \eta_2 \Leftrightarrow U(\eta_1) > U(\eta_2), \tag{18}$$

where η_1 (or η_2) is a matching pair and $U(\eta_1)$ (or $U(\eta_2)$) is the utility of subchannel$_k$ obtained under η_1 (or η_2).

4.2 Algorithm description for terrestrial transmission

The terrestrial transmission optimization problem in (14) has multiple optimization objectives, which aim to obtain a larger network sum rate and save backhaul traffic as much as possible. To solve this problem, we propose a UDM algorithm by dividing all users into two groups according to their request. We denote one group as $\mathcal{U}_{\rm local}$ including the users in the local-cache case and the other group as $\mathcal{U}_{\rm back}$, which consists of the users in the backhaul-retrieving case. Therefore, for the users in $\mathcal{U}_{\rm local}$, the terrestrial transmission optimization problem is converted into the single-objective problem and solved by the matching theory. Then, with the little available resource, we adopt the exhaustive searching algorithm to deal with the users in $\mathcal{U}_{\rm back}$. According to (14), we define the gain of user$_j$ in $\mathcal{U}_{\rm back}$ occupying unmatched SBS-subchannel unit (m,k) as ${\rm Gain}_{j,(m,k)}$, which is given by

$${\rm Gain}_{j,(m,k)} = R'_{m,j,k} - R_{\rm sub} + \mu - \lambda_m U_{\rm back}, \tag{19}$$

where $R'_{m,j,k}$ is the data rate of user$_j$, $R_{\rm sub}$ is the impact of adding user$_j$ to the network sum rate. SBS-subchannel unit (m,k) will select the user with the highest ${\rm Gain}_{j,(m,k)}$ to match.

The whole optimization algorithm for terrestrial transmission is shown in detail in Algorithm 1. Lines 2–21 are the optimization process for users in $\mathcal{U}_{\rm local}$ consisting of the initialization step (lines 2–8) and the matching process (lines 9–21) where multiple iterations are implemented. The following optimization process for users in $\mathcal{U}_{\rm back}$ will not stop until ${\rm Gain}_{j,(m,k)} \leqslant 0$.

4.3 Matching game for satellite-terrestrial communication

(1) Definitions. There are three sets of players: SBSs, SATs and subchannels, which are denoted by $\mathcal{M}$, $\mathcal{S}$ and C, respectively. Similar to the method in Subsection 4.1, we combine SAT$_s$ and the c-th subchannel as a SAT-subchannel unit (s,c), which forms a new set $\mathcal{T}=\mathcal{S}\times\mathcal{C}$. Then, for $m\in\mathcal{M}$ and $(s,c)\in\mathcal{T}$, a matching game $\varPhi$ is $\{\mathcal{M}\cup\mathcal{T}\}\rightarrow\{\mathcal{M}\cup\mathcal{T}\}$ which is defined as

- $\Phi(m)\in\mathcal{T}$ and $|\Phi(m)|\leqslant N_r$;
- $\Phi(s,c)\in\mathcal{M}$ and $|\Phi(s,c)|\leqslant 1$;
- if and only if $m\in\Phi(s,c)$, $\Phi(m)\in(s,c)$.

Accordingly, we convert the LEO backhaul capacity optimization problem into a many-to-one matching game satisfying (11e) and (11f).

(2) Preference relation. Following Subsection 4.1, the preference of matched pair $(m,(s,c))$ to the potential pair $(m_p,(s_p,c))$ is re-defined as

$$w_{m,(s,c)}^{m_p,(s_p,c)} = \left(G_{m_p,s_p}^{m_p,s_p} h_{m_p,s_p,c}^{\rm T}\right) / \left(G_{m,s}^{m,s_p} h_{m,s_p,c}^{\rm T}\right). \tag{20}$$

Therefore, the preference relation $\succ_{(s,c)}$ is given by

$$(m_1,(s_1,c)) \succ_{(s,c)} (m_2,(s_2,c)) \Leftrightarrow w_{m,(s,c)}^{m_1,(s_1,c)} > w_{m,(s,c)}^{m_2,(s_2,c)}. \tag{21}$$

The preference of each subchannel over different matching pairs is also similar to Subsection 4.1, where the utility of the c-th subchannel is defined as $R_c=\sum_{m=1}^{N_{\rm SBS}}\lambda_m\sum_{s=1}^{N_{\rm S}}R_{m,s,c}$. The preference of the c-th subchannel is then given by

$$\Phi_1 \succ_c \Phi_2 \Leftrightarrow R_c(\Phi_1) > R_c(\Phi_2). \tag{22}$$

Algorithm 1 UDM algorithm

Input: Sets of users $\mathcal{J}$ and SBS-subchannel units $\mathcal{D}$; coverage matrix $\boldsymbol{A}$.
Output: An optimal matching pair η^*.

1: Divide all ground users into $\mathcal{U}_{\rm local}$ and $\mathcal{U}_{\rm back}$.
2: **Optimization for users in** $\mathcal{U}_{\rm local}$
3: Denote current matching pair as η.
4: The subchannel side puts all user-SBS units in descending order of its preference.
5: **while** there are unmatch subchannels left **do**
6: The remaining unmatched subchannels select the first preference order of unmatched user-SBS unit to match.
7: User will select SBS-subchannel unit with its preference according to (16) if receive more than one proposal.
8: **end while**
9: The user side puts all SBS-subchannel units in descending order of its preference.
10: **while** there are remaining unmatched users in $\mathcal{J}$ or the utility of matched SBS-subchannel units still exist **do**
11: **for** each unmatched user in $\mathcal{J}$ **do**
12: Send the matching request to the first preference order of unmatched SBS-subchannel unit.
13: **end for**
14: **for** each matched SBS-subchannel unit in $\mathcal{D}$ **do**
15: Select its most preferred pair according to (17) as the candidate pair if this subchannel receives more than one request.
16: **end for**
17: **for** each subchannel **do**
18: Select the best candidate pair among all matched SBS-subchannel units' candidate pairs according to (18).
19: **end for**
20: Repeat Step 7.
21: **end while**
22: **Optimization for users in** $\mathcal{U}_{\rm back}$
23: **for** each unmatched SBS-subchannel unit (m,k) in $\mathcal{D}_{\rm un}$ **do**
24: Select one user in coverage of SBS_m with the largest gain according to $\boldsymbol{A}$ and (19).
25: **end for**
26: **return** the optimal matching pair η^*.

4.4 Algorithm description for satellite-terrestrial communication

Considering the multi-connectivity of each SBS, we convert the LEO backhaul capacity optimization problem into a many-to-one matching game. A modified Gale-Shapely (MGS) algorithm is proposed to address such matching problem. Following the idea of the classical GS algorithm, the subchannel side first finds its preferable SBS-SAT pair in a greedy method. More concretely, the unmatched c-th subchannel finds the unmatched SBS_{m^*} and SAT_{s^*} to match up which satisfying

$$m^*, s^* = \arg \max_{m\in\mathcal{M}_{\rm un}, 1\leqslant s\leqslant N_{\rm S}} |h_{m,s,c}|^2, \tag{23}$$

where $\mathcal{M}_{\rm un}$ is the set of unmatched SBSs. If one SBS is proposed by more than N_r subchannels, then it will select N_r most preferred units (s,c) based on descending order of the channel gain.

Then, according to the preference relation of the SAT-subchannel side, each matched SAT-subchannel unit (s,c) will select the most preferred matching pair $(m_p,(s_p,c))$ as its potential matching pair, which satisfying

$$(m_p,(s_p,c)) = \arg \max_{m_p\in\mathcal{M}_{\rm un}, s_p\in\mathcal{T}_{{\rm un},c}} \left\{ w_{m,(s,c)}^{m_p,(s_p,c)} \right\}, \tag{24}$$

where $\mathcal{T}_{{\rm un},c}$ is the set of unmatched SATs over the c-th subchannel. All potential matching pairs of the c-th subchannel construct a set of candidate pairs. Then, each subchannel will select one candidate matching pair $(m,(s,c))$ with the highest utility of the subchannel, i.e.,

$$(m,(s,c)) = \arg \max_{\Phi\in P_c} R_c(\Phi). \tag{25}$$

The remaining candidate matching pairs will then be removed. Finally, the SBS side will select the SAT-subchannel unit with the best channel condition to accept if receives more than one request from multiple SAT-subchannel units.

The whole optimization algorithm for satellite-terrestrial communication is presented in detail in Algorithm 2. The initialization step is implemented in lines 2–6 and the matching process is executed in lines 7–19.

4.5 Algorithm analysis

(1) Computational complexity.

Algorithm 2 MGS algorithm

Input: Sets of SBSs $\mathcal{M}$ and SAT-subchannel units $\mathcal{T}$;
Output: An optimal matching pair Φ^*.
1: Let Φ denote current matching pair.
2: The subchannel side puts all SBS-SAT units in descending order of its preference.
3: **while** there are unmatch subchannels left **do**
4: The remaining unmatched subchannels select the first preference order of unmatched SBS-SAT unit to match.
5: SBS will select N_r most preferred SAT-subchannel units with its preference if receives more than N_r proposals.
6: **end while**
7: The SBS side puts all SAT-subchannel units in descending order of its preference.
8: **while** there are remaining unmatched SBSs in $\mathcal{M}$ or the utility of matched SAT-subchannel units still exist **do**
9: **for** each unmatched SBS in $\mathcal{M}$ **do**
10: Send the matching request to the first preference order of unmatched SAT-subchannel unit.
11: **end for**
12: **for** each matched SAT-subchannel unit in $\mathcal{T}$ **do**
13: Select its most preferred pair according to (24) as the candidate pair if this subchannel receives more than one request.
14: **end for**
15: **for** each subchannel **do**
16: Select the best candidate pair among all matched SAT-subchannel units' candidate pairs according to (25).
17: **end for**
18: Repeat Step 5.
19: **end while**
20: **return** the optimal matching pair Φ^*.

(a) UDM algorithm. For the initialization step, the maximum number of iterations is up to the number of the users in $\mathcal{U}_{\rm local}$. At each iteration of the matching process, each subchannel will select the best candidate matching pair while users will only accept one BS-subchannel unit with the best channel condition if receives more than one proposal. In particular, we assume the worst case is that in each iteration the same user receives a proposal from all matched pairs where only one new matching pair is formed, while the best case is that in each iteration each subchannel finds a new matching pair, i.e., $N_{\rm sub}$ new matched pairs are formed. Therefore, the iteration number of this part varies between $\lceil N_{\rm local}/N_{\rm sub}\rceil$ and $N_{\rm local}$. The maximum number of iterations in the optimization process for users in $\mathcal{U}_{\rm back}$ is the number of the users in $\mathcal{U}_{\rm back}$.

(b) MGS algorithm. The maximum number of iterations in the initialization step is $N_{\rm SBS}$, while the maximum number of iterations in the matching process varies between $\lceil N_{\rm SBS}/N_{\rm C}\rceil$ and $N_{\rm SBS}$.

(2) Implementation. Owing to the strong data computing capability and high transmission bandwidth of SBSs, the proposed algorithms are executed in each SBS. For each SBS, it will implement the MGS algorithm to obtain the maximum LEO backhaul capacity and the UDM algorithm to achieve the maximum sum rate and the number of accessed ground users of the cell.

5 Simulation results analysis

In this section, we evaluate the performance of the proposed algorithm. Three benchmark algorithms are performed for comparison as follows.

• **Exhaustive search (ES) algorithm.** The algorithm is performed in the constructed settings, which searches all possible results to obtain the optimal solution.

• **Greedy algorithm.** This classic algorithm allocates each available subchannel to the user with the maximum transmission rate [23].

• **Random allocation (random) algorithm.** This algorithm randomly allocates all available subchannels on each SBS to the users in coverage.

In our simulation, users are randomly deployed in a region with the size of 5 km $\times$ 5 km, while SBSs are uniformly deployed. The number of SBSs are 25 and the number of satellites varies from 3 to 8. We set the parameter of Zipf distribution to be 1. Three caching strategies are considered, which are the most popular content scheme (MPC), random scheme (RS), and mixed scheme (Mix) [7]. There are 15 subchannels in C-band and 10 subchannels in Ka-band [2]. We use the Rayleigh fading to depict the small scale fading over C-band, and the Rician fading to depict that over Ka-band [24]. The urban micro path loss model is considered in the terrestrial communication [25]. The locations of the satellites are generated based on the real trajectory data of the satellites in the telesat satellite constellation system which is retrieved by the tool of Satellite Tool Kit (STK 9.2.2). Table 1 lists other simulation parameter settings according to 3GPP standard [26].

Table 1 Simulation parameters

Parameter	Value	Unit
Bandwidth for C-band	20	MHz
Bandwidth for Ka-band	400	MHz
White Gaussian noise	−174	dBm/Hz
Noise figure over Ka-band	1.2	dB
SBS transmit power	33	dBm
Satellite transmit power	47	dBm
Umi path loss	$147{+}36.7\log 10(d/1000)$	–
Antenna gain	43.3	dBi
Lagrangian iteration parameter ε	10^{-7}	–
Ka-band carrier frequency	30	GHz
(β, α, ξ)	(70 dB, 2, 5.2)	–

Table 2 Comparison with ES

$N_{\rm SBS}$	$N_{\rm user}$, $N_{\rm sub}$	ES (time (s), rate (Mbps))	LR (time (s), rate (Mbps))	Percent of reduction (%)
$N_{\rm SBS}$=2	$N_{\rm user}$=4, $N_{\rm sub}$=2	0.00539, 130.64	0.00646, 125.19	−19.8
	$N_{\rm user}$=5, $N_{\rm sub}$=2	0.04436, 135.86	0.01058, 135.86	76.1
	$N_{\rm user}$=6, $N_{\rm sub}$=2	0.36454, 128.38	0.00204, 128.38	99.4
	$N_{\rm user}$=6, $N_{\rm sub}$=3	113.375, 189.09	0.00675, 178.86	99.99
	$N_{\rm user}$=7, $N_{\rm sub}$=3	1750.48, 193.00	0.04756, 193.00	99.99
	$N_{\rm user}$=8, $N_{\rm sub}$=3	>12000, –	0.06084, 186.87	99.99

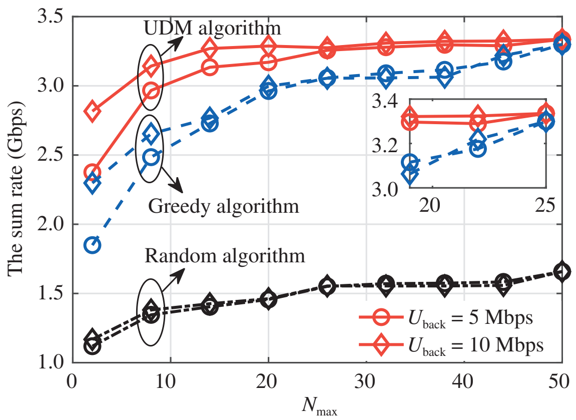

Figure 2 (Color online) System sum rate versus the number of files cached on each SBS ($\mu = 10^6$, $N_r = 2$, $N = 50$, user density = 500 /km^2).

5.1 Comparison with ES

We then verify the gap between the dual optimum and the optimal solution in small-scale testing. Table 2 demonstrates the performance of the proposed method LR, compared to that of the ES algorithm under a varying number of ground users and subchannels. We also show the computation time and the system performance in each cell of the columns. It is shown that the proposed method can significantly reduce the computation time with <1% system performance loss compared to the optimal solution supposing that the number of users is greater than the number of available spectrum resources (i.e., $N_{\rm user}{>}N_{\rm sub} \times N_{\rm SBS}$). Furthermore, we can see that the computation times achieved by ES algorithm have a sharp increase with $N_{\rm user}$ and $N_{\rm sub}$, while the proposed method can effectively save computation time.

5.2 Impact of terrestrial deployments on network performance

Figure 2 shows how the number of files cached on each SBS and the value of $U_{\rm back}$ affect the downlink sum data rate of system with varying algorithms. It can be seen that higher system sum rate can be achieved by the UDM algorithm than other algorithms. Specifically, when each SBS caches 4 files (8% of the entire files in the network) and $U_{\rm back}$= 5 Mbps, the system sum rate could be increased by

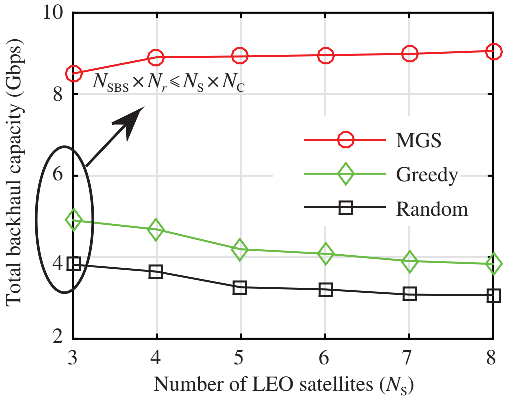

Figure 3 (Color online) The satellite backhaul capacity versus varying number of satellites under different algorithms ($N_{\rm SBS} = 25$, $N_{\rm C} = 10$, $N_r = 1$).

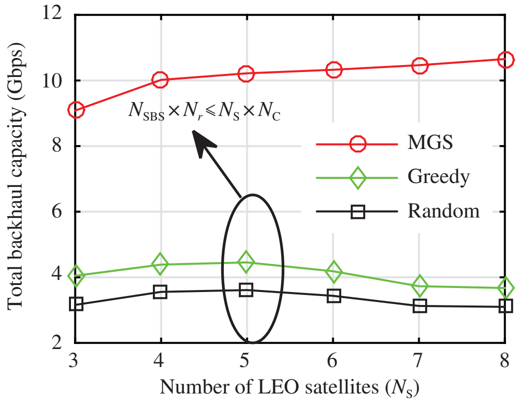

Figure 4 (Color online) The satellite backhaul capacity versus varying number of satellites under different algorithms ($N_{\rm SBS} = 25$, $N_{\rm C} = 10$, $N_r = 2$).

the UDM algorithm with 28.5% and 120.7%, respectively, compared to greedy algorithm and random algorithm. However, further increasing $N_{\max}$ would result in the gain between the UDM algorithm and others algorithms becoming smaller. This is because that more and more user requests could be locally satisfied by SBSs with the increasing $N_{\max}$, which would weaken the superiority of the UDM algorithm in saving backhaul traffic. The above results indicate that our proposed algorithm can effectively improve the system performance in the case of limited cache capacity.

Besides, the value of $U_{\rm back}$ also has a great influence on the system performance as shown in Figure 2. When $N_{\max}$ is small, the downlink sum rate can be improved with larger $U_{\rm back}$. The reason is that users are more likely to request files through backhaul in this case, where the date rates of these users are actually limited by backhaul traffic with a small $U_{\rm back}$. As $N_{\max}$ grows, the probability of consuming backhaul resources decreases, which degrades the difference between varying values of $U_{\rm back}$.

5.3 Impact of satellite deployments on network performance

Figures 3 and 4 plot the total backhaul capacity with varying number of satellites under different algorithms. We can see that the total backhaul capacity achieved by MGS algorithm grows with the number of satellites while the results of other algorithms turn out to be decreasing at the inflection point, where the available spectrum resources exceed the number of users. This is because all SBSs will access to the satellite system in this case, thereby increasing interference and weakening the performance of the satellite backhaul network. Moreover, as N_r increases, the benefit of the multi-connectivity on SBSs results in rapid grow of the satellite backhaul capacity. Accordingly, our proposed algorithm can highlight the gain of multi-connectivity and perform efficiently in different satellite constellation deployments.

5.4 Impact of conversion factor on network performance

Figures 5 and 6 plot the results of two optimization objectives with varying conversion factor under different caching strategies. We can see that the value of μ plays an important role in the preference of the optimization problem. When μ is little, the optimization problem prefers to pursue the target of a largest downlink sum rate. As the value of μ becomes larger, the maximum of sum rate starts to diminish while the number of accessed ground users is increasing. Note that when the value of μ is large enough (approximately after reaching 10), the curves maintain stable which means the maximum of user number has become the main optimization objective. This flexible scheduling of optimization objectives offers a reference for the optimization problems in terrestrial communication.

5.5 Impact of caching strategies on network performance

Figure 7 shows how the number of files cached on each SBS affects the downlink sum data rate of system with varying caching strategies under the UDM algorithm. It can be seen that the downlink sum data rate achieved by three caching strategies increases with the increasing $N_{\max}$ which complies with the results in Subsection 5.2, and the higher system sum rate can be achieved by MPC than other caching strategies.

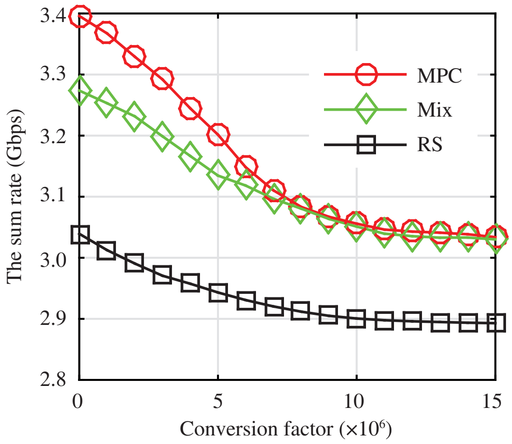

Figure 5 (Color online) The sum rate versus conversion factor ($U_{\rm back}$ = 10 Mbps, N_r = 2, N = 50, $N_{\max}$ = 4, user density = 500 /km^2).

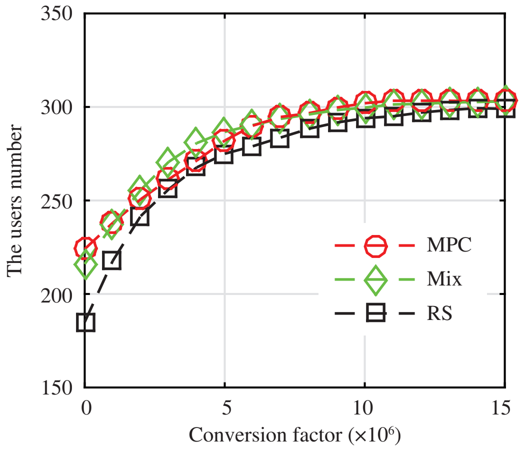

Figure 6 (Color online) The users number versus conversion factor ($U_{\rm back}$ = 10 Mbps, N_r= 2, N = 50, $N_{\max}$ = 4, user density = 500 /km^2).

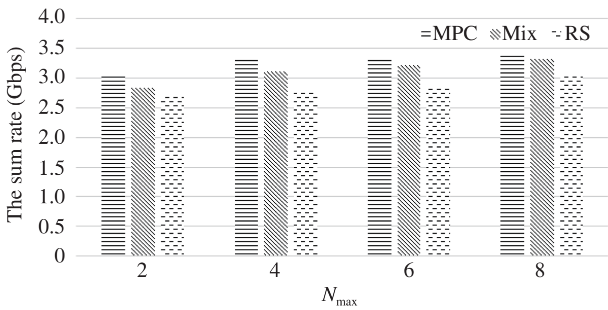

Figure 7 System sum rate versus the number of files cached on each SBS under caching strategies. For the UDM algorithm, μ = 10^6, N_r = 2, N = 50 and user density = 500 /km^2.

This is mainly because users are more likely to get the requested files directly via their associated SBSs in this case, which would enhance the superiority of the UDM algorithm in serving the users in $\mathcal{U}_{\rm local}$ preferentially.

6 Conclusion

In this paper, we investigate the performance of user association and resource allocation in a cache-enabled terrestrial-satellite integrating network. Two algorithms are proposed to jointly optimize user association and resource allocation of both terrestrial and satellite networks. Simulation results show that the proposed algorithms are capable of improving the downlink sum rate of the system and simultaneously guarantee the number of accessed ground users. Therefore, the results in this work are helpful for the design and optimization of the user association and resource allocation in cache-enabled terrestrial-satellite integrating networks.

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Appendix A

Let f_0 denote the original problem (11) and f_i $(\forall i \in \mathcal{M})$ denote terrestrial-satellite coupling constraint (11b). The Lagrangian can be rewritten as

$$\mathcal{L}\left(\boldsymbol{X}, \boldsymbol{B}, \boldsymbol{\lambda}\right) = f_0\left(\boldsymbol{X}, \boldsymbol{B}\right) + \sum_{i=1}^{N_{\rm SBS}} \lambda_i f_i\left(\boldsymbol{X}, \boldsymbol{B}\right), \tag{A1}$$

where $f_0\left(\boldsymbol{X}, \boldsymbol{B}\right) = \sum_{m=1}^{N_{\rm SBS}} R_m + \mu \sum_{m=1}^{N_{\rm SBS}} \sum_{j=1}^{N_{\rm user}} \sum_{k=1}^{N_{\rm sub}} x_{m,j,k}$ and $f_i\left(\boldsymbol{X}, \boldsymbol{B}\right) = C_i - \sum_j x_{m,j,k}(1 - \boldsymbol{q}_j \boldsymbol{y}_i^{\rm T}) U_{\rm back}$. Assuming $\{\hat{\boldsymbol{X}}, \hat{\boldsymbol{B}}\}$ as any feasible point of the original problem, we guarantee the following constraint:

$$\sum_{i=1}^{N_{\rm SBS}} \lambda_i f_i\left(\hat{\boldsymbol{X}}, \hat{\boldsymbol{B}}\right) \geqslant 0, \quad \forall \lambda_i \geqslant 0. \tag{A2}$$

Therefore, we have

$$g\left(\boldsymbol{\lambda}\right) = \sup_{\{\boldsymbol{X}, \boldsymbol{B}\} \in \mathcal{D}} \mathcal{L}\left(\hat{\boldsymbol{X}}, \hat{\boldsymbol{B}}, \lambda\right) = f_0\left(\hat{\boldsymbol{X}}, \hat{\boldsymbol{B}}\right) + \sum_{i=1}^{N_{\rm SBS}} \lambda_i f_i\left(\hat{\boldsymbol{X}}, \hat{\boldsymbol{B}}\right) \geqslant f_0\left(\hat{\boldsymbol{X}}, \hat{\boldsymbol{B}}\right). \tag{A3}$$

Obviously, Eq. (A3) holds for any feasible point and the optimal point is no exception [18]. Accordingly, the dual optimum is the upper bound that is as close as possible to the optimal solution, i.e.,

$$g^* \geqslant f_0^*, \tag{A4}$$

where g^* is the dual optimum and f_0^* is the optimal solution of (11).