electronics

Article

Efficient Resource Allocation for Beam-Hopping-Based Multi-Satellite Communication Systems

Yingjie Wang [1,2], Ming Zeng [1,*] and Zesong Fei [1]

[1] School of Information and Electronics, Beijing Institute of Technology, Beijing 100081, China
[2] Beijing Institute of Technology Chongqing Innovation Center, Chongqing 401120, China
* Correspondence: mzengzm@bit.edu.cn

Abstract: With the rapid growth of data traffic, low earth orbit (LEO) satellite communication networks have gradually ushered in a new trend of development due to its advantages of low latency, wide coverage, and high capacity. However, as a result of the limited on-board resources and rapidly changing traffic demand, it is increasingly urgent to design an efficient resource-allocation scheme to satisfy the traffic demand. In this paper, we propose two resource allocation algorithms in the multi-satellite system based on beam-hopping technology. In the offline case, it is assumed that the channel gains in all time-slots are known in advance, and we propose a heuristic algorithm to allocate time and frequency resources, and a successive convex approximation (SCA) algorithm to allocate power resources. In the online case, it is assumed that only the instant channel gains information is known; therefore, we apply the dynamic programming (DP) algorithm to maximize the system throughput. The simulation results prove that the proposed resource-allocation algorithms based on beam-hopping technology have better performance than the traditional average allocation method, and the online algorithm has acceptable performance loss compared with the offline algorithm.

Keywords: beam-hopping; resource allocation; successive convex approximation; dynamic programming

Citation: Wang, Y.; Zeng, M.; Fei, Z. Efficient Resource Allocation for Beam-Hopping-Based Multi-Satellite Communication Systems. *Electronics* **2023**, *12*, 2441. https://doi.org/10.3390/electronics12112441

Received: 18 April 2023
Revised: 12 May 2023
Accepted: 25 May 2023
Published: 28 May 2023

1. Introduction

1.1. Motivation

Multi-beam low earth orbit (LEO) satellite communication systems generate multiple isolated point beams within their coverage by using multi-beam antenna technology and then provides broadband access services to areas with weak infrastructure [1,2]. However, as a result of the small size and light weight of LEO satellites, their on-board resources face severe limitations [3,4].

In order to solve the problem of limited payload, power and spectrum resources on LEO satellites, multibeam antenna technology has become one of the functions that must be included in the design of satellite communication systems. At first, the use of multibeam antenna technology was mainly based on the fixed allocation of on-board resources. However, the distribution of traffic generated by practical applications is always uneven, which leads to low resource utilization efficiency and reduced system capacity. Therefore, the beam-hopping (BH) technology is adopted in multibeam systems [5–7]. In the BH satellite system, temporal resources are divided into several timeslots. In each timeslot, the satellite selects a portion of beams to allocate frequency bands and power resources based on the current traffic requirements and channel conditions of each cell. In the next timeslot, the satellite "hops" the beam to other cells based on changes in demand and channel conditions. This beam-hopping resource allocation mechanism can have better flexibility and higher resource utilization efficiency, and can adapt well to the uneven distribution of ground users and dynamic changes in communication services [8,9].

1.2. Related Work

Many studies show that satellite systems based on beam-hopping technology has better performance than others. In [8], A. Mokhtar analyzed the throughput of the downlink segment of a LEO global broadband satellite network and presented upper and lower bounds on the downlink throughput as a function of the number of spot beams, the interference constraints, and the coverage area. In [10], the author focused on studying the forward link beam-hopping transmission scheme, and their simulation results showed that the beam-hopping satellite system outperforms traditional systems in terms of matching throughput with ground business requirements, as well as effective utilization of available resources. In [11], J. Anzalchi studied the flexibility of beam-hopping systems and showed that its capacity was higher than that of non-hopping systems. In [12], Juan Lizarraga provided a detailed analysis of the performance improvement brought about by the beam-hopping technology from the perspectives of flexible allocation of on-board resources and satellite load performance.

The design of resource allocation based on beam-hopping technology is another research hotspot. In [13], the author improved the total throughput of the system by optimizing beam allocation. In [14], Feng Tian proposed a greedy algorithm in the LEO satellite system to allocate frequency and power to beams. In [15], the author considered power optimization based on demand and channel quality, which aimed at overall system performance. The study [16] introduced joint power and frequency allocation optimization, focusing on maximizing the minimum ratio between user requests and the signal-to-interference-plus-noise ratio (SINR) provided, but flexibility is limited by orthogonal carrier allocation and binary power allocation assumptions within the beam cluster. At the same time, multi-beam satellite resource allocation is developing from fixed allocation to dynamic joint allocation. In the literature, refs. [17,18] conducted a series of research works to verify the advantages of the highly flexible dynamic beam-hopping method in multi-beam satellite systems. In addition, the DVB-S2X standard has proposed several superframe specifications [19] to support beam-hopping transmission in future multi-beam satellites, which also means that beam-hopping technology has enormous potential.

Some studies have proposed joint research between beam-hopping technology and other technologies. In [20], the author studied the synergistic effects of non-orthogonal multiple access and beam-hopping in multi-beam satellite systems and proposed a greedy algorithm. The authors of [21] proposed a method of combining precoding and beam-hopping, which added precoding to balance inter-beam interference. Reference [22] studied a possible method to improve system performance through the interaction between onboard switching fabric and BH.

1.3. Contribution

The contributions of our paper are summarized as follows:

(1) We present a multi-satellite offline resource allocation algorithm based on beam-hopping technology to address the limited satellite resources and the inability of traditional resource allocation methods to achieve the efficient utilization of resources. We first construct a multi-satellite offline resource allocation model, which divides onboard resources into three dimensions: time, frequency, and power. Subsequently, a heuristic time-frequency resource allocation algorithm is proposed based on the beam interference pattern, and the power resources are allocated using the successive convex approximation (SCA) algorithm [23].

(2) In response to the difficulty of implementing the assumption of non-causal channel information in offline algorithm, we propose a multi-satellite online resource allocation algorithm based on dynamic programming (DP) that only requires instant channel information [24,25]. We first construct a multi-satellite online resource allocation model and propose online optimization problems that evolve over time. Then, starting from the last time-slot, we recursively solve the optimal solution of the Bellman

equation for each time-slot and use this results to solve the optimal solution of the online optimization problem for each time-slot.

(3) The final simulation results demonstrate that compared to the traditional average resource-allocation method, our proposed offline and online schemes achieve significant gains in systems and single-beam throughput. Since the online algorithm only relies on causal channel information for resource allocation, and discretization is performed on the power variables, there is a certain performance loss compared with the offline algorithm, but the results show that the loss is acceptable.

The rest of this paper is organized as follows. Section 2 establishes a multi-satellite resource allocation model and proposes the system-throughput-maximization problem for the joint optimization of time, frequency, and allocation of power resources. In Section 3, a multi-satellite offline resource allocation algorithm based on beam-hopping technology is proposed. Section 4 proposes a multi-satellite online resource allocation algorithm based on DP. In Section 5, numerical results are given to verify the performance of the proposed algorithms. Section 6 concludes the paper.

Notation: In this paper, italic letters represent scalars, and boldface letters represent vectors or matrices. $\mathbb{R}^{m\times n}$ represents a real matrix with m rows and n columns. $\mathbb{E}\{.\}$, $|\cdot|$, and $\bigtriangledown(.)$ represent the expectation, modular, and derivation operations. $[x]^+$ denotes $max\{0,x\}$. $J_1(.)$ and $J_3(.)$ correspond to the first-kind Bessel functions of order 1 and 3, and $\inf(.)$ represents the infimum of function.

2. System Model

2.1. System Setup

Consider a multi-satellite system consisting of J LEO satellites, each serving M cells on the earth. Each satellite is equipped with multi-beam antennas to send service beams to its served cells. Each satellite uses N subcarriers of bandwidth B_{sc}, so the total available system bandwidth is $B_{tot} = N \cdot B_{sc}$. In the time dimension, we divide a period of time into multiple time-segments T_{seg}, and then divide one time-segment into K time-slots with length $T_s = T_{seg}/K$ for scheduling. During each time-slot, each satellite needs to select some cells covered by the beam according to the traffic demand of each cell. For the cell m served by the satellite j, let $\mathbf{A}_m^j \in \mathbb{R}^{N\times K}$ be the temporal and frequency resource-allocation matrix, and its element $a_{m,nk}^j$ of the nth row and kth column is a binary assignment indicator, with $a_{m,nk}^j = 1$ indicating that in the kth time-slot, the beam using the nth subcarrier is allocated to this cell, and $a_{m,nk}^j = 0$ indicating it is not allocated. Meanwhile, let P_{max} denote the maximum transmission power of each satellite and $\mathbf{P}_m^j \in \mathbb{R}^{N\times K}$ denote the power allocation matrix, with the element $p_{m,nk}^j \in (0, P_{max}]$ if $a_{m,nk}^j = 1$.

2.2. Channel Model

Based on reality, we model the channel between the satellite and the ground as a Shadowed-Rician distribution model [26,27]. The channel coefficient $h_{jm,k}^j$ between the satellite j and the cell m served by the satellite j during the kth time-slot can be denoted as

$$h_{jm,k}^j = \sqrt{P_L b(\varphi_{jm,k}^j)}(Ae^{j\psi_{jm,k}^j} + Ze^{j\phi_{jm,k}^j}), \tag{1}$$

$$P_L = (\frac{\lambda}{4\pi})^2 \frac{1}{d^2}, \tag{2}$$

$$b(\varphi_{jm,k}^j) = b_{\max}\left(\frac{J_1(u_{jm,k}^j)}{2u_{jm,k}^j} + 36\frac{J_3(u_{jm,k}^j)}{(u_{jm,k}^j)^3}\right)^2, \tag{3}$$

$$u_{jm,k}^j = 2.07123\frac{sin\varphi_{jm,k}^j}{sin(\varphi_{3\mathrm{dB}})_{jm,k}^j}, \tag{4}$$

where P_L, λ, and d respectively represent the path loss, the carrier wavelength, and the distance between the satellite and the cell. $\varphi_{3\text{dB}}$ denotes the 3-dB angle of antenna. We consider the path between the satellite and the cell as a combination of a direct path and several scattering paths. A represents the amplitude of the direct path, and $\phi^j_{jm,k}$ represents the deterministic phase. Z represents the amplitude of the scattering path, and $\psi^j_{jm,k}$ represents the random phase.

2.3. Problem Formulation

In this section, we propose a resource allocation problem to satisfy the traffic demand of each cell and maximize the total system throughput. The specific form is as follows:

$$\begin{aligned}
&\max_{\mathbf{A},\mathbf{P}} \sum_{j=1}^{J}\sum_{m=1}^{M} R^j_m \\
s.t.\ &R1: R^j_m \geq T^j_m, \forall j, \forall m, \\
&R2: \sum_{m=1}^{M}\sum_{k=1}^{K}\sum_{n=1}^{N} p^j_{m,nk} \leq P_{max}, \forall j, \\
&R3: p^j_{m,nk} \geq 0, \forall j, \forall m, \forall n, \forall k,
\end{aligned} \tag{5}$$

where T^j_m represents the traffic demand of the mth cell served by the satellite j, and R^j_m denotes the throughput, which can be expressed as

$$R^j_m = \sum_{k=1}^{K}\sum_{n=1}^{N} B_{sc} \log_2\left(1 + \gamma^j_{m,nk}\right), \tag{6}$$

where $\gamma^j_{m,nk}$ represents the SINR for users of the mth cell served by the satellite j covered by the beam using the nth subcarrier during the kth time-slot, and it can be expressed as

$$\gamma^j_{m,nk} = \frac{a^j_{m,nk} p^j_{m,nk} H^j_{jm,k}}{\sum\limits_{(i,q)\neq(j,m)} a^i_{q,nk} p^i_{q,nk} H^i_{jm,k} + N_0}, \tag{7}$$

where $H^j_{jm,k} = |h^j_{jm,k}|^2$ represents the channel gain and N_0 represents the noise power.

In (5), constraint $R1$ guarantees that the throughput in each cell satisfies the respective demand. Constraint $R2$ guarantees that the total transmission power of the satellite is less than P_{max}. Constraint $R3$ guarantees that the allocated power is non-negative.

Next, we propose two different algorithms based on the availability of the information to solve problem (5). The information required to solve the problem optimally is the channel gain of the previous, current, and future time slots. In the offline scenario, it is assumed that the precise channel gains within the future time segment have been obtained in advance. Although this assumption is difficult to achieve, it provides the optimal solution performance of the problem (5). The second scenario is the online case, where it is assumed that only instant channel gains are known.

3. Offline Resource Allocation Scheme

In this section, we provide an offline algorithm, and in this algorithm, the channel gains are assumed to be known in advance. Obviously, the optimization problem (5) is a nonconvex mixed integer programming problem. Therefore, we cannot use traditional convex optimization tools to solve the global optimal solution. To address this problem, this paper first assumes an average allocation of power resources and adopts a heuristic algorithm to allocate time-frequency resources. Finally, when the time-frequency resource allocation result is fixed, the SCA algorithm is used for power allocation.

3.1. Temporal and Frequency Resource Allocation

In this subsection, we propose a heuristic scheme to allocate the temporal and frequency resource. First, we construct a graph that reflects major interference occurring among beams from a single satellite or different satellites. According to the graph theory proposed in [28], the corresponding interference graph is denoted by $\mathbf{E}(p,q,k) = \{0,1\}$, where p and q represent any two cells in the network during the kth time-slot. The concrete principles of the interference graph construction are as follows:

(1) If both beams directed to cell p and q are from the same satellite, let $\mathbf{E}(p,q,k) = 1$.
(2) If both beams directed to cell p and q are from different satellites, and interfere seriously with each other when using the same subcarrier, let $\mathbf{E}(p,q,k) = 1$.
(3) If (1) and (2) are not met, let $\mathbf{E}(p,q,k) = 0$.

Note that if $\mathbf{E}(p,q,k) = 1$, both beams directed to cell p and q cannot use the same subcarrier in the same time slot. Hence, principle (1) ensures no interference among beams of the same satellite, and principle (2) prevents major interference among beams of different satellites.

Second, we propose the temporal and frequency resource allocation scheme shown in Algorithm 1. Note that V represents all the cells in the network, and $\overline{p} = p_{max}/NK$ represents average power distribution in advance. Afterward, we select the cells with the highest demand for resource allocation in the current system while avoiding the allocation of connected beams to the same time-frequency resource lattice.

Algorithm 1 Temporal and Frequency Resource Allocation

Input: $H^j_{jm,k}$, T^j_m, $\mathbf{E}(p,q,k), \forall j, \forall m, \forall n, \forall k$
Output: $\mathbf{A}^j_m, \forall j, \forall m$
Initialize: $\mathbf{A}^j_m = \mathbf{0}, \forall j, \forall m$;
for $k = 1$ to K **do**
  for $n = 1$ to N **do**
    $p = 1$; $\Delta^p_{nk} = V$;
    while $p \leq j$ and $\Delta^p_{nk} \neq \emptyset$ **do**
      $m^\star = \underset{m \in \Delta^p_{nk}}{argmax}\, T^j_m$; cell $m^\star$ served by the satellite $j^\star$
      $a^{j^\star}_{m^\star,nk} = 1$;
      $T^{j^\star}_{m^\star} = max\left(T^{j^\star}_{m^\star} - B_{sc}\log_2\left(1 + \frac{\overline{p}H^{j^\star}_{j^\star m^\star,k}}{N_0}\right), 0\right)$
      $\Lambda^{j^\star}_{m^\star} = \emptyset$;
      for $j = 1$ to J **do**
        for $m = 1$ to M **do**
          if $m \neq m^\star$ and $j \neq j^\star$ and $\mathbf{E}(m, m^\star, k) = 0$ **then**
            $\Lambda^{j^\star}_{m^\star} = \Lambda^{j^\star}_{m^\star} \cup m$;
          end if
        end for
      end for
      $\Delta^{p+1}_{nk} = \Delta^p_{nk} \cap \Lambda^{j^\star}_{m^\star}$;
      $p = p + 1$;
    end while
  end for
end for

3.2. Power Resource Allocation

After allocating the temporal and frequency resource, all the matrices $\mathbf{A}^j_m$ in problem (5) are determined. Observing the form of the objective function in this problem, as both the numerator and denominator of the SINR $\gamma^j_{m,nk}$ contain optimization variable $p^j_{m,nk}$, it is evident that this problem is still non-convex. We use the well-known tool of SCA to attain a suboptimal solution [29].

First, the negative value of sum throughput can be written as

$$-\sum_{j=1}^{J}\sum_{m=1}^{M} R_m^j = \sum_{j,m,k,n} B_{sc}\left[U_{m,nk}^j(\mathbf{p}) - V_{m,nk}^j(\mathbf{p})\right] \tag{8}$$

where $U_{m,nk}^j(\mathbf{p})$ and $V_{m,nk}^j(\mathbf{p})$ are convex functions given by:

$$U_{m,nk}^j(\mathbf{p}) = \log_2\left(\sum_{(i,q)\neq(j,m)} a_{q,nk}^i p_{q,nk}^i H_{jm,k}^i + N_0\right), \tag{9}$$

$$V_{m,nk}^j(\mathbf{p}) = \log_2\left(\sum_{(i,q)} a_{q,nk}^i p_{q,nk}^i H_{jm,k}^i + N_0\right). \tag{10}$$

Now when we give an approximation point $\overline{\mathbf{p}}$, a convex minimization problem can be formulated as

$$\min_{\mathbf{P}} \sum_{j,m,k,n} B_{sc}\left[\widetilde{U}_{m,nk}^j(\mathbf{p},\overline{\mathbf{p}}) - V_{m,nk}^j(\mathbf{p})\right], \tag{11}$$

where $\widetilde{U}_{m,nk}^j(\mathbf{p},\overline{\mathbf{p}})$ can be expressed as

$$\widetilde{U}_{m,nk}^j(\mathbf{p},\overline{\mathbf{p}}) = U_{m,nk}^j(\overline{\mathbf{p}}) + \triangledown U_{m,nk}^j(\overline{\mathbf{p}})(\mathbf{p}-\overline{\mathbf{p}})^T. \tag{12}$$

In the above formula, $\triangledown U_{m,nk}^j(\overline{\mathbf{p}})$ is a derivative vector, and its elements are given by

$$\frac{\partial U_{m,nk}^j(\overline{\mathbf{p}})}{p_{q,nk}^i} = \frac{a_{q,nk}^i H_{jm,k}^i}{\ln 2\left(\sum_{(i,q)\neq(j,m)} a_{q,nk}^i \overline{p}_{q,nk}^i H_{jm,k}^i + N_0\right)}. \tag{13}$$

Note that the constraint function $R1$ in problem (5) is still non-convex, and we can convert it into a convex function in the same way

$$T_m^j - \sum_{j,m,k,n} B_{sc}\left[\widetilde{U}_{m,nk}^j(\mathbf{p},\overline{\mathbf{p}}) - V_{m,nk}^j(\mathbf{p})\right] \leq 0. \tag{14}$$

Finally, the original non-convex problem is transformed into the following convex problem:

$$\begin{aligned}
&\min_{\mathbf{P}} \sum_{j,m,k,n} B_{sc}\left[\widetilde{U}_{m,nk}^j(\mathbf{p},\overline{\mathbf{p}}) - V_{m,nk}^j(\mathbf{p})\right]\\
&s.t.\ R1: T_m^j - \sum_{j,m,k,n} B_{sc}\left[\widetilde{U}_{m,nk}^j(\mathbf{p},\overline{\mathbf{p}}) - V_{m,nk}^j(\mathbf{p})\right] \leq 0, \forall j, \forall m,\\
&R2: \sum_{m=1}^{M}\sum_{k=1}^{K}\sum_{n=1}^{N} p_{m,nk}^j - P_{max} \leq 0, \forall j,\\
&R3: p_{m,nk}^j \geq 0, \forall j, \forall m, \forall n, \forall k,
\end{aligned} \tag{15}$$

We use the classical Lagrange dual method to solve the convex problem. First, the Lagrange function of $\mathbf{P}$ can be expressed as

$$\begin{aligned}
&L(\mathbf{P},\lambda,\mu) = \sum_{j,m,k,n} B_{sc}\left[\widetilde{U}_{m,nk}^j(\mathbf{p},\overline{\mathbf{p}}) - V_{m,nk}^j(\mathbf{p})\right] +\\
&\sum_{j=1}^{J}\sum_{m=1}^{M}\lambda_{j,m}\left(T_m^j - \sum_{j,m,k,n} B_{sc}\left[\widetilde{U}_{m,nk}^j(\mathbf{p},\overline{\mathbf{p}}) - V_{m,nk}^j(\mathbf{p})\right]\right) + \sum_{j=1}^{J}\mu_j\left(\sum_{m=1}^{M}\sum_{k=1}^{K}\sum_{n=1}^{N} p_{m,nk}^j - P_{max}\right)
\end{aligned} \tag{16}$$

where $\lambda_{j,m}$ and μ_j represent the Lagrange multiplier. Subsequently, according to Karush–Kuhn–Tucker (KKT) conditions $\partial L(\cdot)/p^j_{m,nk} = 0$, we can obtain the optimal solution $p^{j,\star}_{m,nk}$:

$$p^{j,\star}_{m,nk} = \left[\frac{1}{\frac{-\mu_j \ln 2}{(\lambda_{j,m}B_{sc} - B_{sc})} + \frac{a^j_{m,nk}H^j_{jm,k}}{\sum\limits_{(i,q)\neq(j,m)} a^i_{q,nk}\overline{p}^i_{q,nk}H^i_{jm,k} + N_0}} - \frac{N_0}{a^j_{m,nk}H^j_{jm,k}} \right]^+, \tag{17}$$

Then, we study the dual problem of the original problem:

$$\begin{aligned} &\max_{\lambda,\mu} \inf L(\cdot) \\ &s.t. \lambda_{j,m} \geq 0, \forall j, \forall m, \\ &\mu_j \geq 0, \forall j, \end{aligned} \tag{18}$$

Finally, we use the gradient-descent method to solve dual variables:

$$\begin{aligned} \lambda^{t+1}_{j,m} &= \left[\lambda^t_{j,m} - \Delta_{\lambda_{j,m}} \left(\sum_{j,m,k,n} B_{sc} \left[\widetilde{U}^j_{m,nk}(\mathbf{p}^*, \overline{\mathbf{p}}) - V^j_{m,nk}(\mathbf{p}^*) \right] \right) \right]^+ \\ \mu^{t+1}_j &= \left[\mu^t_j - \Delta_{\mu_j} \left(P_{max} - \sum_{m=1}^{M} \sum_{k=1}^{K} \sum_{n=1}^{N} p^{j,*}_{m,nk} \right) \right]^+ \end{aligned} \tag{19}$$

When the initial values of $\lambda_{j,m}$ and μ_j are given, they can be updated iteratively through the above formulas until they converge. Finally, the power allocation scheme based on SCA is shown in Algorithm 2.

Algorithm 2 Power Allocation through the SCA

Input: $\mathbf{A}^j_m$, $H^j_{jm,k}$, T^j_m, $\forall j, \forall m, \forall n, \forall k$
Output: $\mathbf{P}^j_m$, $\forall j, \forall m$
Initialize: $\left(\mathbf{P}^j_m\right)^0, \forall j, \forall m;$
for $t = 1$ to t_{max} **do**
  $\mathbf{p}^\star = \operatorname{argmin} \sum\limits_{j,m,k,n} \left[\widetilde{U}^j_{m,nk}(\mathbf{p}, \mathbf{p}^{t-1}) - V^j_{m,nk}(\mathbf{p}) \right];$
  $\mathbf{p}^{t+1} = \mathbf{p}^t + \eta(\mathbf{p}^\star - \mathbf{p}^t)$; % η is iteration step
  $t = t + 1;$
end for

For this offline algorithm, the computational complexity is mainly focused on convex optimization in power allocation. We let $f(J, M, K, N)$ denote the complexity of the convex optimization in (11), which depends on the values of variables J, M, N, K. Finally, the complexity of the offline algorithm is $\mathcal{O}(t_{max} f(J, M, K, N))$.

4. Online Resource Allocation Scheme

In the previous section, we propose an offline solution assuming that complete information about the channel gains is available. As discussed before, this assumption is too optimistic for most of practical scenarios. Therefore, in this section, we design an online resource allocation scheme through the dynamic programming algorithm.

4.1. Problem Formulation

First, let us define the available power of satellite j at the kth time-slot as B_k^j which is given as

$$\begin{aligned} B_1^j &= P_{max}, \\ B_k^j &= B_{k-1}^j - \sum_{m,n} p_{m,n(k-1)}^j (k = 2, 3, \ldots K). \end{aligned} \tag{20}$$

The online problem with K time slots is to design K resource allocation schemes $(\mathbf{A}_1, \ldots, \mathbf{A}_K)$ and $(\mathbf{P}_1, \ldots, \mathbf{P}_K)$. For the first time slot, we facing the optimization problem:

$$\begin{aligned} \max_{\mathbf{A}_1,\mathbf{P}_1} &\sum_{j,m,n} B_{sc} \log_2\left(1 + \gamma_{m,n1}^j\right) \\ &\quad + \mathbb{E}\left\{\sum_{k=2}^{K} \sum_{j,m,n} B_{sc} \log_2\left(1 + \gamma_{m,nk}^j\right)\right\} \\ s.t.\ R1 : &\sum_{m,n} p_{m,n1}^j \leq B_1^j, \forall j, \\ R2 : &\ p_{m,n1}^j \geq 0, \forall j, \forall m, \forall n, \end{aligned} \tag{21}$$

In the above optimization problem, the first item represents the system throughput achieved in the first time slot, and the second item represents the expected system throughput achieved in the future $K-1$ time slots. Therefore, the optimization problem is to balance the throughput between the first time slot and the future $K-1$ time slots. Constraint $R1$ indicates that the total power allocated in the first time-slot is not greater than the current remaining allocatable total power.

Under instant channel information, throughput balancing for multiple time slots is a dynamic process. Over time, the channel gain information gradually changes from previously unknown to known, and at the same time, online optimization problems continue to evolve forward:

$$\begin{aligned} \max_{\mathbf{A}_{k'},\mathbf{P}_{k'}} &\sum_{j,m,n} B_{sc} \log_2\left(1 + \gamma_{m,nk'}^j\right) \\ &\quad + \mathbb{E}\left\{\sum_{(k=k'+1)}^{K} \sum_{j,m,n} B_{sc} \log_2\left(1 + \gamma_{m,nk}^j\right)\right\} \\ s.t.\ R1 : &\sum_{m,n} p_{m,nk'}^j \leq B_{k'}^j, \forall j, \\ R2 : &\ p_{m,nk'}^j \geq 0, \forall j, \forall m, \forall n, \\ R3 : &\ B_{k'}^j = B_{k'-1}^j - \sum_{m,n} p_{m,n(k'-1)}^j, \forall j, \end{aligned} \tag{22}$$

which is a subproblem of (15). Due to the fact that the future channel gains are random variables, this problem is inherently stochastic, and the current channel gains will have an impact on resource allocation schemes for different time-slots in the future, thus coupling optimization problems for different time-slots.

4.2. Bellman Equation

After giving the initial states B_1^j of all satellites j, we can recursively solve the optimal value of the first time-slot online problem through the Bellman equation. Recursive computation starts from the last time-slot K and maximizes the current throughput by designing the optimal resource allocation scheme $\mathbf{A}_K$ and $\mathbf{P}_K$:

$$\mathcal{F}_K(B_K) = \max_{\mathbf{A}_K,\mathbf{P}_K} \mathbb{E}\left[\sum_{j,m,n} B_{sc}\log_2\left(1+\gamma^j_{m,nK}\right)\right] \tag{23}$$

where B_K represents the available power set of all satellites at the time-slot K and $\mathcal{F}_K(B_K)$ represents the maximum expected throughput at the time-slot K. The maximum expected throughput at the time-slots $K-1$ to 1 can be recursively solved using the Bellman equation:

$$\begin{aligned}\mathcal{F}_k(B_k) = \max_{\mathbf{A}_k,\mathbf{P}_k} \mathbb{E}\left[\sum_{j,m,n} B_{sc}\log_2\left(1+\gamma^j_{m,nk}\right) + \mathcal{F}_{k+1}(B_{k+1})\right] \\ k = K-1,\ldots 1\end{aligned} \tag{24}$$

where B_k represents the available power set of all satellites at the time-slot k and $\mathcal{F}_k(B_k)$ represents the maximum expected throughput at the time-slot k.

4.3. Problem-Solving

In this subsection, we introduce how to solve the Bellman Equations (23) and (24). First, we define the sum power of satellite j consumed in the time-slot k as $T^j_k = \sum\limits_{m,n} p^j_{m,nk}$. Then, we let the available power B^j_k and the consumed power T^j_k be discretized to finite sets:

$$\begin{aligned} &B^j_k \in \mathcal{B}^P = (\mathcal{B}_1,\ldots,\mathcal{B}_P), \forall k \\ &T^j_k \in \mathcal{T}^Q = (\mathcal{T}_1,\ldots,\mathcal{T}_Q), \forall j, \forall k\end{aligned} \tag{25}$$

where $\mathcal{B}^P$ is a finite set containing P elements, and $\mathcal{T}^Q$ is a finite set containing Q elements. Finally, the optimization for time-slot K in (23) is given by

$$\begin{aligned}\mathcal{F}_K(B_K) = \max_{\mathbf{A}_K,\mathbf{P}_K} \mathbb{E}\left[\sum_{j,m,n} B_{sc}\log_2\left(1+\gamma^j_{m,nK}\right)\right] \\ s.t. \quad T^j_K \le B^j_K, \forall j, \quad B^j_K \in \mathcal{B}^P, T^j_K \in \mathcal{T}^Q, \forall j\end{aligned} \tag{26}$$

For the Bellman equation in time-slot k, its form is transformed into

$$\begin{aligned}\mathcal{F}_k(B_k) = \max_{\mathbf{A}_k,\mathbf{P}_k} \mathbb{E}\left[\sum_{j,m,n} B_{sc}\log_2\left(1+\gamma^j_{m,nk}\right) + \mathcal{F}_{k+1}(B_{k+1})\right] \\ k = K-1,\ldots 1 \\ s.t. \quad T^j_k \le B^j_k, \forall j, \quad B^j_k \in \mathcal{B}^P, T^j_k \in \mathcal{T}^Q, \forall j\end{aligned} \tag{27}$$

Because the available power B^j_k and the consumed power T^j_k are all in the finite set, we can solve for the optimal value through traversal.

Algorithm 3 shows the complete process of the online resource-allocation scheme. We divide it into two phases: planning and transmission. In the planning phase, we calculate the optimal value $\mathcal{F}_k(B_k)$ for all time slots. Note that $\mathcal{F}_k(B_k)$ represents the maximized expected throughput after the kth time-slot. Hence, in the transmission phase, when we need to balance the current consumed resource and the future consumed resource in problem (22), we can solve it by replacing the mean term, which represents the future expected throughput, with $\mathcal{F}_k(B_k)$.

Algorithm 3 Online Resource Allocation

Planning phase:
Calculate the optimal value $\mathcal{F}_K(B_K)$ by solving (26);
for $k = K - 1$ to 1 **do**
  Calculate the optimal value $\mathcal{F}_k(B_k)$ by solving (27);
end for
Transmission phase:
for $k = 1$ to K **do**
  1: Replace the mean term in problem (22) with $\mathcal{F}_{k'+1}(B_{k'+1})$ obtained from the planning phase;
  2: For realistic channel gain, calculate the optimal resouce allocation scheme $\mathbf{A}_k$ and $\mathbf{P}_k$ by solving problem (22);
  3: Update the available power B_k using equation (20).
end for

For the online algorithm, in the planning phase, the computational complexity is mainly focused on the calculation of Bellman equations (19) and (20). We let f_B denote the complexity of calculating one Bellman equation for a state B_k, and we calculate the Bellman equations for all possible P states at each time slot and for all the K time slots. Therefore, the complexity in the planning phase is $\mathcal{O}(KPf_B)$. Then, in the transmission phase, we let f_c denote the complexity of the convex optimization in (16), and the complexity in the transmission phase is $\mathcal{O}(Kf_c)$. Finally, the complexity of the online algorithm is $\mathcal{O}(KPf_B + Kf_c)$.

5. Numerical Result

In this section, we conduct performance simulations for the proposed offline and online algorithms. We consider a multi-satellite system consisting of $J = 3$ satellites, and each serves $M = 20$ cells on the Earth. The total available system bandwidth is $B_{tot} = 210$ MHz, with each satellite using $N = 7$ subcarriers of bandwidth $B_{sc} = 30$ MHz. We set the length of a time segment as $T_{seg} = 1$ s, and the length of a time-slot as $T_s = 100$ ms. Meanwhile, we assume that the traffic demand of each cell follows the Poisson distribution. To compare with traditional non-beam-hopping systems, we propose an average resource allocation method. Average resource allocation means that satellites do not consider the current channel conditions and traffic requirements of different cells, and we allocate time-frequency resources and power resources equally to each cell. Due to the absence of beam-hopping, the value of all elements $a^j_{m,nk}$ in $\mathbf{A}^j_m$ is 1, and $p^j_{m,nk}$ in $\mathbf{P}^j_m$ is equal to P_{max}/NK for satellite j.

Figure 1 shows the time-frequency resource allocation result of a certain satellite in the system. In Figure 1, five random cells are selected from the twenty cells it serves, and each is represented by a pattern. And when the time-frequency resource corresponding to a grid is allocated to one of the five cells, the grid is filled with the corresponding pattern. From Figure 1, we can see that some cells will be allocated more time-frequency resource grids, but other cells will be allocated fewer time-frequency resource grids. This is due to the different traffic demands and channel conditions of cells. And this reflects the advantage of on-demand allocation in the beam-hopping system.

Figure 2 shows the convergence performance of power allocation using the SCA algorithm under different iteration steps η. It is observed that, although the iteration step will not affect the final convergence result, it will have an impact on the convergence speed of the algorithm. Therefore, in the subsequent simulation, we set the iteration step size to 0.9 and the maximum number of iterations to 15.

Figure 3 shows the system throughput performance of the proposed offline algorithm and online algorithm under different satellite transmission powers. We can find that, compared with the average resource allocation with no beam-hopping, both proposed algorithms achieve $1.5 \sim 1.8$ times performance gain. From Figure 3, we can also see that, compared with the upper bound obtained by the offline algorithm, the online algorithm has a performance gap of about 20%.

In Figure 4, we randomly select ten satellite beams in the system, count their respective traffic demand, and compare them with the single-beam throughput achieved by applying the proposed algorithms. It is observed that, when the average resource allocation is applied, the throughput of some beams is lower than the traffic demand, such as beam 8 and beam 9. However, when the offline algorithm or online algorithm is applied, because relevant constraints are added to the optimization, we can ensure that the traffic demand of all beams is met.

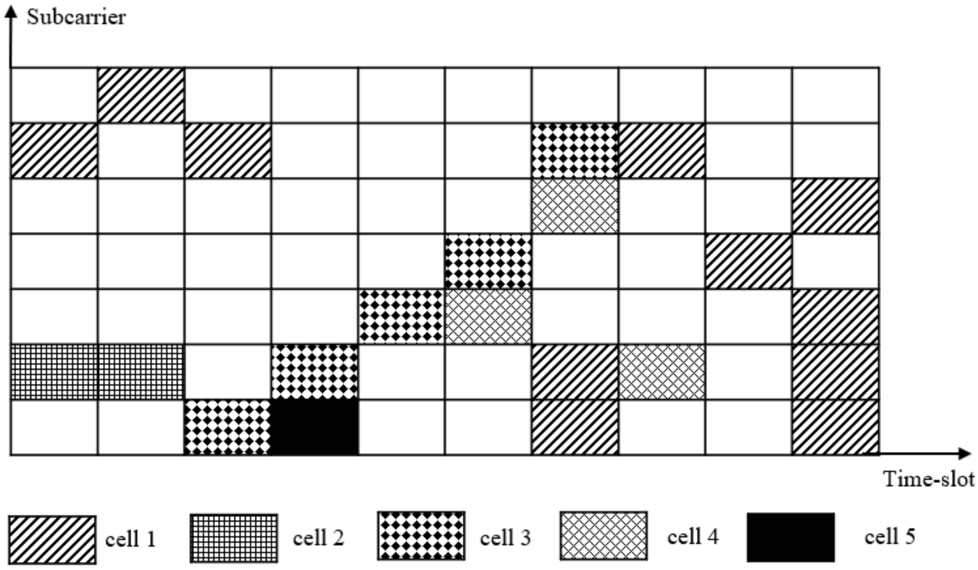

Figure 1. Time-frequency resource allocation pattern.

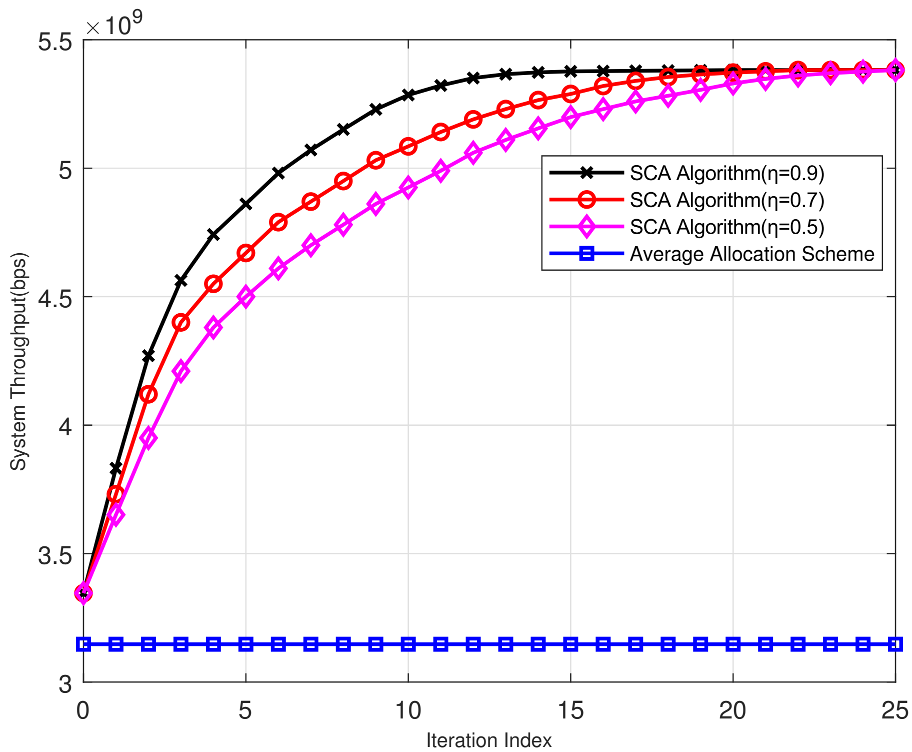

Figure 2. Convergence of the SCA Algorithm in power allocation.

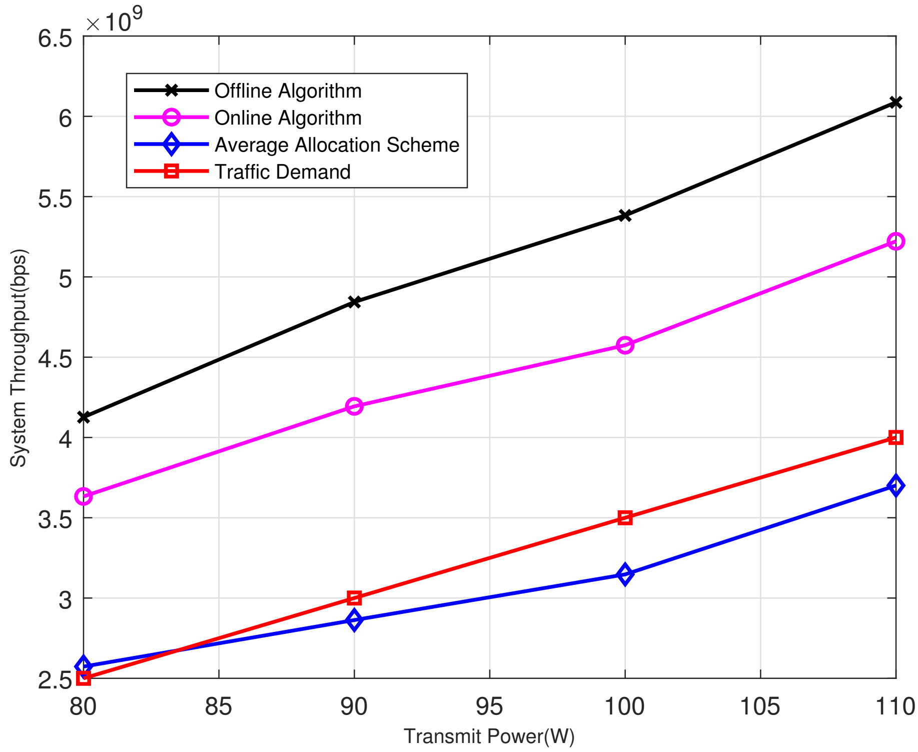

Figure 3. System throughput of proposed algorithms.

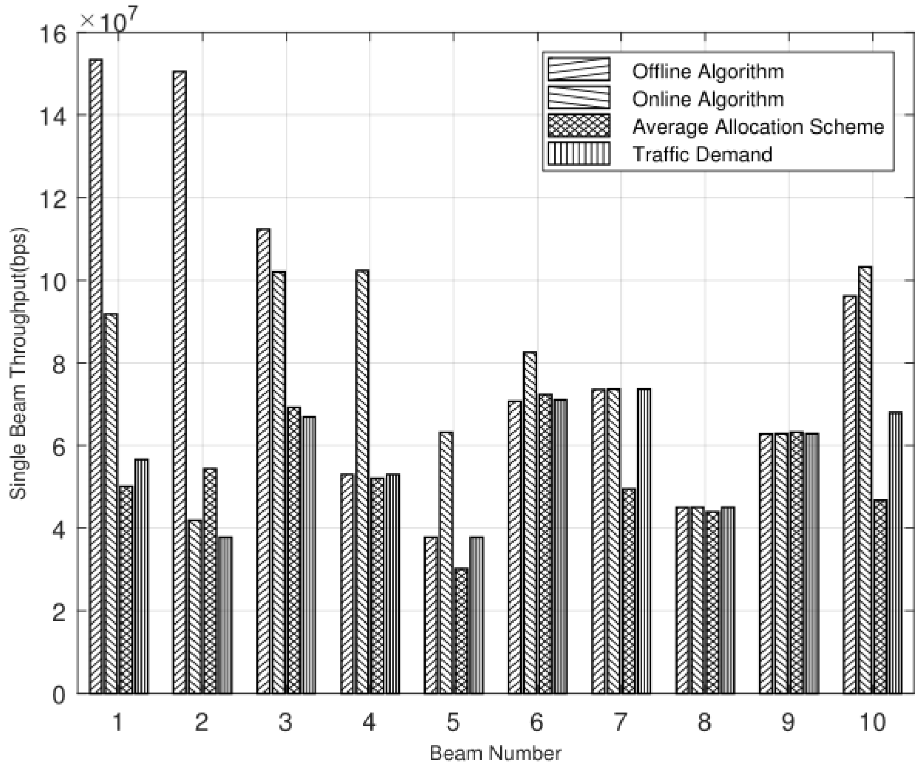

Figure 4. Single-beam throughput performance.

6. Conclusions

In this paper, we formulated a resource-allocation problem in the multi-satellite system and investigated two algorithms based on beam-hopping technology. Firstly, a multi-satellite offline resource-allocation algorithm based on beam-hopping technology was proposed to address the satellite resource limitation problem and improve the efficiency of resource utilization. A heuristic time-frequency resource-allocation algorithm was proposed based on the beam interference pattern, and the power resources were allocated using the SCA algorithm. However, it was assumed that future channel information should be obtained in advance in the offline resource allocation algorithm, which is difficult to achieve in the real world. Therefore, we proposed a dynamic programming algorithm to design a multi-satellite online resource allocation algorithm that only relies on instant channel information.

The final simulation results demonstrate that, compared with traditional average resource-allocation methods, our proposed offline algorithm improves system throughput by about 60% to 65%, and the online algorithm improves system throughput by about 45% to 50%. Since the online algorithm only relies on instant channel information for resource allocation and uses discrete power values, there is a certain performance loss compared with the offline algorithm, but the results show that this loss is acceptable.

The algorithm proposed in this paper is only tested in the scenario consisting of three satellites. The computation complexity of the proposed algorithm may increase sharply with the number of satellites and whether the algorithm complexity can be tolerant should be tested in the real satellite communication system.

Author Contributions: Methodology, Y.W.; Writing—original draft, Y.W.; Writing—review & editing, M.Z.; Funding acquisition, M.Z. and Z.F. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by National Key R&D Program of China under grant 2020YFB1806000.

Data Availability Statement: The data and code are available from the corresponding authors upon reasonable request.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Di, B.; Zhang, H.; Song, L.; Li, Y.; Li, G.Y. Ultra-Dense LEO: Integrating Terrestrial-Satellite Networks Into 5G and Beyond for Data Offloading. *IEEE Trans. Wirel. Commun.* **2019**, *18*, 47–62. [CrossRef]
2. Chen, S.; Sun, S.; Kang, S. System integration of terrestrial mobile communication and satellite communication—The trends, challenges and key technologies in B5G and 6G. *China Commun.* **2020**, *17*, 156–171. [CrossRef]
3. Darwish, T.; Kurt, G.K.; Yanikomeroglu, H.; Bellemare, M.; Lamontagne, G. LEO Satellites in 5G and Beyond Networks: A Review from a Standardization Perspective. *IEEE Access* **2022**, *10*, 35040–35060. [CrossRef]
4. Giambene, G.; Kota, S.; Pillai, P. Satellite-5G Integration: A Network Perspective. *IEEE Netw.* **2018**, *32*, 25–31. [CrossRef]
5. Tang, J.; Bian, D.; Li, G.; Hu, J.; Cheng, J. Resource Allocation for LEO Beam-Hopping Satellites in a Spectrum Sharing Scenario. *IEEE Access* **2021**, *9*, 56468–56478. [CrossRef]
6. Shi, D.; Liu, F.; Zhang, T. Resource Allocation in Beam Hopping Communication Satellite System. In Proceedings of the 2020 International Wireless Communications and Mobile Computing (IWCMC), Limassol, Cyprus, 15–19 June 2020; pp. 280–284. [CrossRef]
7. Whitefield, D.; Gopal, R.; Arnold, S. Spaceway now and in the Future: On-Board IP Packet Switching Satellte Communication Network. In Proceedings of the MILCOM 2006—2006 IEEE Military Communications conference, Washington, DC, USA, 23–25 October 2006; pp. 1–7. [CrossRef]
8. Mokhtar, A.; Azizoglu, M. On the downlink throughput of a broadband LEO satellite network with hopping beams. *IEEE Commun. Lett.* **2000**, *4*, 390–393. [CrossRef]
9. Zhang, T.; Zhang, L.; Shi, D. Resource Allocation in Beam Hopping Communication System. In Proceedings of the 2018 IEEE/AIAA 37th Digital Avionics Systems Conference (DASC), London, UK, 23–27 September 2018; pp. 1–5. [CrossRef]
10. Alberti, X.; Cebrian, J.M.; Del Bianco, A.; Katona, Z.; Lei, J.; Vazquez-Castro, M.A.; Zanus, A.; Gilbert, L.; Alagha, N. System capacity optimization in time and frequency for multibeam multi-media satellite systems. In Proceedings of the 2010 5th Advanced Satellite Multimedia Systems Conference and the 11th Signal Processing for Space Communications Workshop, Cagliari, Italy, 13–15 September 2010; pp. 226–233. [CrossRef]
11. Anzalchi, J.; Couchman, A.; Gabellini, P.; Gallinaro, G.; D'Agristina, L.; Alagha, N.; Angeletti, P. Beam hopping in multi-beam broadband satellite systems: System simulation and performance comparison with non-hopped systems. In Proceedings of the 2010 5th Advanced Satellite Multimedia Systems Conference and the 11th Signal Processing for Space Communications Workshop, Cagliari, Italy, 13–15 September 2010; pp. 248–255. [CrossRef]

12. Lizarraga, J.; Angeletti, P.; Alagha, N.; Aloisio, M. Multibeam satellites performance analysis in non-uniform traffic conditions. In Proceedings of the 2013 IEEE 14th International Vacuum Electronics Conference (IVEC), Paris, France, 21–23 May 2013; pp. 1–2. [CrossRef]
13. Wang, L.; Zhang, C.; Qu, D.; Zhang, G. Resource Allocation for Beam-hopping User Downlinks in Multi-beam Satellite System. In Proceedings of the 2019 15th International Wireless Communications Mobile Computing Conference (IWCMC), Tangier, Morocco, 24–28 June 2019; pp. 925–929. [CrossRef]
14. Tian, F.; Huang, L.; Liang, G.; Jiang, X.; Sun, S.; Ma, J. An Efficient Resource Allocation Mechanism for Beam-hopping Based LEO Satellite Communication System. In Proceedings of the 2019 IEEE International Symposium on Broadband Multimedia Systems and Broadcasting (BMSB), Jeju, Republic of Korea, 5–7 June 2019; pp. 1–5. [CrossRef]
15. Choi, J.; Chan, V. Optimum power and beam allocation based on traffic demands and channel conditions over satellite downlinks. *IEEE Trans. Wirel. Commun.* **2005**, *4*, 2983–2993. [CrossRef]
16. Lei, J.; Vázquez-Castro, M.A. Joint Power and Carrier Allocation for the Multibeam Satellite Downlink with Individual SINR Constraints. In Proceedings of the 2010 IEEE International Conference on Communications, Cape Town, South Africa, 23–27 May 2010; pp. 1–5. [CrossRef]
17. Du, X.; Hu, X.; Wang, Y.; Wang, W. Dynamic Resource Allocation for Beam Hopping Satellites Communication System: An Exploration. In Proceedings of the 2022 IEEE International Conference on Trust, Security and Privacy in Computing and Communications (TrustCom), Wuhan, China, 9–11 December 2022; pp. 1296–1301. [CrossRef]
18. Han, Y.; Zhang, C.; Zhang, G. Dynamic Beam Hopping Resource Allocation Algorithm Based on Deep Reinforcement Learning in Multi-Beam Satellite Systems. In Proceedings of the 2021 3rd International Academic Exchange Conference on Science and Technology Innovation (IAECST), Guangzhou, China, 10–12 December 2021; pp. 68–73. [CrossRef]
19. Rohde, C.; Rainish, D.; Freedman, A.; Lesthievent, G.; Alagha, N.; Delaruelle, D.; Mocker, G.; Giraud, X. Beam-hopping system configuration and terminal synchronization schemes. In Proceedings of the Advances in Communications Satellite Systems. Proceedings of the 37th International Communications Satellite Systems Conference (ICSSC-2019), Okinawa, Japan, 29 October–1 November 2019; pp. 1–13. [CrossRef]
20. Joroughi, V.; Lagunas, E.; Andrenacci, S.; Maturo, N.; Chatzinotas, S.; Grotz, J.; Ottersten, B. Deploying joint beam hopping and precoding in multibeam satellite networks with time variant traffic. In Proceedings of the 2018 IEEE Global Conference on Signal and Information Processing (GlobalSIP), Anaheim, CA, USA, 26–29 November 2018; pp. 1081–1085. [CrossRef]
21. Kibria, M.G.; Lagunas, E.; Maturo, N.; Spano, D.; Chatzinotas, S. Precoded Cluster Hopping in Multi-Beam High Throughput Satellite Systems. In Proceedings of the 2019 IEEE Global Communications Conference (GLOBECOM), Waikoloa, HI, USA, 9–13 December 2019; pp. 1–6. [CrossRef]
22. Pecorella, T.; Fantacci, R.; Lasagni, C.; Rosati, L.; Todorova, P. Study and Implementation of Switching and Beam-Hopping Tchniques in Satellites with On Board Processing. In Proceedings of the 2007 International Workshop on Satellite and Space Communications, Salzburg, Austria, 13–14 September 2007; pp. 206–210. [CrossRef]
23. Wang, T.; Vandendorpe, L. Successive convex approximation based methods for dynamic spectrum management. In Proceedings of the 2012 IEEE International Conference on Communications (ICC), Ottawa, ON, Canada, 10–15 June 2012; pp. 4061–4065. [CrossRef]
24. Zeng, W.; Zheng, Y.R.; Xiao, C. Online Precoding for Energy Harvesting Transmitter With Finite-Alphabet Inputs and Statistical CSI. *IEEE Trans. Veh. Technol.* **2016**, *65*, 5287–5302. [CrossRef]
25. Loodaricheh, R.A.; Mallick, S.; Bhargava, V.K. QoS Provisioning Based Resource Allocation for Energy Harvesting Systems. *IEEE Trans. Wirel. Commun.* **2016**, *15*, 5113–5126. [CrossRef]
26. Li, B.; Fei, Z.; Chu, Z.; Zhou, F.; Wong, K.K.; Xiao, P. Robust Chance-Constrained Secure Transmission for Cognitive Satellite–Terrestrial Networks. *IEEE Trans. Veh. Technol.* **2018**, *67*, 4208–4219. [CrossRef]
27. Wang, Y.; Zheng, Z.; Zeng, M.; Fei, Z. Coordinated precoding for Multi-Satellite Communications: A Deterministic Equivalent Approach. In Proceedings of the 2022 IEEE International Conference on Communications Workshops (ICC Workshops), Seoul, Republic of Korea, 16–20 May 2022; pp. 1165–1170. [CrossRef]
28. Yu, Y.; Dutkiewicz, E.; Huang, X.; Mueck, M. Downlink Resource Allocation for Next Generation Wireless Networks with Inter-Cell Interference. *IEEE Trans. Wirel. Commun.* **2013**, *12*, 1783–1793. [CrossRef]
29. Efrem, C.N.; Panagopoulos, A.D. Dynamic Energy-Efficient Power Allocation in Multibeam Satellite Systems. *IEEE Trans. Wirel. Commun.* **2020**, *9*, 228–231. [CrossRef]