Power Allocation and Beam Illumination Design for Time-Flexible Satellite Systems

Lin Chen[1], Anyue Wang[1], Eva Lagunas[1], Lei Lei[2], and Symeon Chatzinotas[1]

[1]Interdisciplinary Centre for Security, Reliability and Trust (SnT), University of Luxembourg, Luxembourg
[2]School of Information and Communications Engineering, Xi'an Jiaotong University, China
[1,2]*Emails: {lin.chen; anyue.wang; eva.lagunas; symeon.chatzinotas}@uni.lu; lei.lei@xjtu.edu.cn*

***Abstract*—Satellite beam hopping provides time-domain flexibility with proven benefits in improving supplied capacity-demand matching while reducing the power and mass of the satellite payload. However, due to the combinatorial properties of beam scheduling and coupling in the time domain, resource optimization of beam hopping can be challenging. This paper presents an efficient optimization framework for addressing complex beam-hopping problems from the perspective of frame-level planning. In the framework, we first introduce continuous variables to represent each beam's timeslot usage of a frame (or each beam's illumination probability at an arbitrary timeslot), thereby converting the mixed-integer problem into a continuous one with a smaller problem scale. Based on optimized power allocation and timeslot usage (or illumination probability), we then map continuous solutions to binary ones and determine the beam-timeslot scheduling on a demand-aware basis. Numerical results demonstrate the feasibility of the proposed framework, with benefits including power saving, complexity reduction, and improved capacity-demand matching.**

***Index Terms*—Beam hopping satellite systems, flexible resource allocation, mixed-integer nonconvex programming**

I. Introduction

Beam hopping is envisioned as one of the promising solutions for the next-generation flexible satellite communications systems [1]. High Throughput Satellite (HTS) systems will operate in the upper K-band (i.e. 20-30 GHz) and make use of spot-beam technology to direct the communication signals from the satellite antenna towards a specific region on Earth [2]. Unlike conventional HTS systems which operate with all beams activated permanently, beam hopping enables illumination of a subset of beams for a specific duration in time [3]. This time flexibility not only allows to focus satellite capacity over high-demand regions but also relaxes the number of RF chains to be deployed on board, thus reducing mass and power consumption [4]–[6].

By leveraging time-domain flexibility, beam illumination plans can be adaptively optimized to meet heterogeneity and dynamics in traffic distribution such that a good match between supplied capacity and demand can be achieved, and thus resource utilization can be further improved [7], [8]. Even when all illuminated beams re-use the same bandwidth, the fact that fewer beams are illuminated at each time instance significantly helps in reducing co-channel inter-beam interference [8]–[10].

However, resource optimization involving beam hopping, generally in the format of mixed-integer programming, is typically challenging. The combinatorial properties in beam scheduling cause exponential expansion of integer solution space as the number of beams/timeslots grows, leading to considerable computational efforts in attaining the optimum/near-optimum [8], [11]. Besides, the coupling across the time domain complicates the beam illumination design, especially for large problem sizes (e.g., a large number of beams) [10]. One conventional idea of complexity reduction is to decompose a difficult problem into several simpler subproblems, e.g., [8], [12]. Solving these subproblems, however, is still non-trivial in practical implementation when the number of beams/timeslots is large. In [7] and [11], machine learning techniques were applied to capture useful features of beam hopping to assist the problem-solving. Still, the learning-based methods are challenged by the appropriate features to learn from, and the availability of accurate and complete training datasets.

Recently, the authors in [13] designed an insightful method to simplify the beam scheduling process from the perspective of frame-level planning. Instead of addressing the problem of optimizing beam-timeslot mapping, [13] proposed to find out the optimal timeslot usage ratio of each beam (which can also be viewed as the illumination probability of a beam at an arbitrary timeslot). This method can offer an accurate estimation of a beam's capacity over the whole frame without knowing the exact beam-timeslot assignment, which has already been widely applied to radio planning in cellular systems [14]. Such a method can provide the following benefits:

- The complex combinatorial properties can be removed by converting binary variables (conventionally used for beam scheduling) into continuous ones (indicating timeslot usage ratio or illumination probability);
- For each beam, only one ratio/probability variable is employed to represent the scheduling status over a frame, which is irrelevant to the number of timeslots. The number of variables as well as the problem size can be largely reduced;
- For practical implementation, delivering information of illumination probability rather than beam-timeslot mapping can potentially reduce the signaling message size.

Compared to the early-stage study in [13], we provide a more robust and detailed optimization framework for adaptive beam illumination design from the perspective of frame-level planning. Unlike the semi-random beam illumination design in [13], we jointly address the power allocation and beam illumination design from an optimization viewpoint. In our framework, the first step is to transform the cumbersome mixed-integer problem into a light continuous problem. The transformed problem aims at jointly optimizing power allocation and illumination probability, which is solved by a tailored algorithm based on particle swarm optimization (PSO). With optimized power allocation and illumination probability, we then propose a demand-aware beam scheduling strategy to decide beam-timeslot assignment. Numerical results verify the efficiency of the proposed framework in minimizing power consumption, reducing complexity, and matching capacity to demand.

II. System Model

We consider downlink data transmission in a geostationary earth orbit (GEO) satellite system. The area of interest is partitioned into B cells, each of which is covered by one spot beam. Remark that the indices of cells and beams are interchangeable in this paper. The satellite payload is assumed to be equipped with beam hopping capabilities, i.e. a maximum of K out of the B beams ($K < B$) can be illuminated at each timeslot. The beam hopping scenario is illustrated in Fig. 1. The telemetry, tracking, and command (TT&C) station is in charge of communicating the beam illumination planning to both satellite and user terminals on the ground. Power distribution among active beams is realized by the digital transparent processor at the payload side. The scheduling period lasts one frame with T consecutive timeslots. Note that we focus on

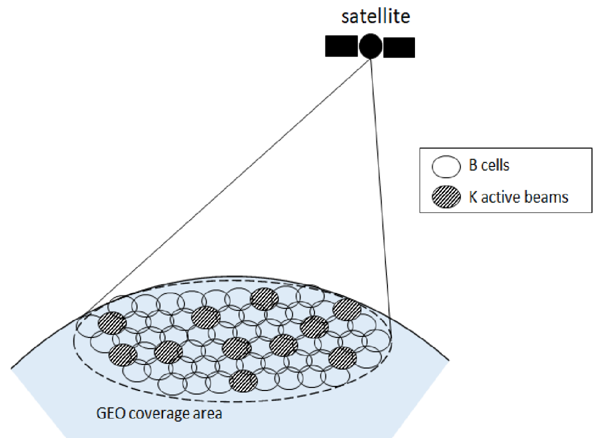

Fig. 1: The considered beam hopping system model.

resource optimization at a beam/cell level and details of user scheduling are beyond the scope of the paper. This means that the users' demand is abstracted by the cell's overall demand, which is obtained by aggregating the demand of individual users in each particular cell. For the sake of simplicity, we assume that a virtual super-user terminal is located at each cell's center with aggregated traffic demand of users in the cell.

The channel gain of cell b receiving signals from beam b' is expressed as $|h_{b'b}|^2 = G^{\mathrm{Tx}}_{b'b} G^{\mathrm{Rx}}_{b} A_{b'b} L_b / N$, where $G^{\mathrm{Tx}}_{b'b}$ denotes the transmit antenna gain from beam b' to cell b and G^{Rx}_{b} denotes the receive antenna gain of the terminal in cell b. $A_{b'b}$ represents the rain attenuation of the link [15]. N represents the noise distribution. L_b is the propagation loss in free space, which is derived by $L_b = \left(\frac{c}{4\pi d_b f}\right)^2$, where c is the light speed, d_b is the distance from the satellite to cell b, and f is the frequency.

We derive the signal-to-interference-plus-noise ratio (SINR) of cell b at timeslot t as,

$$\gamma_{bt} = \frac{P_b |h_{bb}|^2}{\sum\limits_{b' \neq b} x_{b't} P_{b'} |h_{b'b}|^2 + \sigma^2}, \tag{1}$$

where P_b is the transmit power of beam b and σ^2 is the noise power. $x_{bt} = \{0, 1\}$ indicates whether the b-th beam is illuminated at timeslot t ($x_{bt} = 1$ if yes and $x_{bt} = 0$ otherwise). The offered capacity of cell b is derived as,

$$R_b = \frac{W}{T} \sum_{t=1}^{T} x_{bt} \log_2 \left(1 + \gamma_{bt}\right). \tag{2}$$

III. Problem Formulation and Reformulation

A. Problem Formulation

We formulate a resource allocation problem in $\mathcal{P}_0$ to jointly optimize beam illumination pattern and power allocation to minimize the average power consumption within a frame.

$$\mathcal{P}_0 : \min_{x_{bt}, P_b} \frac{1}{T} \sum_{b=1}^{B} \sum_{t=1}^{T} x_{bt} P_b \tag{3a}$$

$$\text{s.t. } R_b \geq D_b, \forall b = 1, \ldots, B, \tag{3b}$$

$$\sum_{b=1}^{B} x_{bt} \leq K, \forall t = 1, \ldots, T, \tag{3c}$$

$$\sum_{b=1}^{B} x_{bt} P_b \leq P_{\max}, \forall t = 1, \ldots, T, \tag{3d}$$

$$\sum_{t=1}^{T} x_{bt} \geq 1, \forall b = 1, \ldots, B. \tag{3e}$$

The optimization variables are $P_b \geq 0$ and $x_{bt} = \{0, 1\}$. In (3b), each cell's capacity should be no smaller than the required demand D_b (in bps). Constraints (3c) convey that the maximum number of illuminated beams at each timeslot is K. Power consumption for all the illuminated beams is restricted below or equal to the power budget $P_{\max}$ in (3d). Considering the restriction of terminals' revisiting time, constraints (3e) express that each beam should be at least scheduled once within one frame.

With the exhibition of binary variables x_{bt} and nonconvexity in the rate functions (2), $\mathcal{P}_0$ is identified as mixed-integer nonconvex programming. The number of potential beam illumination patterns grows exponentially with the frame scale due to the combinatorial properties of the problem. Finding the optimal/near-optimal beam-timeslot assignment solution would cost unaffordable computational efforts. Solving $\mathcal{P}_0$ is a challenging task.

B. Problem Reformulation: From Cumbersome Mixed-Integer Problem to Light Continuous Problem

We tackle $\mathcal{P}_0$ from a frame-level planning perspective and reformulate the problem into a simpler one. Instead of directly searching for the optimal beam-timeslot assignment, we view resource allocation over a frame as a stochastic process in which beam scheduling at each timeslot is a sample. Let $\rho_b = \frac{\sum_{t=1}^{T} x_{bt}}{T}$ $(0 < \rho_b \leq 1)$ be the timeslot usage of beam b within a frame, which can also be viewed as the probability of illuminating beam b at an arbitrary timeslot. Oppositely, $1 - \rho_b$ is denoted as the probability of beam b being inactive at an arbitrary timeslot. Replacing x_{bt} by ρ_b, we can estimate offered capacity of beam b in the whole frame frame as [14],

$$\bar{R}_b = \rho_b W \log_2 \left(1 + \frac{P_b |h_{bb}|^2}{\sum\limits_{b' \neq b} \rho_{b'} P_{b'} |h_{b'b}|^2 + \sigma^2} \right). \tag{4}$$

Then we reformulate $\mathcal{P}_0$ as,

$$\mathcal{P}_1 : \min_{\rho_b, P_b} \sum_{b=1}^{B} \rho_b P_b \tag{5a}$$

$$\text{s.t. } \bar{R}_b \geq D_b, \forall b = 1, \ldots, B, \tag{5b}$$

$$\sum_{b=1}^{B} \rho_b \leq K, \tag{5c}$$

$$\sum_{b=1}^{B} \rho_b P_b \leq P_{\max}, \tag{5d}$$

$$T \rho_b \geq 1, \forall b = 1, \ldots, B, \tag{5e}$$

where (3b) to (3e) are converted into (5b) to (5e), respectively.

Compared to $\mathcal{P}_0$, solving $\mathcal{P}_1$ is less complicated. On the one hand, we can solve a continuous problem from a frame-level planning perspective by optimizing the probabilities of beam illumination rather than optimizing the whole frame's beam-timeslot mapping with challenging combinatorial properties. On the other hand, with ρ_b representing resource usage of the whole frame, $\mathcal{P}_1$'s scale is irrelevant to the number of timeslots. As time-domain coupling is decomposed, fewer variables exist compared to $\mathcal{P}_0$, and thus the problem size is reduced.

IV. Proposed Time-Flexible Beam-Hopping Optimization Framework

In this section, we design a two-step framework to jointly optimize beam hopping and power allocation:

- Step 1: At a frame level, the estimated power allocation P_b and beam illumination probability ρ_b are optimized by solving $\mathcal{P}_1$.
- Step 2: Depending on optimized P_b and ρ_b, we decide beam scheduling x_{bt} timeslot by timeslot according to cells' demand satisfaction.

A. Step 1: Frame-Level Planning based on PSO

We proposed a PSO-based algorithm to solve $\mathcal{P}_1$. Since nonconvex constraints (5b) could lead to difficulties in identifying the feasibility of particles' positions in PSO, we move (5b) to the objective with penalty factor χ. The corresponding problem reads,

$$\mathcal{P}_2 : \min_{\rho_b, P_b} \sum_{b=1}^{B} \rho_b P_b + \chi \sum_{b=1}^{B} \max \left\{ -\bar{R}_b + D_b, 0 \right\} \tag{6a}$$

$$\text{s.t. } (5c), (5d), (5e), \tag{6b}$$

where the objective is penalized if the demand constraints (5b) are violated.

Let L and I be the numbers of particles and iterations in PSO, respectively. For presentation simplicity, we use $\boldsymbol{\rho}$ and $\mathbf{P}$ to collect all ρ_b and P_b, respectively. Note that the vectors also represent the positions of particles. For particle l, the positions w.r.t. $\boldsymbol{\rho}$ and $\mathbf{P}$ at iteration i are $\boldsymbol{\rho}_l^{(i)}$ and $\mathbf{P}_l^{(i)}$, respectively. The fitness value of particle l at the i-th iteration is defined as the objective value, i.e.,

$$z_l^{(i)} = \sum_{b=1}^{B} \rho_b^{(i)} P_b^{(i)} + \chi \sum_{b=1}^{B} \max \left\{ -\bar{R}_b^{(i)} + D_b, 0 \right\}. \tag{7}$$

For particle l, the best (minimum) fitness value is denoted as $\bar{z}_l$ and the best positions are denoted as $\bar{\boldsymbol{\rho}}_l$ and $\bar{\mathbf{P}}_l$. Among all the particles, the best fitness value is defined as $\widetilde{z}$ and the best positions are defined as $\widetilde{\boldsymbol{\rho}}$ and $\widetilde{\mathbf{P}}$. We define the velocities of particle l at iteration i regarding $\boldsymbol{\rho}$ and $\mathbf{P}$ are $\mathbf{u}_l^{(i)}$ and $\mathbf{v}_l^{(i)}$, whose update rules are expressed as follows,

$$\begin{aligned} \mathbf{u}_l^{(i)} =& \mathbf{u}_l^{(i-1)} + c_1 \cdot \text{rand}() \cdot (\bar{\boldsymbol{\rho}}_l - \boldsymbol{\rho}_l^{(i-1)}) \\ &+ c_2 \cdot \text{rand}() \cdot (\widetilde{\boldsymbol{\rho}}_l - \boldsymbol{\rho}_l^{(i-1)}), \end{aligned} \tag{8}$$

$$\begin{aligned} \mathbf{v}_l^{(i)} =& \mathbf{v}_l^{(i-1)} + c_3 \cdot \text{rand}() \cdot (\bar{\boldsymbol{P}}_l - \boldsymbol{P}_l^{(i-1)}) \\ &+ c_4 \cdot \text{rand}() \cdot (\widetilde{\boldsymbol{P}}_l - \boldsymbol{P}_l^{(i-1)}), \end{aligned} \tag{9}$$

where c_1, c_2, c_3, c_4 are constant and rand() is a function generating a random real number between 0 and 1. With $\mathbf{u}_l^{(i)}$ and $\mathbf{v}_l^{(i)}$, particles' positions are updated as,

$$\boldsymbol{\rho}_l^{(i)} = \boldsymbol{\rho}_l^{(i-1)} + \mathbf{u}_l^{(i)}, \tag{10}$$

$$\mathbf{P}_l^{(i)} = \mathbf{P}_l^{(i-1)} + \mathbf{v}_l^{(i)}. \tag{11}$$

The process of the PSO-based algorithm is summarized in Alg. 1 Before iterations, we generate L particles with randomized positions. Within each iteration, we first compute the fitness value for each particle in line 2. Then the best fitness values and positions are updated in line 3 and line 4. Next, we calculate the velocity for each particle in line 5, based on which positions are updated in line 6. Finally, in line 7, we need to restrict particles within the feasible range if they violate any constraints.

B. Step 2: Demand-Aware Beam Scheduling with Optimized Power Allocation and Beam Illumination Probability

With optimized $\mathbf{P}$ and $\boldsymbol{\rho}$, the next step is to decide the beam scheduling timeslot by timeslot so as to satisfy cells' demands. We normalize $\boldsymbol{\rho}$ as $\hat{\boldsymbol{\rho}} = \boldsymbol{\rho}/K$,

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Algorithm 1 PSO-based frame-level planning

Input: $|h_{bb'}|^2$, D_b; L, I, χ; Initialized $\boldsymbol{\rho}_l^{(0)}, \mathbf{P}_l^{(0)}, \mathbf{u}_l^{(0)}$, $\mathbf{v}_l^{(0)}$, $\bar{z}_l = \text{inf}$.

1: **for** $i = 1, \dots, I$ **do**

2: Calculate $z_l^{(i)}$, $\forall l = 1, \dots, L$, in (7).

3: Replace $\bar{z}_l = z_l^{(i)}$, $\bar{\boldsymbol{\rho}}_l = \boldsymbol{\rho}_l^{(i)}$, and $\bar{\mathbf{P}}_l = \mathbf{P}_l^{(i)}$, if $z_l^{(i)} < \bar{z}_l$, $\forall l = 1, \dots, L$.

4: Select the best fitness value among all particles $\widetilde{z} = \min_{l=1,\dots,L}\{\bar{z}_l\}$ and update $\widetilde{\boldsymbol{\rho}}$ and $\widetilde{\mathbf{P}}$ accordingly.

5: Calculate velocity $\mathbf{u}_l^{(i)}$ and $\mathbf{v}_l^{(i)}$, $\forall l = 1, \dots, L$, in (8) and (9), respectively.

6: Update positions $\boldsymbol{\rho}_l^{(i)}$ and $\mathbf{P}_l^{(i)}$, $\forall l = 1, \dots, L$, in (10) and (11), respectively.

7: Restrict $\boldsymbol{\rho}_l^{(i)}$ and $\mathbf{P}_l^{(i)}$ in the feasible domain enclosed by constraints (5c) to (5e) if necessary.

8: **end for**

Output: Optimized $\mathbf{P}$, $\boldsymbol{\rho}$.

Algorithm 2 Demand-aware beam scheduling

Input: Optimized $\boldsymbol{\rho}$ and $\mathbf{P}$; set of beams with unsatisfied demands: $\mathcal{B}_0$.

1: **for** $t = 1, \dots, T$ **do**

2: Update normalized $\hat{\boldsymbol{\rho}}$ for the beams in $\mathcal{B}_0$.

3: Randomly activate K beams in $\mathcal{B}_0$ at timeslot t based on the illumination probability distribution $\hat{\boldsymbol{\rho}}$ and determine x_{bt} accordingly.

4: Remove beam b from $\mathcal{B}_0$ if the offered rate is already larger than or equal to D_b, $\forall b = 1, \dots, B$.

5: Break if $\mathcal{B}_0 = \emptyset$

6: **end for**

Output: Optimized x_{bt}.

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which can be viewed as the illumination probability distribution over all the beams at an arbitrary timeslot. For each timeslot, K beams are selected to be activated based on this distribution.

The details of the beam scheduling process are displayed in Alg. 2. For each timeslot, we first normalize $\boldsymbol{\rho}$ as $\hat{\boldsymbol{\rho}}$ for the beams in $\mathcal{B}_0$ in line 2, where $\mathcal{B}_0$ includes the beams with unsatisfied demands. Then in line 3, we randomly choose K beams from $\mathcal{B}_0$ for activation following the probability distribution $\hat{\boldsymbol{\rho}}$. In line 4, we abandon beams with satisfied demands from $\mathcal{B}_0$. At last, the iteration terminates if all the beams meet the demand constraints (3b) in line 5.

In Alg. 1, computational efforts for each iteration mainly lie in updating particles' fitness values, velocities, and positions, which are at the level of $\mathcal{O}(BL)$. Thus the complexity of Alg. 1 is $\mathcal{O}(IBL)$. In Alg. 2, the complexity for each timeslot is $\mathcal{O}(B)$, and thus

TABLE I: Simulation parameters

Parameter	Value
Frequency, f	20 GHz
Bandwidth, W	500 MHz
Satellite height	35,786 km
Satellite location	13° E
Receive antenna gain, G_b^{Rx}	42.1 dBi
Noise power, σ^2	-126.47 dBW
Power budget, $P_{\max}$	400 Watts
Number of beams, B	16
Maximum active beams, K	5
Number of timeslots, T	500
Number of iteration, I	10^4

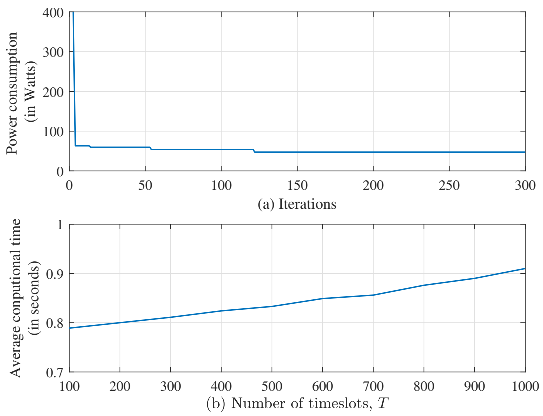

Fig. 2: (a) Evolution of an instance of Alg. 1 over iterations; (b) Average computational time of the proposed framework versus T.

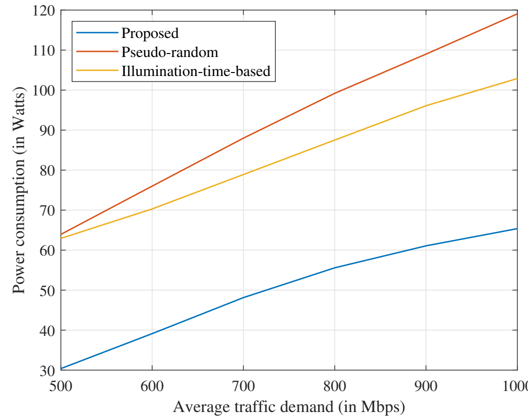

Fig. 3: Power consumption of different schemes w.r.t. average traffic demand.

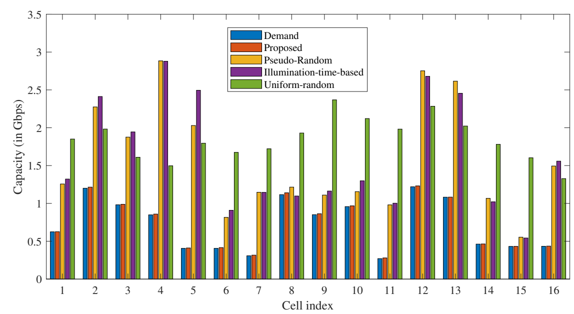

Fig. 4: Distribution of demand and supplied capacity among different cells.

the complexity for all the T timeslots is $\mathcal{O}(BT)$. The overall complexity of the framework is $\mathcal{O}(BIL+BT)$.

V. Numerical Results

We emulate downlink transmission in a multi-beam satellite system and evaluate the performance of the proposed beam-hopping optimization framework. We summarize simulation parameters in Table I unless otherwise stated. The applied beam radiation patterns are provided by the European Space Agency (ESA) [16]. The results are averaged by 500 instances. We consider the following benchmarks for comparison:

- Uniform-random: Power is distributed uniformly to active beams whereas beams are scheduled randomly.
- Pseudo-Random: Frame-level planning is realized by Alg. 1 but beam scheduling is determined by the pseudo-random approach in [13].
- Illumination-time-based: We solve $\mathcal{P}_1$ by Alg. 1 and decide beam scheduling based on required illumination timeslots instead of demands [10].

We first discuss algorithmic performance in convergence and computational time in Fig. 2. We can observe that Alg. 1 converges rapidly within 150 iterations in Fig. 2(a). As the problem size grows with the increase of T in Fig. 2(b), the average computational time of the designed framework rises slowly and maintains below 1 second.

In Fig. 3, we evaluate the power consumption of the proposed framework and benchmarks regarding average traffic demand. The proposed framework consumes the least power, with reductions of 46.0% and 39.9% compared to pseudo-random and illumination-time-based schemes, respectively. In Fig. 4, we present the demand and capacity distribution among cells achieved by different schemes. Among the considered schemes, the proposed framework can obtain a good match between capacity and demand, with a gap (i.e., $\sum_{b=1}^{B}|R_b - D_b|$) of 8.15 Mbps. In pseudo-random and illumination-time-based schemes, the capacity-demand gaps are 897 and 851 Mbps, respectively.

VI. Conclusion

In this paper, we have provided a beam-hopping optimization framework to jointly optimize power allocation and beam scheduling from the perspective of frame-level planning. To tackle the combinatorial nature of the original problem, we have reformulated it into a smaller-scale continuous problem by adopting the concept of beam illumination probability. Based on optimized power and illumination probability, we have designed to decide beam scheduling to meet the demand of cells. Numerical results have demonstrated the benefits of the framework in reducing power consumption, complexity, and capacity-demand mismatch.

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