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Massive Beam Scheduling in LEO Systems: Low Complexity via Effective Interference Approximation

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***Abstract*—Multi-beam Low Earth Orbit (LEO) satellites are poised to play a central role in integrated 6G in space. Existing approaches for beam scheduling, with exact inter-beam interference modeling in every time slot, greatly suffer from prohibitive computational complexity as the number of beams scales up. This paper introduces a tractable interference approximation model that captures inter-beam interference in an aggregated form, completely removing slot-level computations while maintaining high accuracy. The model admits efficient numerical solutions that yield the probabilities of beam activation, enabling near-instantaneous construction of beam scheduling with minimum computational cost. Simulation results show that our method maintains over 95% accuracy in predicting scheduling performance compared to exact interference modeling, with less than 6% loss relative to the global optimum for capacity-demand ratio optimization. These results highlight the effectiveness of the proposed model as a foundation for efficient beam scheduling in next-generation large-scale LEO satellite systems.**

***Index Terms*—Low earth orbit satellite, inter-beam interference, scheduling optimization.**

I. Introduction

With the evolution from 5G to 6G, multi-beam low earth orbit (LEO) satellite networks are becoming a major component of the new generation integrated space-air-ground communication systems. LEO satellite constellations provide global coverage and agile networking capabilities, effectively bridging connectivity gaps across oceans, deserts, and remote regions [1]. Yet, the surging global demand for communication services presents major challenges to satellite systems in meeting both high throughput and stringent reliability requirements.

A key innovation in modern satellite systems is the adoption of multi-beam technology, which enables hundreds or even thousands of beams to deliver high-capacity coverage [2]. However, as the beam count grows, the combinatorial nature of beam scheduling and resource allocation leads to an explosion in complexity, poses a fundamental challenge to scalable LEO operations. This challenge is further exacerbated by the stringent real-time requirement for scheduling: With reconfiguration needed within seconds, the immense computational burden of optimal or near-optimal iterative algorithms becomes a critical bottleneck for massive beam counts [3].

From a theoretical standpoint, problems such as the beam management formulation in [4], collaborative beam scheduling in [5], quality of service optimization in [6], joint throughput and latency optimization in [7], and joint power allocation and beam hopping (BH) pattern design in [2], are all proven to be $\mathcal{NP}$-hard and/or non-convex. The combination of this inherent computational hardness and the requirement for scalable, real-time operation serves as a primary motivation for research on low-complexity yet highly effective scheduling strategies that can sustain performance in large-scale LEO systems.

Existing solutions for beam scheduling can be broadly classified into two categories.

1) Slot-level interference modeling. These methods rely on exact modeling of inter-beam interference in every time slot, where the optimization variables (e.g., power or beam activation state) appear in both the numerator and denominator of the signal-to-interference-and-noise ratio (SINR) [8] [9]. The modeling approach introduces strong non-convexity - the computational complexity to grow rapidly with the number of beams and the scheduling horizon, rendering such approaches impractical for large-scale systems.
2) Beam-group-based scheduling. This approach considers beam groups and assigns each group a variable representing its share of scheduling time, instead of scheduling over individual time slots [10]. The rationale is that for each group, the SINR can be (pre-)determined to remove non-linearity. For massive beam scheduling, however, the number of beam groups grows exponentially, and the computational cost remains prohibitive for real-time scheduling.

While both categories of approaches strive to address the beam scheduling problem, they ultimately fall short in resolving the fundamental tension between computational tractability and solution accuracy in large-scale settings. This persistent gap underscores the critical need for a novel modeling paradigm that can overcome this trade-off.

In this paper, we present a new approach for massive beam scheduling with both low complexity and high accuracy, enabled by an effective interference approximation model. To our knowledge, this is the first paper deploying and validating such a model for scalable beam scheduling. The contributions are as follows.

- We propose a novel inter-beam interference approximation (BIA) model, via which the SINR and achievable rate can be computed rapidly, and we analyze its approximation performance. By capturing interference in an average sense, the BIA model's accuracy improves as the number of beams grows.
- We demonstrate two use cases of the BIA model: minimum-time scheduling and capacity-demand ratio optimization. In both scenarios, the BIA model guarantees convergence to a unique fixed point representing the optimal probabilities of scheduling the respective beams. This enables generation of deterministic schedules with negligible computational cost.
- Simulation results show that the proposed approach achieves over 95% accuracy relative to exact interference modeling in characterizing the minimum schedule length, and for capacity-demand ratio optimization it performs within 6% of global optimality.

II. System Model

A. The Satellite-to-Ground Link Model

Consider downlink communication for a multi-beam LEO satellite. The satellite is equipped with phased array antennas to generate multiple directional beams, creating multiple footprints on the ground. Each of the users located within these beams is equipped with a single directional antenna. The LEO satellite achieves BH by scheduling beams in each time slot. Define the set of beams as $\mathcal{B} = \{1, ..., b, ..., B\}$, the set of scheduling time slots as $\mathcal{T} = \{1, ..., t, ..., T\}$, and the set of users as $\mathcal{J} = \{1, ..., j, ..., J\}$. The user subset served by beam b is denoted by $\mathcal{J}_b$. The channel gain between beam b and user j can be expressed by

$$g_{bj} = G(\phi_{bj}) L_{bj} |h_{bj}|^2, \tag{1}$$

where the entities are defined as follows.

1) Beam Gain: For user j within the coverage area of beam b, the beam gain $G(\phi_{bj})$ is calculated by the nadir angle ϕ_{bj} between the user's position and the center point of beam b, which is given by [11, Eq. (3)]

$$G(\phi_{bj}) = G_b G_j \left(\frac{J_1(u_{bj})}{2u_{bj}} + 36 \frac{J_3(u_{bj})}{u_{bj}^3} \right)^2, \tag{2}$$

where G_b and G_j represent the satellite transmit antenna gain and the user receiver antenna gain, respectively. Here, $J_1(\cdot)$ and $J_3(\cdot)$ are the first-kind Bessel function of orders 1 and 3, respectively. The parameter $u_{bj} = 2.07123 \frac{\sin \phi_{bj}}{\sin \phi_{b3\text{dB}}}$ with $\phi_{b3\text{dB}}$ being the 3-dB angle for beam b.

2) Free Space Loss: The free space loss is as follows,

$$L_{bj} = \left(\frac{c}{4\pi f_c \ell_{bj}} \right)^2, \tag{3}$$

where c is the light speed, f_c is the carrier frequency, and ℓ_{bj} is the link distance between the transmit antenna and user j.

3) Fading Model: Assuming independent and identically distributed shadowed-Rician fading distribution, the probability density function of the fading gain $|h_{bj}|^2$ can be modeled by

$$f_{|h_{bj}|^2}(x) = \alpha_{bj} e^{-\beta_{bj} x} {}_1F_1(m_{bj}; 1; \delta_{bj} x), \tag{4}$$

where $\alpha_{bj} = \frac{1}{2\kappa_{bj}} \left(\frac{2\kappa_{bj} m_{bj}}{2\kappa_{bj} m_{bj} + \Omega_{bj}} \right)^{m_{bj}}$, $\beta_j = \frac{1}{2\kappa_{bj}}$, $\delta_{bj} = \frac{\Omega_{bj}}{2\kappa_{bj}(2\kappa_{bj} m_{bj} + \Omega_{bj})}$, and ${}_1F_1(a; b; c)$ is the confluent hypergeometric function. The parameters Ω_{bj}, $2\kappa_{bj}$, and m_{bj} represent the average power of the line-of-sight path component, the average power of the non-line-of-sight path component, and the Nakagami parameter, respectively, for beam b and user j.

B. User SINR in Beam Hopping Systems

For a BH LEO satellite communication system, the time-varying traffic demands across different beam coverage areas are satisfied by adaptively configuring beam activation states in each time slot. Generally, for an arbitrary time slot t, the received signal r_j at user j comprises both the desired signal transmitted by beam b and inter-beam interference from other active beams, expressed as

$$r_j = \sqrt{P_b g_{bj}} s_b + \sum\nolimits_{\substack{b' \neq b \\ b' \in \mathcal{B}}} \sqrt{P_{b'} g_{b'j}} s_{b'} + n_j, \tag{5}$$

where s_b is the desired signal transmitted, P_b is the transmit power allocated to beam b, and noise n_j follows a complex Gaussian distribution. Let x_{bjt} be a binary variable indicating whether or not beam b is active (i.e., transmitting) in slot t for user j. The SINR of user $j \in \mathcal{J}_b$ is then

$$\text{SINR}_{bjt} = \frac{x_{bjt} g_{bj} P_b}{I_{bjt} + N_0}, \tag{6}$$

where $I_{bjt} = \sum\nolimits_{\substack{b' \neq b \\ b' \in \mathcal{B}}} x_{b'jt} g_{b'j} P_{b'}$, N_0 denotes the noise power.

Remark 1. *To ease the presentation, unit bandwidth is assumed. All subsequent derivations and results hold for any bandwidth via simple scaling.* □

C. The Minimum-Time Scheduling Problem

The minimum time scheduling problem (MTSP) amounts to constructing a schedule to satisfy given user demand $D_j, j \in \mathcal{J}$, such that the schedule length, i.e., the number of time slots used, is minimized. MTSP can be formulated using the following integer programming model.

$$\min \sum_{t \in \mathcal{T}} y_t \tag{7a}$$

$$\text{s.t. } y_t \geq \sum_{j \in \mathcal{J}_b} x_{bjt}, b \in \mathcal{B}, t \in \mathcal{T} \tag{7b}$$

$$\sum_{t \in \mathcal{T}} \log_2(1 + \text{SINR}_{bjt}) \geq D_j, j \in \mathcal{J}_b, b \in \mathcal{B} \tag{7c}$$

$$\boldsymbol{x} \in \{0,1\}^T, \boldsymbol{y} \in \{0,1\}^T$$

In addition to the x-variables, binary variable $y_t = 1$ signifies if time slot t is used, and hence the sum of the y-variables corresponds to the schedule length. Constraint (7b) characterizes the relationship between the two sets of variables. Constraint (7c) ensures that the user demands are satisfied.

D. Capacity-demand Ratio Optimization

Consider the problem of optimizing offered capacity and demand ratio (OCDR). The task is to schedule beams and transmissions to the users, such that the offered capacity to the users proportionally match their (non-uniform) demands. Hence, a reasonable objective is to maximize the minimum capacity-demand ratio over the users. For B beams, there are $M = 2^B - 1$ possible combinations of beam groups with at least one active beam. Let $\mathcal{M} = \{1, ..., m, ..., M\}$ be the index set of the groups, and denote the subset of beams in group m by $\mathcal{B}_m$. Note that for any given group m, since its composition is known, we can (pre-)compute the per-slot rate R_j of user $j \in \mathcal{J}_b, b \in \mathcal{B}_m$, if beam b serves user j. Namely, $R_j = \log_2(1 + \frac{g_{bj} P_b}{\sum_{b' \in \mathcal{B}_m \setminus \{b\}} g_{b'j} P_{b'} + N_0})$. The optimization decisions are the number of time slots allocated to each beam group $m \in \mathcal{M}$, and that of each user $j \in \mathcal{J}_b$ for each $b \in \mathcal{B}_m$, denoted by z_m and τ_{bjm}, respectively.

$$\max \quad \zeta \tag{8a}$$

$$\text{s.t.} \quad \zeta \leq \frac{\sum_{m \in \mathcal{M}} \tau_{bjm} R_j}{D_j}, j \in \mathcal{J}_b, b \in \mathcal{B} \tag{8b}$$

$$\sum_{m \in \mathcal{M}} z_m = T \tag{8c}$$

$$\sum_{j \in \mathcal{J}_b} \tau_{bjm} = z_m, b \in \mathcal{B}_m, m \in \mathcal{M} \tag{8d}$$

$$\boldsymbol{\tau} \geq 0, \text{ integer} \tag{8e}$$

Here, ζ is an auxiliary variable, which by (8b) will take the minimum of the ratios over the users. The next constraint states that the total time allocated to the beam groups equals the total BH period. Then, by (8d), for each beam of a beam group, the allocated time is split among the beam users.

Remark 2. *We choose to formulate MTSP and OCDR using SINR in individual time slots and beam groups, respectively. In fact this can be done vice versa. That is, the optimization formulation is not unique for either of the problems. In* (7), (7c) *is highly nonlinear and contains binary variables. For* (8), *the size of* $\mathcal{M}$ *is exponential. As for the problem complexity, based on [12] both are strongly NP-hard.* □

Remark 3. *In OCDR, it is easy to see that the achieved ratios of all users are equal at optimum, if the* τ*-variables are continuous. In addition, OCDR is particularly relevant when the maximum* $\zeta < 1.0$ *(i.e., not all demands can be met), as the min-max objective addresses fairness. Indeed, the two problems are complementary: If all demands can be delivered within* T *time slots, MTSP is justified for minimizing the (time) resource usage, otherwise OCDR comes into play.* □

III. The BIA Model

The BIA model tackles the complexity by approximating the inter-beam interference with a rather intuitive notion: The more a beam is scheduled for transmission, the more interference it generates. To this end, we introduce a new vector of variables $\boldsymbol{\rho} = [\rho_1, ..., \rho_B]^T$, $\boldsymbol{\rho} \in [0, 1]$, representing the beam illumination intensity (BII), defined as the proportion of time of scheduling beam b in relation to the entire scheduling time window. Thus, if ρ_b is 0.5, beam b will be active in half of the time slots. The BIA model uses BII to obtain an interference-averaging effect. Specifically, the inter-beam interference caused by beam b' to user j served by beam b takes the form of $I_{b'j} = \rho_{b'} g_{b'j} P_{b'}$; the intuition is seen in two extreme cases: $\rho_{b'} = 1$, with b' transmitting in all time slots with constant interference, and $\rho_{b'} = 0$ with no interference.

Lemma 1. *In long-term beam scheduling, the BII-based interference approximation is unbiased. The variance is given by*

$$\mathbb{D}\left(\Delta_{b'j}^{\text{BII}}\right) = \rho_{b'}\left(1 - \rho_{b'}\right) P_{b'}^2 g_{b'j}^2, \tag{9}$$

where $\mathbb{D}(.)$ *denotes the variance. Thus, the error is minimized when* ρ *approaches 0 or 1, and maximized when* ρ *approaches 0.5.*

Proof: The average interference caused by beam b' to user j is $\frac{1}{T} \sum_t X_{b'jt} P_{b'} g_{b'j}$, where X is a random variable following a Bernoulli distribution with parameter ρ. According to the law of large numbers, when T is sufficiently large, the sample mean converges to its expected value, i.e., $\mathbb{E}(X_{b'jt} P_{b'} g_{b'j}) = \rho_{b'} P_{b'} g_{b'j}$, where $\mathbb{E}(.)$ denotes the expectation. For an arbitrary time slot, the bias between the expected interference and the instantaneous interference is expressed as

$$\Delta_{b'j}^{\text{BII}} = X_{b'jt} P_{b'} g_{b'j} - \rho_{b'} P_{b'} g_{b'j}. \tag{10}$$

The expectation is zero, and its variance is given by (9). ■

The SINR under the BIA model for user j served by beam b in any time slot is given by the following, where the sum of individual interference sources scaled by the BII levels gives the interference-averaging effect.

$$\text{SINR}_{bj}^{\text{BIA}} = \frac{g_{bj} P_b}{\sum_{\substack{b' \neq b \\ b' \in \mathcal{B}}} \rho_{b'} g_{b'j} P_{b'} + N_0}. \tag{11}$$

With $\text{SINR}_{bj}^{\text{BIA}}$, the achievable rate of user j, for any time slot, is $\log_2(1 + \text{SINR}_{bj}^{\text{BIA}})$. Therefore, to deliver demand D_j, $D_j / \log_2(1 + \text{SINR}_{bj}^{\text{BIA}})$ time slots are required. We arrive at the BII expression below.

$$\rho_b = \frac{1}{T} \sum_{j \in \mathcal{J}_b} \frac{D_j}{\log_2(1 + \text{SINR}_{bj}^{\text{BIA}})}, b \in \mathcal{B}. \tag{12}$$

Note that the sum in (12) gives the total number of time slots that beam b need for its users, and normalizing the sum with T yields nothing but the BII definition itself.

Lemma 2. *Using the BIA approximation for the rate of beam* *b in any time slot yields a biased result, the expected bias $\Delta_{bj}^{\mathrm{BIA}}$ is given by*

$$\mathbb{E}\left(\Delta_{bj}^{\mathrm{BIA}}\right) = \frac{2P_b g_{bj}\left(I_{bj}^{\mathrm{BIA}}+N_0\right)+P_b^2 g_{bj}^2}{2\ln 2\left(I_{bj}^{\mathrm{BIA}}+N_0\right)^2\left(I_{bj}^{\mathrm{BIA}}+P_b g_{bj}+N_0\right)^2} \times \sum\nolimits_{\substack{b'\neq b\\ b\in B}} \rho_{b'}\left(1-\rho_{b'}\right)P_{b'}^2 g_{b'j}^2, \tag{13}$$

where I_{bj}^{BIA} represents the estimated sum of interference. It can be seen that when $\rho_{b'}$ approaches 1, the expectation of the error approaches 0. Moreover, the expected error is inversely proportional to the square of the number of beams, i.e., $\mathbb{E}\left(\Delta_{bj}^{\mathrm{BIA}}\right) \propto 1/B^2$. The proposed BIA model is more suitable for performance approximation in high BII and massive beam systems.

Proof: The bias in approximating the rate of beam b using BIA can be expressed as

$$\Delta_{bj}^{\mathrm{BIA}} = \rho_b T\left(\mathbb{E}\left(f_b\left(I_{bjt}\right)\right) - f_b\left(\mathbb{E}\left(I_{bj}^{\mathrm{BIA}}\right)\right)\right), \tag{14}$$

where $f_b(x) = \log_2\left(1+\frac{P_b g_{bj}}{x+N_0}\right)$. Therefore, using Jensen's inequality, it can be proven to be biased. Utilizing a second-order Taylor expansion, (13) is obtained. Due to space constraints, the detailed derivation is not presented here. ■

By (12), the BII level of beam b is a monotonic increasing function of the BII levels of the other beams. Treating $\rho_b, b \in \mathcal{B}$ as unknowns, we obtain a nonlinear $B \times B$ equation system. Interestingly, one can prove this system falls within the type of standard interference function [13]. Thus the solution is unique and submits to a fixed-point method. Moreover, by a recent discovery, at minimum, geometric convergence rate is guaranteed [14].

To summarize, given user demand, one can efficiently solve (12), to obtain an estimate of the BII levels required to meet the demand subject to the average interference defined in (11).

Remark 4. *Since BII represents the proportion in time, its value shall be within* $[0, 1]$. *However, if the user demand is large, some of the values computed by* (12) *may exceed 1.0; this signals lack of resource and/or too high user demand. Notably, whether or not any BII level exceeds 1.0 is highly instructive in applying the BIA model to MTSP and OCDR.* □

IV. Approaching MTSP and OCDR with BIA

For MTSP, suppose the maximum BII level of the beams, obtained from (12), equals 1.0 (i.e., some beam need to transmit in all T time slots), then on average, the schedule length is T. However, if the maximum BII level is less than 1.0, fewer time slots are required on average. Thus, one can revise the number of time slots using bi-section search, until the maximum BII equals 1.0, to estimate the time required.

Since the above estimate is in an average sense, we still need to make a specific transmission schedule. To this end, recall that the BII levels ρ_b, can be interpreted as the probability that beam b transmits in any time slot. Therefore, we can construct a slot-by-slot schedule using the BII levels: For a generic time slot, the beams are randomly activated with probabilities $\rho_b, b \in \mathcal{B}$. The user to be served by an active beam is then randomly selected. The exact SINR and rate values are computed. For each served user, its demand is reduced by the corresponding amount, and the process repeats.

An algorithmic description for MTSP is outlined in Algorithm 1. The first part (Lines 1-8) performs bi-section search over time, and the second phrase constructs a specific schedule. Apparently, one can do multiple runs of schedule construction (in parallel) and select the one giving the minimum time. Also, note that only beams having any remaining user demand will be subject to activation in a time slot. Furthermore, since T^* is an estimated value, the length of the deterministic schedule may be shorter or longer than T^*.

For OCDR, bi-section search applies to the capacity-demand ratio variable ζ instead of time. For a trial ζ, we examine if a demand of ζD_j can be met for user $j, j \in \mathcal{J}$. That is, (12) is solved for these demand values. The ζ-value is then doubled or halved by examining whether or not the maximum BII level exceeds 1.0. Once bi-section search converges, one (or multiple) deterministic schedule can be constructed in the same way as for MTSP, i.e., the second phrase of Algorithm 1. Note that, again because (12) is an estimate, the ratio achieved by constructing a specific schedule may be higher or lower than the ζ-value from the bi-section search.

Algorithm 1 Low-complexity scheduling with the BIA model

1: $T^* = \frac{T}{2}$, $\underline{T} \leftarrow 1$, $\bar{T} \leftarrow T$
2: $\boldsymbol{\rho}^* \leftarrow$ Solve (12) with T^* time slots
3: **while** $\max_{b\in\mathcal{B}} \rho_b \neq 1.0$ **do**
4:   **if** $\max_{b\in\mathcal{B}} \rho_b > 1.0$ **then**
5:     $\underline{T} \leftarrow T^*$
6:   **else**
7:     $\bar{T} \leftarrow T^*$
8: $T^* \leftarrow$ round(T^*)
9: $t \leftarrow 1$
10: **while** $\max_{j\in\mathcal{J}} D_j > 0$ **do**
11:   $x_{bjt}^* \leftarrow 0, j \in \mathcal{J}_b, b \in \mathcal{B}$
12:   **for** $b \in \mathcal{B} : \sum_{j\in\mathcal{J}_b} D_j > 0$ **do**
13:     Activate beam b with probability ρ_b^*
14:     **if** Beam b activated **then**
15:       $j_b^* \leftarrow$ Select randomly one user from $\{\mathcal{J}_b : D_j > 0\}$
16:       $x_{bj_b^*t}^* \leftarrow 1$
17:   **for** $b \in \mathcal{B} : \sum_{j\in\mathcal{J}_b} D_j > 0$ and b activated **do**
18:       Compute $\text{SINR}_{bj_b^*t}$
19:       $D_j^* \leftarrow D_j^* - \max\{\log_2(1+\text{SINR}_{bj_b^*t}), D_j\}$
20:   **if** Any beam activated **then**
21:     $t \leftarrow t+1$

V. Performance Results

We have simulated downlink communications for massive beam LEO system scenarios, and validated the effectiveness of the proposed approach in two aspects: BIA model accuracy and its effectiveness in approaching optimality. The parameters used in the simulations are summarized in Table I.

TABLE I
SIMULATION PARAMETERS

Parameter	Value
Satellite antenna gain G_s	30 dB
User antenna gain G_j	$0 \sim 5$ dB
3dB-beam width of the antenna $\phi_{3\text{dB}}$	$0.4°$
Angle between user and LEO satellite ϕ_j	$0 \sim 10°$
Signal frequency of LEO satellites f_c	1.6×10^9 Hz
Number of beams B	120
Nakagami-m parameter m_j	5
Average power of multipath component b_j	0.25
Average power of LoS component Ω_j	0.28
Noise power N_0	1.44×10^{-13} W

A. Accuracy of the BIA Model

To evaluate the accuracy of the BIA model proposed in Eq. (11), we use the system sum rate as an example, and compare the approximate sum rate obtained from the BIA model with the exact sum rate calculated slot-by-slot. Specifically, the beam scheduling strategy is first generated by randomly activating the beams, while maintaining an identical number of activated time slots per beam. Then, the exact sum rate is obtained by calculating each beam's rate slot-by-slot using (6). Next, the BII ρ of each beam is substituted into (11) to obtain the approximate system sum rate.

Figure 1 illustrates the percentage deviation in sum rate of the BIA model from the exact model with respect to the number of beams. A total of 1000 simulations are performed and the average is taken. One can see that the sum rate gap of the BIA model decreases significantly with the increase of the BII, which is consistent with Lemma 2. Furthermore, as the number of beams increases, the difference between the sum rate predicted by the BIA model and the exact result is significantly reduced. When the number of beams exceeds 60, the estimation accuracy of the BIA model surpasses 95%. Therefore, these results validate that the proposed BIA model provides an accurate approximation of the actual system performance in massive beam and high demand scenarios.

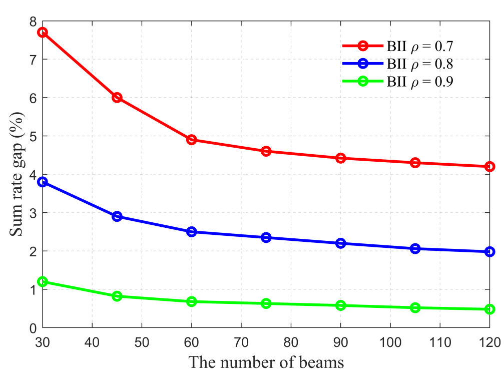

Fig. 1. Comparison of system sum rate of the proposed BIA model and the exact model, where $T = 100$ and BII $\boldsymbol{\rho} = \{0.7, 0.8, 0.9\}$.

B. Effectiveness in Approaching Optimality

In multi-beam LEO satellite scenarios, if the user demand is relatively low, the objective of minimizing the schedule length (i.e., delivering the demand as fast as possible) is sensible. We evaluate the low-complexity scheduling strategy given in Algorithm 1. For comparison, the conventional BH approach was considered. In this approach, half of the beams are activated in each time slot, such that the activations of adjacent beams are alternated to mitigate interference. This alternating pattern repeats until all user demand becomes satisfied.

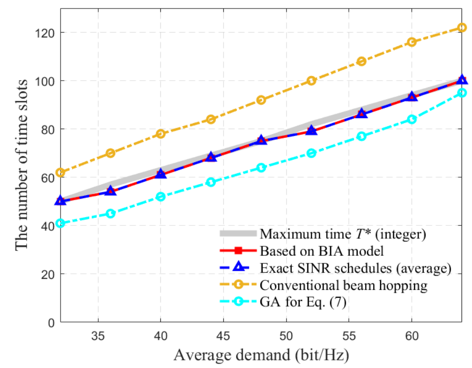

Fig. 2. The number of time slots with respect to the data demand, with $T = 120$ and $B = 8$. The gray thick line represents the (integer) number of time slots T^*. The red line represents the product of T and the maximum BII, which typically is a fractional number, and the triangles are the maximum number of time slots from simulated exact SINR schedules based on the BII values.

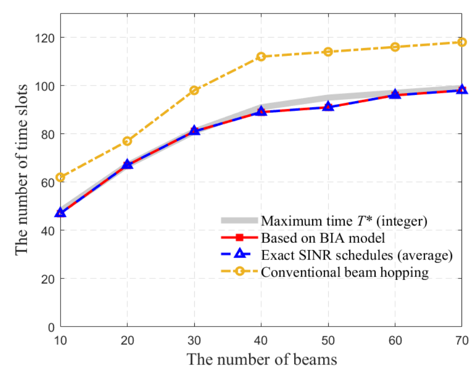

Fig. 3. The number of time slots vs. beam count for the proposed low-complexity approach.

Figure 2 demonstrates the performance of the proposed BIA-based low complexity BH approach for the MTSP problem with respect to user demand. As expected, the number of time slots for data transmission increases with rising demand. Notably, there is virtually no difference in the performance by the BIA model and that of the exact SINR simulations. Moreover, the schedule made based on BIA outperforms conventional BH by approximately 20% and sometimes more. Compared to the scheduling approach obtained by solving (7) using genetic algorithms (GA) [8], it shows a performance decrease of about 8.5%, but achieves feasibility of rapid computation in large-scale beam scenarios. Figure 3 shows the consistent superiority of the proposed method over traditional scheduling approaches with increasing beam count. In contrast, GA fails to maintain its timeliness and becomes computationally prohibitive at large-scale beam scheduling. Therefore, the proposed low complexity beam scheduling approach achieves good performance in solving the MTSP problem while maintaining low computational complexity.

In another common scenario with high user demand, the LEO satellite may have to utilize the entire scheduling horizon for data transmission. In this case, the objective of beam scheduling is to maximize the OCDR, so as to achieve fairness.

Figure 4 compares achieved OCDR of the BIA-based low complexity BH approach and the optimal BH approach based on solving (8) to optimum. It can be observed that the optimal schedule based on (8) gradually decreases in OCDR, as the average demand increases. The proposed approach exhibits only 6% performance gap relative to this globally optimal benchmark, while the conventional BH approach shows significantly worse results. Notably, the computational complexity of the optimal approach grows exponentially with the number of beams, rendering it impractical for massive beam scheduling. Thus, the BIA-based low complexity BH approach demonstrates superior performance for jointly considering communication efficacy and computational tractability.

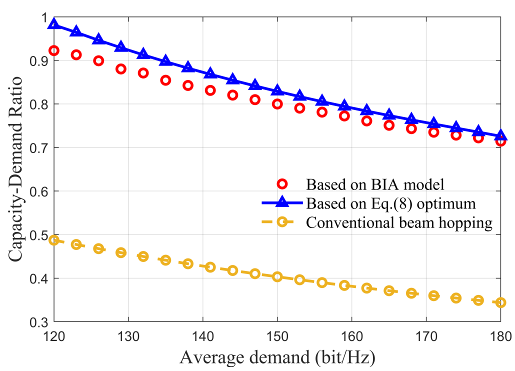

Fig. 4. Comparison of the OCDR between the BIA-based low-complexity approach and the optimum of (8) under varying user demands, with $T = 100$ and $B = 15$. The red circles represent the low complexity approach, the blue triangles represent the optimum of (8), and the orange circles indicate conventional beam hopping approach.

VI. Conclusions

To address the high complexity in existing LEO satellite beam scheduling approaches, this paper has proposed a novel BIA model for developing low complexity solutions. Based on the BIA model and capitalizing on two practical scenarios with low and high user demand, we have developed low-complexity approaches for two corresponding optimization problems. This approach ensures strategic reliability while guaranteeing computational timeliness for large-scale beam scheduling. Experimental results show that the proposed BIA model achieves 95% accuracy compared to precise modeling. Furthermore, the proposed low-complexity method incurs a performance loss of less than 6% compared to the optimal approach, while still maintaining high computational timeliness in large-scale beam scheduling. Future work will explore extending the BIA framework for online scheduling and multi-satellite coordination.

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