A Novel Base Station Deployment Scheme for Network Planning in 6G Outdoor Hotspot Scenarios

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***Abstract*—The explosive growth of the sixth-generation (6G) wireless system necessitates efficient base station (BS) deployment to balance coverage, data rates, and economic costs. In this paper, we propose a novel BS deployment scheme that jointly optimizes the number and locations of the deployed BSs, considering limited BS throughputs and practical non-uniform user distributions. A variant multi-dimensional knapsack problem is formulated and then solved by proposing a novel depth-limited backtracking dynamic programming (DLB-DP) algorithm with a BS-user association (BSUA) algorithm. We compare the proposed DLB-DP algorithm with three state-of-the-art benchmark algorithms in a hotspot scenario. The results demonstrate that the proposed algorithm outperforms the considered alternatives in terms of coverage, data rates, and robustness under varying user densities.**

***Index Terms*—BS deployment, knapsack problem, dynamic programming, hotspot scenarios, network planning.**

I. Introduction

The vision of the 6G wireless system is evolving towards "global coverage, all spectra, full applications, all senses, all digital, and strong security" [1]. The proliferation of smart devices and data-intensive applications has triggered an explosive growth in demands for high Quality of Service (QoS) services [2], [3], particularly in hotspot scenarios [4], creating significant challenges for network planning. These challenges make it necessary to rethink the BS deployment problem (BSDP), with jointly optimized coverage, data rates, and economic costs considering non-uniform user distributions [5].

Over the past decades, extensive research has been conducted on BSDPs. Some studies focused on adjusting BS parameters, such as the number of sectors and transmission power, via channel measurements under different scenarios and frequency bands [6]–[8]. Similarly, others employed channel modeling for specific scenarios to assist BS deployment planning. For instance, authors in [9] utilized ray tracing to evaluate communication quality and deployed additional BSs in areas with weaker performances. Although these studies offer good performance for specific scenarios, the cost of channel measurements and modeling limits the scalability. In [10], authors formulated the joint optimization problem of BS placement and power control as a mixed-integer convex programming. The study was based on a predefined fixed number of BSs to find the optimal deployment scheme, while users were simplified as service areas with fixed distributions in the scenario, ignoring the impact of user density. In [11], a ray-tracing-based indoor wireless resource optimization algorithm was proposed to meet the predefined capacity requirements. However, comparative analysis across multiple scenarios revealed that the method did not perform well in high-density, high-user-demand scenarios. The authors in [12] proposed a hybrid method for BSDP in outdoor scenarios with uniform user distributions, where the BS-user association was based on QoS, ignoring downlink overload for BSs. In [13], the improved Hooke-Jeeves algorithm was proposed to find the optimal locations of BS for a large indoor office to jointly optimize the coverage and interference, while the number of BS is fixed and the users are uniformly distributed.

In summary, most existing studies address BSDP with a given number of BSs, inherently restricting the optimization scope of deployment configurations. Meanwhile, the downlink overload of BSs in hotspot scenarios resulting from high user density is often ignored. Therefore, the joint optimization problem for the number and locations of BSs in outdoor hotspot scenarios, a multi-objective problem with constraints, requires rethinking. The knapsack problem, a classic combinatorial optimization problem with great flexibility, has been extensively applied in BSDPs [14]–[16]. It can be extended into different variants, such as the multi-dimensional knapsack problem [14], the knapsack-like problem [15], and the multiple-choice nested knapsack problem [16], by incorporating additional constraints or using more complex objective functions.

Motivated by the discussion above, the main contributions of this paper are summarized as follows

- We propose a novel BS deployment scheme that jointly optimizes the number and locations of the deployed BSs by formulating a variant multi-dimensional knapsack-problem with a practical non-uniform user distribution.
- We solve the deployment problem by proposing a novel DLB-DP algorithm with the proposed BSUA algorithm considering the limited BS throughputs.
- We demonstrate the advantages of the proposed DLB-DP algorithm with BUSA regarding coverage, data rates, and robustness through comprehensive comparisons with state-of-the-art benchmark schemes.

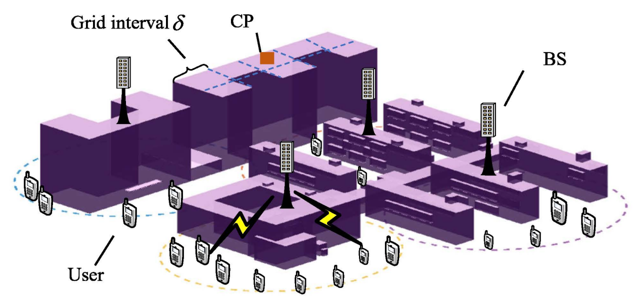


Fig. 1. The outdoor hotspot scenario.

The rest of the paper is organized as follows. Section II introduces the system model of an outdoor hotspot scenario. In Section III, the considered BSDP with the joint optimization is formulated and solved. Section IV analyzes the coverage, data rates, and robustness of the proposed scheme. Finally, Section V draws the conclusions.

II. System Model

As illustrated in Fig. 1, we consider an outdoor hotspot scenario, where the buildings are represented by geometric shapes and the BSs are to be mounted on rooftops. The potential locations of the BSs, referred to as *candidate points (CPs)*, are located at the centers of grids divided with an interval of δ. The users are independently uniformly distributed in the coverage area according to a Thomas cluster point process (TCPP) to reflect practical hotspot patterns. We denote by $\mathcal{U} = \{1, \ldots, K\}$ and $\mathcal{B} = \{1, \ldots, L\}$ the index sets of users and CPs, respectively. We let $\overline{\mathcal{B}} = \{l : z_l = 1, l \in \mathcal{B}\}$ with cardinality $\bar{L} = |\overline{\mathcal{B}}|$ denote the set of locations of deployed BSs with binary variable $z_l = 1$ if a BS is deployed at CP l and $z_l = 0$ otherwise.

A. Large-Scale Fading Model

We adopt the large-scale fading model under an urban micro (UMi) street canyon scenario. The path loss between CP l and User k is calculated in dB as [17]

$$\mathrm{PL}_{kl} = \begin{cases} 32.4+21.0\log_{10}(\frac{d_{kl}}{1\mathrm{m}})+20\log_{10}(\frac{f_c}{1\mathrm{GHz}})+F^{\mathrm{L}}, & p_{kl}=1, \\ 32.4+31.9\log_{10}(\frac{d_{kl}}{1\mathrm{m}})+20\log_{10}(\frac{f_c}{1\mathrm{GHz}})+F^{\mathrm{N}}, & p_{kl}=0 \end{cases} \quad (1)$$

where d_{kl} is the distance, f_c is the carrier frequency, and binary variable p_{kl} is the line-of-sight (LoS) probability with $p_{kl} = 1$ indicating a LoS path between CP l and User k and $p_{kl} = 0$ otherwise. The shadow fading in the LoS and non-LoS (NLoS) cases are represented by $F^{\mathrm{L}} \sim \mathcal{N}(0, 4^2)$ and $F^{\mathrm{N}} \sim \mathcal{N}(0, 8.1^2)$, respectively.

B. Coverage Ratio and Data Rate

The received signal power at User k from the BS at CP l is denoted by $S_{kl} = P_{\mathrm{BS}}/\mathrm{PL}_{kl}$, where P_{BS} is the transmit power of BSs. Consequently, the signal-to-noise ratio (SNR) is

$$\mathrm{SNR}_{kl} = S_{kl}/P_{\mathrm{n}} \quad (2)$$

where P_{n} is the noise power at users. A user is *reachable* by a BS if their SNR exceeds a predefined threshold $\underline{\mathrm{SNR}}$. The reachable user set of the BS at CP l is given by

$$\overline{\mathcal{U}}_l = \{k : \mathrm{SNR}_{kl} > \underline{\mathrm{SNR}}, \forall k\}. \quad (3)$$

However, due to limited downlink throughput, a BS cannot simultaneously serve all its reachable users. Therefore, a BS must select the best users to serve from the reachable user set by performing BSUA, which will be elaborated on in Section III. For now, we let $\mathcal{U}_l = \{k : \varphi_{kl} = 1, k \in \overline{\mathcal{U}}_l\}$ denote the subset of users served (or *coverd*) by the BS at CP l, where binary variable $\varphi_{kl} = 1$ if User k is served by the BS at CP l and $\varphi_{kl} = 0$ otherwise. Therefore, the coverage ratio is defined as the percentage of served users compared to all, which can be calculated as

$$r_c = \frac{1}{K}\left|\bigcup\nolimits_{l\in\overline{\mathcal{B}}}\mathcal{U}_l\right| = \frac{1}{K}\sum\nolimits_{k=1}^{K}\sum\nolimits_{l\in\overline{\mathcal{B}}}\varphi_{k,l}. \quad (4)$$

The signal-to-interference-plus-noise ratio (SINR) of User k from its serving BS at CP l_k is given by

$$\mathrm{SINR}_k = S_{kl_k}/(I_k + P_{\mathrm{n}}) \quad (5)$$

where $I_k = \sum_{l'\in\overline{\mathcal{B}}, l'\neq l_k} S_{kl'}$ is the interference power from other BSs. The data rate of User k is calculated by $R_k = B \cdot \log_2(1 + \mathrm{SINR}_k)$ where B is the bandwidth. The average data rate of all users is calculated as $\bar{R} = \frac{1}{K}\sum_{k=1}^{K}\sum_{l\in\overline{\mathcal{B}}}\varphi_{kl}R_k$.

III. BS Deployment Through DLB-DP with BSUA

In this section, we propose a novel BS deployment scheme that jointly optimizes the number and locations of the deployed BSs considering throughput limitations and economic costs. A variant multi-dimensional knapsack problem is formulated and solved by our proposed DLB-DP algorithm with BSUA.

A. Problem Formulation

We aim to jointly improve the coverage ratio and average data rate with the lowest economic costs constrained by limited downlink throughputs. By assuming that all deployed BSs share identical configurations, we formulate the multi-objective and combinatorial optimization problem as a variant muti-dimensional knapsack problem P_1, which is given by

$$\begin{aligned}
\mathsf{P}_1: \quad & \underset{\{z_l, \varphi_{kl}\}}{\text{maximize}} \quad \lambda\frac{\bar{R}}{\max_k z_l\varphi_{kl}R_k} + (1-\lambda)r_c && (6a)\\
& \text{s.t.} \quad \sum\nolimits_{l=1}^{L}\varphi_{kl} \le 1, \quad \forall l && (6b)\\
& \qquad \sum\nolimits_{l=1}^{L} z_l\omega_l \le \Omega, \quad \forall l && (6c)\\
& \qquad \sum\nolimits_{k=1}^{K} z_l\varphi_{kl}R_k < C_{\max}, \quad \forall k && (6d)\\
& \qquad z_l \in \{0,1\}, \quad \forall l && (6e)\\
& \qquad \varphi_{kl} \in \{0,1\}, \quad \forall k, \ \forall l && (6f)
\end{aligned}$$

where ω_l is deployment cost at the CP l, Ω is the deployment budget, and $C_{\max}$ is the maximum throughput at BSs.

The objective function of problem P_1 in (6a) optimizes a weighted combination of rate fairness and coverage performance. The first term $\bar{R}/\max_k z_l\varphi_{kl}R_k$ encourages equitable data rate distribution and the parameter λ is used to balance the rate fairness and coverage. Constraint set in (6b) guarantees that each user is served by at most one BS. The deployment cost and BS throughput constraints are represented in (6c) and (6d), respectively. Constraint sets in (6e) and (6f) indicate the binary nature of the optimization variables.

While theoretically rigorous, the throughput constraints in (6d) introduce unaffordable computational complexity by coupling with the dynamic data rates R_k. Therefore, a lower bound $C_{\min}$ is defined to represent the minimum acceptable data rate. Given $C_{\min}$, the maximum number of users served by a BS can be calculated as $N_{\max} = \lfloor C_{\max}/C_{\min} \rfloor$. With this assumption, the constraints in (6d) can be simplified as

$$\sum\nolimits_{k=1}^{K} \varphi_{kl} \leq N_{\max}, \quad \forall k. \tag{7}$$

Then the problem can be rewritten as

$$\begin{aligned} \mathsf{P}_2: \quad & \underset{\{z_l\},\{\varphi_{kl}\}}{\text{maximize}} \quad \lambda \frac{\bar{R}}{\max_k z_l \varphi_{kl} R_k} + (1-\lambda) r_{\mathrm{c}} & \text{(8a)} \\ & \text{s.t.} \quad (6\text{b}), (6\text{c}), (6\text{e}), (6\text{f}), (7) & \end{aligned}$$

B. DLB-DP Algorithm with BSUA

The formulated problem P_2 is a variant multi-dimensional knapsack problem that shares fundamental similarities with the 0-1 knapsack problems, particularly in its binary decision process. To this end, inspired by the traditional DP [18], we propose a novel DLB-DP algorithm outputting the deployed BS set $\overline{\mathcal{B}}$ and the serving indicators $\{\varphi_{kl}\}$, summarized in Algorithm 1, The algorithm proceeds as follows.

1) Subproblem Decomposition: The formulated problem P_2 is divided into nested subproblems

$$\begin{aligned} \mathsf{P}_{mn}: \quad & \underset{\{z_l\},\{\varphi_{kl}\}}{\text{maximize}} \quad F_{mn} & \text{(9a)} \\ & \text{s.t.} \quad (6\text{b}), (6\text{c}), (6\text{e}), (6\text{f}), (7) & \end{aligned}$$

where P_{mn} represents the optimal deployment for the first m CPs under deployment budget n and $F_{mn} = \lambda \frac{\bar{R}}{\max_k z_l \varphi_{kl} R_k} + (1-\lambda) r_{\mathrm{c}}$ with $\bar{R}$ and R_k calculated by utilizing $\{z_l\}$ and $\{\varphi_{kl}\}$ in the current iteration, $m = 1, \ldots, L$, $n = 1, \ldots, \Omega$.

2) State Transition with BSUA: The set $\mathcal{B}_{mn}$ is used to record the set of deployed BSs for the subproblem P_{mn}. A state transition flag γ is used at lines 4, 11, 17 and 19 in Algorithm 1, to indicate the direction of the state transition. The state transition function of the algorithm is expressed as

$$F_{mn} \leftarrow \max\{F_{(m-1)n}, F'_{mn}\} \tag{10}$$

where $F_{(m-1)n}$ and F'_{mn} are $F_{m'n}$ and F' given in lines 5 and 9 in Algorithm 1, respectively.

The proposed BSUA algorithm, which is summarized in Algorithm 2, employs an iterative greedy strategy comprising two sequential phases , subject to constraint (7). Initially, unserved users are prioritized by sorting candidate users within each BS's coverage through SNR metrics, exclusively assigning the top $(N_{\max} - \sum_i \varphi_{il})$ users to BSs with available capacity. Subsequently, the algorithm resolves multi-BS associations by retaining only the highest-SNR connection for over-associated users, systematically eliminating cross-cell interference.

Algorithm 1: The DLB-DP Algorithm.

Input: $\boldsymbol{\omega}$, L, Ω, $N_{\max}$, d.
Output: $\overline{\mathcal{B}}$, $\{\varphi_{kl} : \forall k, l\}$

1 **Initiation**: $m = 0$, $n = 0$, $F_{mn} \leftarrow 0$, $\mathcal{B}_{mn} \leftarrow \emptyset$, $\{\varphi_{kl} = 0 : \forall k, l\}$;
2 **for** $m = 1, \ldots, L$ **do**
3   **for** $n = 1, \ldots, \Omega$ **do**
4   Reset the state transition flag $\gamma \leftarrow 0$;
5   Update $F_{mn} \leftarrow F_{m'n}$ and $\mathcal{B}_{mn} \leftarrow \mathcal{B}_{m'n}$ with $m' = m-1$;
6   **if** $\omega_m < n$ **then**
7   Update $\mathcal{B}' \leftarrow \mathcal{B}_{m'n'} \cup \{m\}$ with $n' = n - \omega_m$;
8   Update $\{\varphi_{kl} : \forall k, \forall l \in \mathcal{B}'\}$ via BSUA with inputs $\mathcal{B}'$, $N_{\max}$, and $\{\varphi_{kl} : \forall k, \forall l \in \mathcal{B}'\}$;
9   Calculate F' via (6a) with $\overline{\mathcal{B}}$ replaced by $\mathcal{B}'$ and the updated $\{\varphi_{kl} : \forall k, \forall l \in \mathcal{B}'\}$;
10   **if** $F' > F_{m'n'}$ **then**
11         $\gamma \leftarrow 1$;
12   **else**
13   Update $\mathcal{B}' \leftarrow \{$the last d elements of $\mathcal{B}'\}$;
14   **while** $F' < F_{m'n'}$ **do**
15   Remove one element from $\mathcal{B}'$ and update F' via (6a);
16   **if** $F' > F_{m'n'}$ **then**
17             $\gamma \leftarrow 1$;
18   **break**;
19   **if** $\gamma = 1$ **then**
20       $F_{mn} \leftarrow F'$ and $\mathcal{B}_{mn} \leftarrow \mathcal{B}'$;
21 $\overline{\mathcal{B}} \leftarrow \mathcal{B}_{mn}$;
22 **Return** $\overline{\mathcal{B}}$, $\{\varphi_{kl} : \forall k, l\}$.

3) Depth-Limited Backtracking (DLB): According to (6a), the value of the objective function F depends on the combination of deployed BS. Introducing a new BS may not always improve F, but potentially lead to its degradation. Rather than discarding such a CP immediately, which could lead to a local optimum, we propose a DLB scheme with a search depth d from lines 13 to 18 in Algorithm 1 to balance solution quality and computational feasibility.

C. Complexity Analysis

The overall time complexities are compared based on the number of evaluations of the network. The proposed DLB-DP achieves $\mathcal{O}((1+d)\Omega L)$ complexity through dynamic programming with backtracking depth d, outperforming Hooke-Jeeves' complexity $\mathcal{O}(D\Omega^2)$ [13] that scales quadratically. Here, D is related to the step size and other parameters in the algorithm. Greedy methods maintain linear complexity $\mathcal{O}(\Omega L)$ [19] but suffer from suboptimal performance. The random deployment requires no optimization, with the complexity of $\mathcal{O}(1)$.

Algorithm 2: The BSUA Algorithm.

Input: $\mathcal{B}'$, $N_{\max}$, $\{\varphi_{kl} : \forall k, \forall l \in \mathcal{B}'\}$

Output: $\{\varphi_{kl} : \forall k, \forall l \in \mathcal{B}'\}$

Obtain the reachable user sets $\{\overline{\mathcal{U}}_l : \forall l \in \mathcal{B}'\}$ via (3);

repeat

  for BS at CP $l \in \mathcal{B}' \setminus \{j : \sum_k \varphi_{kj} = N_{\max}\}$ **do**

    Sort $\{\text{SNR}_{kl} : k \in \overline{\mathcal{U}}_l$ and $\sum_j \varphi_{kj} = 0\}$ in descending order and include $(N_{\max} - \sum_i \varphi_{il})$ users with the largest values in set $\mathcal{C}_l$;

    Serve the users in $\mathcal{C}_l$ by letting $\varphi_{kl} = 1$, $k \in \mathcal{C}_l$;

  for user $k \in \{i : \sum_l \varphi_{il} > 1\}$ **do**

    Find BS at CP $l_k = \arg\max_{l \in \mathcal{B}', \varphi_{kl}=1} \text{SNR}_{kl}$;

    Let $\varphi_{kl} = 0$, $\forall l \in \{j : j \in \mathcal{B}'$ and $j \neq l_k\}$;

until $\sum_k \varphi_{kl} = N_{\max}, \forall l \in \mathcal{B}'$;

Return $\{\varphi_{kl} : \forall k, \forall l \in \mathcal{B}'\}$.

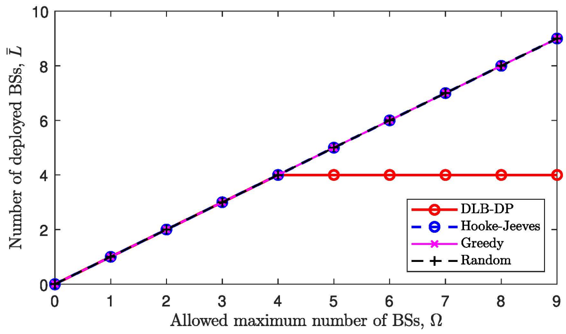


Fig. 2. Number of deployed BSs versus maximum allowed number of BSs with different deployment algorithms (1.5×10^4 users/km^2).

IV. Results and Analysis

In this section, the performance of the proposed DLB-DP algorithm is evaluated through comparative analysis with the Hooke-Jeeves algorithm [11], [13], the greedy algorithm [19], and the random algorithm. We consider a hotspot scenario of 312.18×330.51 m^2, where the users are distributed according to a TCPP. Each CP has a unit deployment cost, i.e., $\omega_l = 1$, $\forall l$, making the budget constraint Ω equivalent to the maximum allowed number of BSs. Other key parameters are summarized in Table I, where the value of the coverage-rate tradeoff factor λ in (6a) is determined via Pareto analysis to balance coverage and rate fairness objectives. The minimum QoS requirement is set to $C_{\min} = 10$ Mbps for high-definition videos.

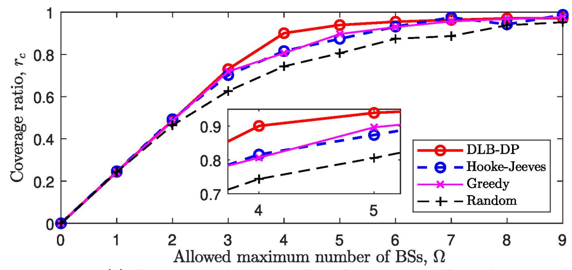
Fig. 2 demonstrates the number of deployed BSs $\bar{L}$ varying with the maximum allowed number of BSs Ω. The proposed DLB-DP algorithm converges with 4 BSs when $\Omega \geq 4$ while the other schemes keep deploying the maximum allowed BSs, highlighting the effectiveness of the DLB-DP algorithm in cutting the deployment costs by optimizing the number of deployed BSs.

Fig. 3 illustrates the coverage and data rate performance of our proposed algorithm, with a user density of 1.5×10^4 users/km^2. In Fig. 3(a), both Hooke-Jeeves and greedy algorithms exhibit competitive coverage performance. The coverage performance of the proposed DLB-DP algorithm converges when $\Omega = 4$, outperforming the Hooke-Jeeves algorithm and the greedy algorithm by more than 12%. Fig. 3(b) demonstrates that the DLB-DP algorithm achieves the best data rate performance. It outperforms the Hooke-Jeeves algorithm by 10% when $\Omega = 3$ and improves by approximately 16% as Ω increases. The greedy algorithm exhibits a slightly lower average data rate compared to the random algorithm by prioritizing immediate gains in coverage rather than a globally balanced distribution of BSs. This strategy may result in higher inter-cell interference, ultimately deteriorating the overall average data rate.

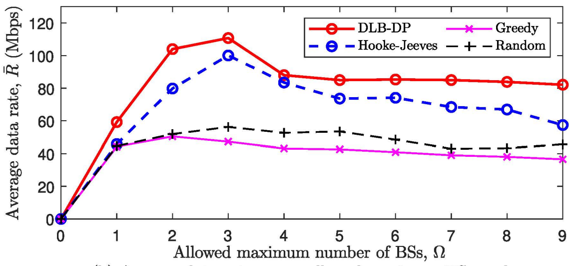
Fig. 4 focuses on impacts of user density on the coverage and data rate performance, where $\Omega = 5$. We include the DLB-DP algorithm without BSUA in comparison to evaluate the proposed BSUA strategy, which follows a fixed association scheme, connecting users to the nearest BS without load balancing or interference mitigation. It can be seen in Fig. 4(a) that DLB-DP (w/ BSUA) maintains a consistently high coverage ratio of over 95% while the others keep losing as the user density increases. The DLB-DP (w/o BSUA) demonstrates

TABLE I
Simulation Parameters.

Parameters	Values
Carrier frequency (f_c)	2.4 GHz
Transmission power (P_{BS})	30 dBm
Signal bandwidth (B)	20 MHz
BS max downlink throughput ($C_{\max}$)	2 Gbps [20]
QoS requirement ($C_{\min}$)	10 Mbps
SNR threshold ($\underline{\text{SNR}}$)	30 dB
Coverage-rate tradeoff factor (λ)	0.5
Grid interval (δ)	10 m

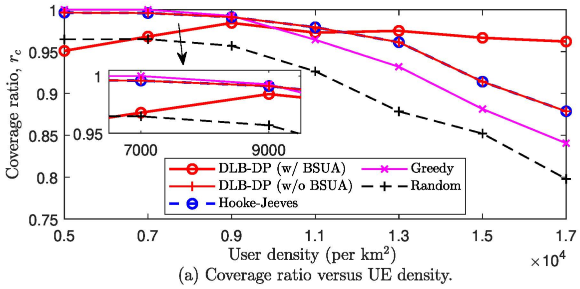


(a) Coverage ratio versus allowed maximum BS number.

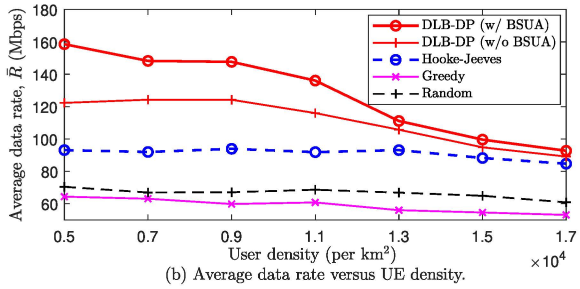


(b) Average data rate versus allowed maximum BS number.

Fig. 3. (a) Coverage ratio and (b) average data rate versus maximum allowed number of BSs with different deployment algorithms (1.5×10^4 users/km^2).



(a) Coverage ratio versus UE density.



(b) Average data rate versus UE density.

Fig. 4. (a) Coverage ratio and (b) average data rate versus user density with different deployment algorithms (maximum allowed number of BSs $\Omega = 5$).

a similar coverage performance to that of the Hooke-Jeeves but with significantly lower complexity. Fig. 4(b) shows that DLB-DP (w/ BSUA) achieves a 70% improvement in low-density scenarios and a 10% enhancement in high-density scenarios, while DLB-DP (w/o BSUA) ranks second in data rate performance, confirming the effectiveness of the BSUA strategy in optimizing both coverage and data rates. Due to the same reason as in Fig. 3, the data rate performance of the greedy algorithm is slightly lower than that of the random algorithm.

V. Conclusions

In this paper, we have proposed a novel DLB-DP BS deployment algorithm with the proposed BSUA strategy to jointly optimize BS deployment and user association in 6G outdoor hotspots. Based on a knapsack-like optimization framework, the proposed scheme can effectively determine both the number and locations of BSs while ensuring efficient interference management. It has been demonstrated that the DLB-DP algorithm with BSUA outperforms three state-of-the-art benchmarks, achieving the highest data rates and the lowest economic costs while maintaining a 95% coverage ratio. Moreover, the proposed algorithm exhibits strong robustness to varying user densities and can improve the average user data rate by more than 10% even in high-density scenarios.

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