Research on the optimization of mm-wave UAV-BSs by using IRSs

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***Abstract*—When mobile base stations are disabled due to natural disasters such as earthquakes, or when network congestion occurs during large-scale events where many people gather, a method is required to deploy a temporary network that does not depend on terrestrial base stations. This paper investigates the use of millimeter-wave UAV (Unmanned Aerial Vehicle) base stations to provide wireless communication infrastructure. However, in areas with clusters of high-rise buildings, there is a high possibility that a line of sight between UAVs and user terminals cannot be secured. To address this, we propose to create new propagation paths using IRS (Intelligent Reflecting Surfaces) and further extend coverage by optimizing UAV placement with 3D city models.**

***Index Terms*—6G, mmWave, UAV, UAV cellular networks, interference control, IRS, Optimization, NTN**

I. Introduction

When mobile base stations become inoperative due to earthquakes or other disasters, or when network congestion occurs as a result of large-scale events, it is necessary to deploy a temporary network that does not rely on terrestrial base stations. Non-Terrestrial Networks (NTNs), represented by Low Earth Orbit (LEO) satellites and High Altitude Platform Stations (HAPS), have recently been studied intensively as technologies to address this issue. Among these technologies, UAV base stations have attracted considerable attention as a promising solution.

UAV base stations can provide services quickly where needed and can flexibly change their placement in three-dimensional space. UAV base stations have been studied from various perspectives. In [1], the authors investigated the three-dimensional placement of UAV base stations to maximize the number of covered users with minimum power consumption. In [2], Particle Swarm Optimization (PSO) was employed to determine the optimal UAV placement for maximizing coverage. Most previous studies on UAV base stations have mainly focused on connectivity using the microwave band. However, as communication speeds increase, the size of web pages has also grown rapidly [3], and in disaster-stricken areas, there are increasing cases where large-capacity transmission is required, such as for rescue operations using remotely controlled equipment. Therefore, this study focuses on UAV base stations using the millimeter-wave band to realize high-speed and high-capacity communication.

The millimeter-wave band allows for high-speed data transmission due to its large available bandwidth. However, it also has strong directivity and is highly susceptible to blockage by obstacles. To mitigate this drawback, especially in densely built-up urban areas, the introduction of IRS (Intelligent Reflecting Surface), a reconfigurable reflecting surface that can dynamically control the direction of reflected radio waves, is expected. According to the Beyond 5G white paper by the Beyond 5G Promotion Consortium [4], IRS is positioned as an important and energy-efficient technology for expanding coverage and improving communication quality in the Beyond 5G era. In [5], the authors investigated UAV networks supported by IRS installed on buildings and UAVs equipped with IRS for enhancing ground network performance.

This study integrates IRS into millimeter-wave UAV base station networks and expands coverage by creating new paths with IRS in areas where direct paths from UAV base stations are blocked. In addition, under the “PLATEAU” project [6] promoted by the Ministry of Land, Infrastructure, Transport and Tourism of Japan, 3D city models have been developed and made publicly available. We use these 3D models to conduct radio propagation simulations that reflect actual urban structures and investigate methods to address blockage problems in millimeter-wave communications through global optimization of UAV base station placement and effective IRS utilization.

Our previous work [7] [8] demonstrated that integrating IRS into UAV base station networks can expand high-speed communication coverage and that the placement of multiple UAV base stations can be optimized in urban environments with IRS using optimization algorithms.

The main contributions of this study are summarized as follows:

- UAV placement optimization in an urban model with IRS through cooperative control.
- QoS-aware optimization for user equipment (UE).
- LoS probability model construction and validation.

II. Architecture and System Model

A. Architecture

Figure 1 illustrates the overall architecture proposed by us [7]. We consider a scenario in which base stations become inoperative due to natural disasters such as earthquakes, hurricanes, or lightning strikes, and a temporary communication area must be rapidly established. Thanks to their characteristics, UAVs can be flexibly deployed in three dimensions, making it easier to secure line-of-sight conditions essential for millimeter-wave communications and enabling rapid network deployment.

In this study, two types of UAVs are used for UAV base station network deployment: access UAVs and backhaul UAVs. The backhaul UAV acts as a relay node, bridging the connection between the access UAVs and undamaged terrestrial base stations. By using a backhaul UAV, it is possible to mitigate the impact of distance attenuation and rain attenuation, which can become problems in the communication link between base stations and access UAVs. The access UAV delivers traffic transmitted from the backhaul UAV to the UEs on the ground. Since the access UAV provides data directly to UEs, the number of UEs that can be covered is strongly influenced by its placement. Moreover, when UAVs operate autonomously, challenges arise such as interference management, ensuring sufficient throughput, and avoiding redundancy of relay nodes. To address these challenges, cooperative operation among multiple UAVs is required. In this study, UAVs are connected and managed via the control plane of a ground base station. This paper focuses on the placement problem of access UAVs, aiming to solve the placement optimization problem while considering the three-dimensional structure of the city and leveraging IRS deployed in the urban environment.

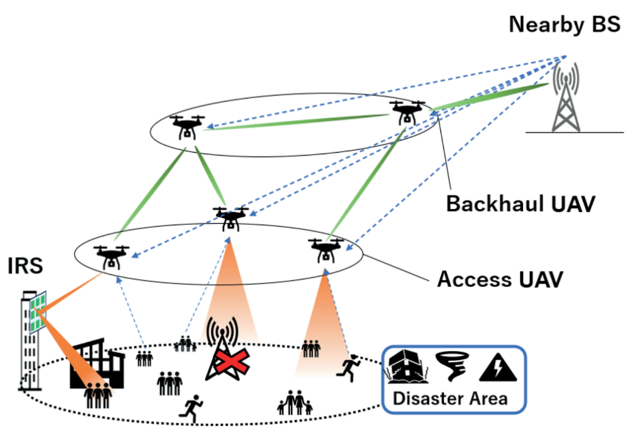

Fig. 1: Overall system architecture

B. System model

The air-to-ground channel between UAVs and ground users is modeled based on ray tracing using MATLAB. Using the 3D building model of the target area, Line-of-Sight (LoS) and Non-Line-of-Sight (NLoS) propagation paths are extracted for each transmitter–receiver pair. The path loss of each path is expressed as

$$L_l(d_l) = 20\log_{10}\left(\frac{4\pi d_l f_c}{c}\right) + L_{\mathrm{ref},l} \tag{1}$$

where d_l is the path length, f_c is the carrier frequency, c is the speed of light, and $L_{\mathrm{ref},l}$ is the additional loss due to reflection or diffraction.

The corresponding complex path gain in the linear domain is obtained from (1) as

$$\alpha_l = 10^{-L_l(d_l)/20}, \tag{2}$$

The antenna gain for each link is configured according to [9]. Specifically, the main lobe gain G_{main} is applied to the desired UAV–UE link, and the side lobe gain G_{side} is applied to interfering links. This allows the directional effect of beamforming to be reflected in the channel gain and simplifies interference power calculations.

Furthermore, an IRS (Intelligent Reflecting Surface) is introduced. When there is no LoS link between a UAV and a user, a new reflected path is generated via the IRS. The IRS is assumed to have ideal reflection characteristics, with an amplitude reflection coefficient of 1 and fully controllable phase. As a result, high-gain reflection paths can be established even for NLoS users.

Let s and i denote the indexes of the serving and interfering UAVs, respectively. For a generic link between UAV k and user u, where $k \in \{s, i\}$, the overall complex baseband channel coefficient is expressed as

$$h_{k,u} = \sum_{l=1}^{L_{k,u}} \alpha_{l,k,u} G_{t,l} G_r e^{-j2\pi f_c \tau_l}, \quad k \in \{s, i\}. \tag{3}$$

where $L_{k,u}$ is the number of propagation paths between UAV k and user u, $\alpha_{l,k,u}$ is the complex gain of the path, $G_{t,l}$ and G_r are the transmit and receive antenna gains, respectively, and τ_l is the propagation delay. Communication via IRS is assumed to occur only along the desired path, and the reflected path is incorporated into the equation under the assumption of ideal reflection.

Let s denote the index of the UAV providing service to user u. The received signal power at user u, $P_{\mathrm{rx},u}$, is expressed as

$$P_{\mathrm{rx},u} = P_{\mathrm{tx}}\, G_{\mathrm{main},s,u}\, G_r\, |h_{s,u}|^2 \tag{4}$$

where $G_{main,s,u}$ is the main lobe gain of the UAV s toward user u, G_r is the receive antenna gain, and $h_{s,u}$ is the complex channel coefficient between UAV s and user u. This channel coefficient includes the LoS path, NLoS path, and the ideal reflection path generated by the IRS.

The interference signal power I_u from other UAVs i ($i \neq s$) using the same time–frequency resources is given by

$$I_u = \sum_{i \neq s}^{N_{\mathrm{UAV}}} P_{\mathrm{tx}}\, G_{\mathrm{side},i,u}\, G_r\, |h_{i,u}|^2 \tag{5}$$

where $G_{side,i,u}$ is the side lobe gain from UAV i to user u. The thermal noise power N_0 is expressed as

$$N_0 = N_{\mathrm{d}} B \tag{6}$$

where B is the bandwidth and N_{d} is the noise power spectral density.

Based on the above, the signal-to-interference-plus-noise ratio (SINR) at user u is defined as

$$\mathrm{SINR}_u = \frac{P_{\mathrm{rx},u}}{I_u + N_0}. \tag{7}$$

This channel model comprehensively accounts for directional antennas, IRS reflections, interference from multiple UAVs, and multipath propagation effects, enabling high-fidelity UAV network performance evaluation.

III. Simulation results and discussion

A. Simulation parameters

In this section, numerical analysis is conducted based on the system and channel models described in the previous section. The simulation parameters are summarized in Table I.

TABLE I: Simulation Parameters

Parameter	Value
Carrier frequency	28 GHz
Bandwidth	100 MHz
Ray-tracing method	SBR
Max. number of reflections	1
Max. number of diffractions	0
Environment	Tokyo Metropolitan Gov. area
UAV altitude (min / max)	50 m / 150 m
UAV transmit power	27 dBm
UAV main lobe gain	18 dBi
UAV side lobe gain	-2 dBi
Number of IRSs	1000 (4 × 250)
IRS height	10 m
IRS incident/reflect angle range	15 ° –75 °
Number of UEs	6970
UE height	1 m
UE spacing	10 m
UE antenna gain	0 dBi
Noise power density	-174 dBm/Hz
Number of particles	30
Number of iterations	30
Inertia weight w	0.1–1.1
c_1, c_2	1.49

The optimization algorithm employed in this study is Particle Swarm Optimization (PSO) [10]. The design of the objective functions for the optimization problem will be described in the following subsections.

B. Objective function design

In this study, the UAV base station placement problem is formulated as a global optimization problem that maximizes a given objective function. The design variables are the positions of multiple UAVs, $\mathbf{x}_s = (x_s, y_s, h_s)$, PSO is employed to search for UAV placements that maximize the objective function.

This subsection compares several objective functions to identify the most appropriate one from the perspective of fairness in user communication quality.

1) **Maximization of average throughput**

$$f_1(\mathbf{x}) = \frac{1}{N_{\mathrm{UE}}} \sum_{u=1}^{N_{\mathrm{UE}}} \frac{B}{C_{k(u)}} \log_2(1+\gamma_u) \tag{8}$$

where N_{UE} is the number of UEs, γ_u is the received SINR of user u, B is the bandwidth, and $C_{k(u)}$ is the number of UEs simultaneously connected to UAV $k(u)$. This objective function maximizes the average throughput of all UEs. Since UAV resources are shared among multiple UEs, the throughput is scaled by $B/C_{k(u)}$.

2) **Maximization of average throughput with a coverage constraint**

$$f_2(\mathbf{x}) = \frac{1}{N_{\mathrm{UE}}} \sum_{u=1}^{N_{\mathrm{UE}}} \frac{B}{C_{k(u)}} \log_2(1+\gamma_u)$$

$$\text{s.t.} \quad \frac{1}{N_{\mathrm{UE}}} \sum_{u=1}^{N_{\mathrm{UE}}} 1(\gamma_u \geq \gamma_{\mathrm{th}}) \geq 0.8 \tag{9}$$

where γ_{th} is the SINR threshold for a user to be considered in coverage. This objective function maximizes the average throughput while ensuring that at least 80% of UEs can communicate.

3) **Maximization of peak average throughput**

$$f_3(\mathbf{x}) = \frac{1}{N_{\mathrm{UE}}} \sum_{u=1}^{N_{\mathrm{UE}}} B \log_2(1+\gamma_u) \tag{10}$$

where the throughput is evaluated under the assumption that all resources are allocated to user u. This function evaluates the theoretical peak performance without considering actual resource sharing.

4) **Maximization of CDF 20% SINR**

$$f_4(\mathbf{x}) = \gamma_{\mathrm{CDF20\%}}(\mathbf{x}) \tag{11}$$

where $\gamma_{\mathrm{CDF20\%}}$ represents the 20th percentile of the SINR distribution across all UEs. Since some UEs are inevitably out of coverage due to building blockages, the objective focuses on maximizing the 20th percentile SINR rather than the minimum SINR.

5) **Maximization of CDF 20% throughput**

$$f_5(\mathbf{x}) = R_{\mathrm{CDF20\%}}(\mathbf{x}) \tag{12}$$

where $R_{\mathrm{CDF20\%}}$ is the 20th percentile of the throughput distribution among all UEs. By maximizing this metric, fairness from a throughput perspective can be considered.

6) **Maximization of the number of connected users**

$$f_6(\mathbf{x}) = \sum_{u=1}^{N_{\mathrm{UE}}} 1\big(\gamma_u \geq \gamma_{\mathrm{th}}\big) \tag{13}$$

where γ_{th} is the SINR threshold for determining whether a user is connected. This objective function simply maximizes the number of users that can be served.

Based on these objective functions, we performed placement optimization for five UAVs, repeating the optimization ten times for each objective function. Figure 2 shows the CDF of user throughput for the representative optimal placement obtained for each objective function.

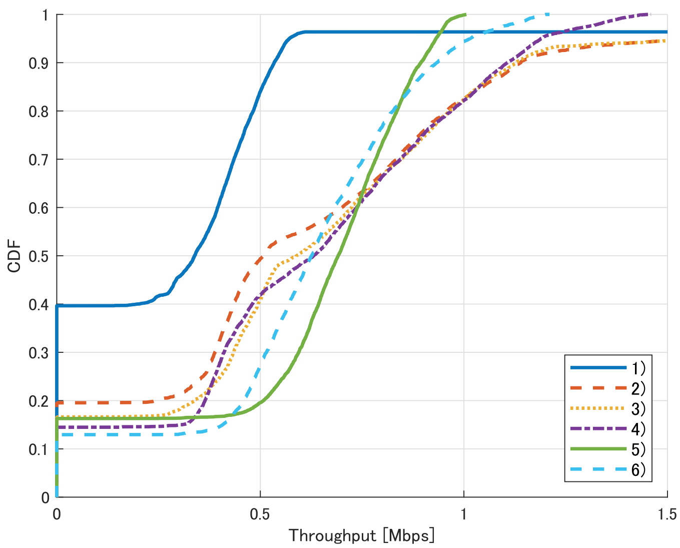

Fig. 2: CDF of user throughput under different objective functions.

The comparison of the objective functions revealed that functions such as (1) and (2), which aim to maximize average throughput, tend to neglect low-throughput UEs, resulting in a significant disparity in throughput distribution. In contrast, objective function (5), which maximizes the 20th percentile throughput, maintains fairness in terms of throughput and provides balanced communication performance. Since the goal of this study is to construct a system capable of temporarily providing high-speed and high-capacity communication, we employ objective function (5), in the subsequent analysis to ensure both performance and fairness.

C. Construction of LoS probability model

To evaluate the propagation environment between UAV base stations and ground users more efficiently, we introduce a LoS probability model in addition to the detailed ray tracing model. The LoS probability model is based on the method proposed in [11], where the LoS probability is formulated using statistical building parameters.

In [11], the LoS probability between a transmitter and receiver, $P(\mathrm{LoS}, \theta)$, is approximated using the statistical building parameters α, β, and γ as

$$P(\mathrm{LoS}, \theta) = \frac{1}{1 + a\exp[-b(\theta - a)]} \tag{14}$$

where θ is the elevation angle, and a and b are parameters derived from α, β, and γ. This model enables the calculation of LoS probabilities between UAVs and UEs from statistical information without explicit building geometry. Since it is significantly faster than ray tracing, the combination of the two models can be leveraged for efficient UAV network system design.

The ray tracing model can accurately evaluate propagation losses by identifying the UAV–UE propagation paths based on 3D building data, but it incurs a high computational cost, which limits its applicability in large-scale optimization problems. In contrast, the LoS probability model probabilistically determines LoS/NLoS states and evaluates path loss using $PL_{\mathrm{LoS}}(\theta)$ for LoS and $PL_{\mathrm{NLoS}}(\theta)$ for NLoS conditions, thereby drastically reducing computation time. Subsequent numerical analyses confirmed that the evaluation time of the objective function using the LoS probability model was approximately $1/166$ of that with the ray tracing model.

Furthermore, we confirmed that UAV placement optimization can be performed within the LoS probability model as well. Figure 3 shows the optimal UAV placement and the received SINR map of UEs obtained by optimizing the placement of five UAVs using both the LoS probability model and the ray tracing model.

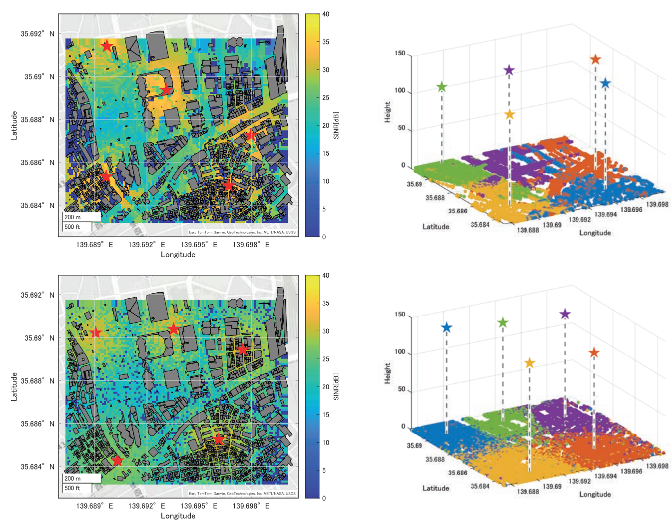

Fig. 3: Comparison of UAV placement optimization results between the two models (top: ray tracing, bottom: LoS probability).

The upper panel shows the result of the ray tracing model, where the building geometry is precisely considered, resulting in clearly defined cell boundaries. In contrast, the lower panel shows the result of the LoS probability model. Since the model does not explicitly handle building geometry and instead determines LoS probability based on elevation angle, the cell boundaries appear blurred.

To further demonstrate the similarity between the two models, we optimized UAV placements for 3, 5, 7, and 9 UAVs in both environments and compared the CDF of the received throughput of all UEs, as shown in Fig. 5. The blue line represents the ray tracing model, while the red line represents the LoS probability model. The optimization objective function used here is the 20th percentile throughput maximization (objective function (5)).

The results show that the throughput CDF characteristics with respect to the number of UAVs are generally similar between the two models. This indicates that the LoS probability model can be effectively utilized for UAV number estimation and as an auxiliary tool for UAV placement optimization.

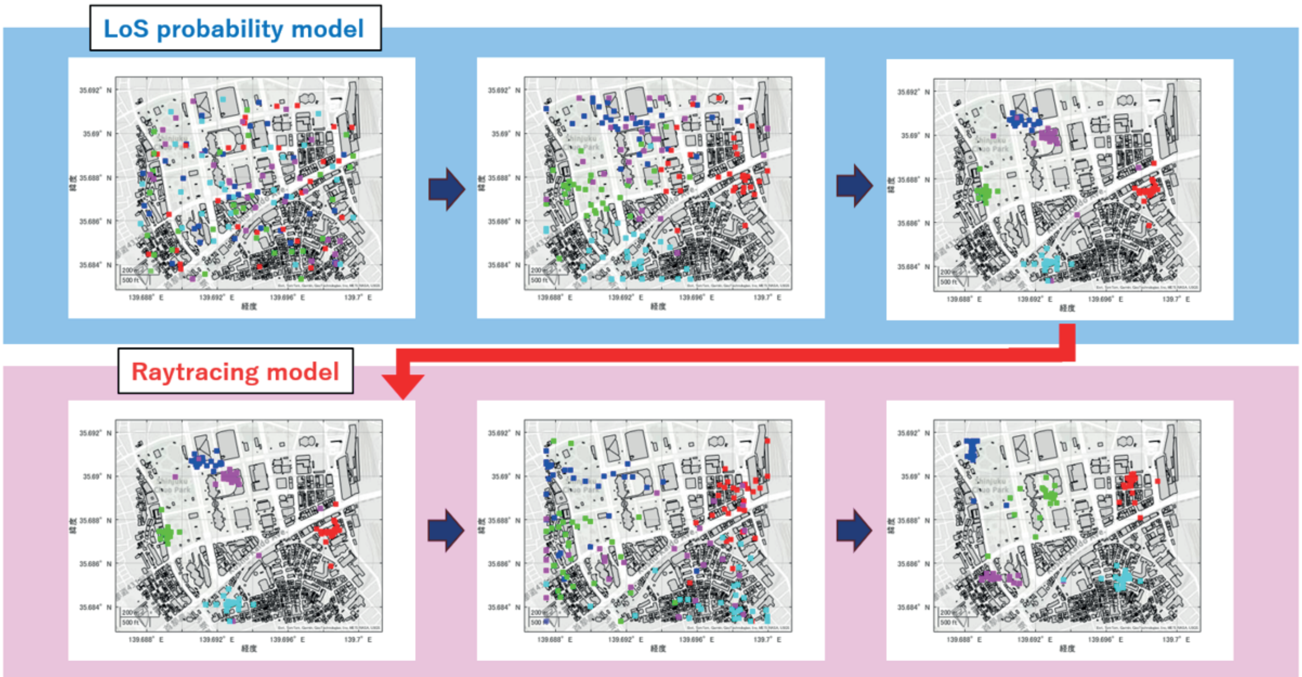

Fig. 4: Overview of the proposed method

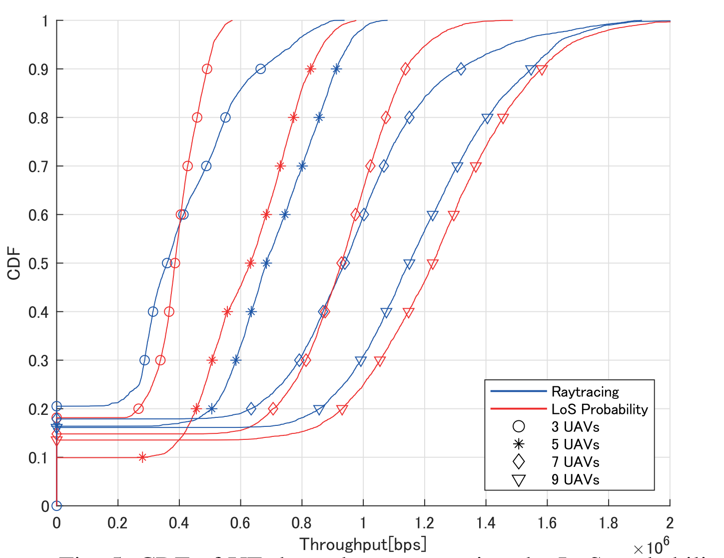

Fig. 5: CDF of UE throughput comparing the LoS-probability model (red) and the ray-tracing model (blue) for different numbers of UAVs.

D. *Optimization support using the LoS probability model*

While optimization using the ray tracing model provides high accuracy, it requires a large amount of computation time and can become impractical for optimization problems with large search spaces. To address this, we propose a two-stage optimization approach that combines the LoS probability model with the ray tracing model to balance computational efficiency and high accuracy. An overview of the proposed method is shown in Fig. 4.

In the first stage, Particle Swarm Optimization is performed using the LoS probability model. Because the LoS probability model probabilistically determines LoS/NLoS states based on elevation angle, its computational cost is significantly lower than that of ray tracing, making it possible to efficiently carry out large-scale optimization with a large number of particle evaluations. The particle position distribution obtained at the final iteration provides useful information for exploring global solutions in UAV placement.

In the second stage, the final particle positions from the LoS probability model are directly used as initial solutions for optimization with the ray tracing model. This enables the search to focus on promising candidate points expected to yield high objective function values, thereby accelerating convergence to the optimal solution.

By combining the lightweight LoS probability model with the high-accuracy ray tracing model, this approach achieves efficient and accurate optimization that leverages the strengths of both models.

Figure 6 shows the convergence characteristics of the objective function values for both the conventional and proposed methods. The objective function is set to maximize the 20th percentile throughput (objective function (5)). The figure plots the objective function values as a function of the number of evaluations in the UAV placement optimization with five UAVs. The blue curve represents the conventional method (ray tracing model only), and the red curve represents the proposed method (initialized with pre-optimization results using the

LoS probability model). The shaded regions indicate the 95% confidence intervals for each method.

Although the final objective function values of both methods are similar, the proposed method shows a much faster increase in the objective function during the initial search phase, indicating significantly improved exploration efficiency. This improvement results from narrowing the search space in advance using the LoS probability model, enabling the ray tracing model optimization to proceed more efficiently.

This difference is expected to become even more pronounced in scenarios with more complex objective functions. Therefore, the proposed approach is considered an effective method for UAV group placement optimization.

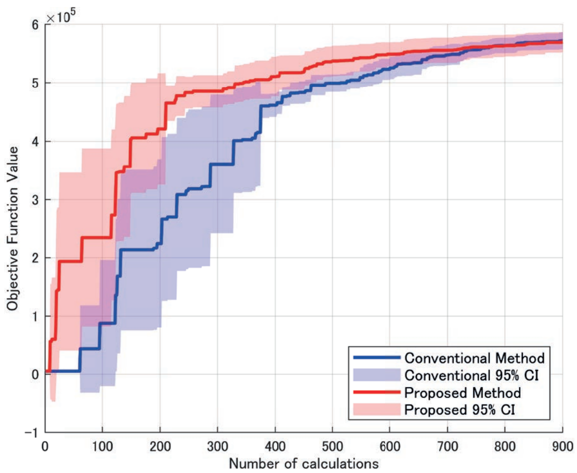

Fig. 6: Comparison of objective function values between the conventional method and the proposed method.

IV. Conclusion and Future Work

In this paper, we investigated a placement optimization method that integrates IRS into millimeter-wave UAV base station networks to enhance coverage and communication quality in urban environments. First, we constructed a high-fidelity communication environment evaluation framework based on 3D city models and ray tracing. By comparing multiple objective functions, we quantitatively evaluated overall system performance and fairness. The results confirmed that using objective function (5), which maximizes the 20th percentile throughput (CDF 20%), achieves a good balance between high throughput and fairness.

Furthermore, in addition to the detailed ray-tracing model, a LoS probability model with a computation time reduced to 1/166 was introduced. The results demonstrated the similarity between the two models and indicated that the LoS probability model can potentially be used to estimate the optimal number of UAVs and serve as a complementary tool for UAV placement optimization.

We also proposed a two-stage optimization method that combines the LoS probability model and the ray tracing model. By using the pre-optimization results obtained with the LoS probability model as initial solutions for the ray tracing model, we confirmed that convergence in the early search phase can be significantly accelerated. While the final objective function value was comparable to that of the conventional method, the proposed approach reduced the number of iterations required for convergence, demonstrating its effectiveness for large-scale and high-fidelity optimization.

Future work includes optimizing UAV placement considering dynamic UAV movement, improving the optimization algorithms, and evaluating the feasibility of UAV base stations using IRS in practical scenarios. Through these efforts, we aim to realize highly efficient wireless communication networks for disaster response and large-scale events.

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