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Exploring UAV Networking From the Terrain Information Completeness Perspective: A Tutorial

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ABSTRACT Terrain information is a crucial factor affecting the performance of unmanned aerial vehicle (UAV) networks. As a tutorial, this article provides a unique perspective on the completeness of terrain information, summarizing and enhancing the research on terrain-based UAV deployment. In the presence of complete terrain information, two highly discussed topics are UAV-aided map construction and dynamic trajectory design based on maps. We propose a case study illustrating the mutually reinforcing relationship between them. When terrain information is incomplete, and only terrain-related feature parameters are available, we discuss how existing models map terrain features to blockage probabilities. By introducing the application of this model with stochastic geometry, a case study is proposed to analyze the accuracy of the model. When no terrain information is available, UAVs gather terrain information during the real-time networking process and determine the next position by collected information. This real-time search method is currently limited to relay communication. In the case study, we extend it to a multi-user scenario and summarize three trade-offs of the method. Finally, we conduct a qualitative analysis to assess the impact of three factors that have been overlooked in terrain-based UAV deployment.

INDEX TERMS UAV deployment, terrain information, blockage verification, network performance.

I. INTRODUCTION

A. MOTIVATION

In urban areas, factors such as high population density, towering buildings, and complex terrain may pose challenges to the stability and coverage of wireless communication networks [1], [2]. Moreover, in places with large gatherings and high population mobility, such as sports stadiums and event venues, ensuring the reliability and stability of network connections is also an important issue [3]. It is foreseeable that future networks will achieve more granular and seamless coverage [4]. Furthermore, with the real-time changes in user demands, network services should be adaptive and self-evolving [5]. The UAV network is one of the best solutions to meet these advanced communication requirements [6], [7]. It can assist ground networks in providing coverage for wireless network blind spots. Additionally, it is expected to serve forthcoming aerial users and vehicles, including electric vertical take-off and landing (eVTOL) aircraft, in urban air mobility (UAM) [8]. At the same time, the mobility of UAVs enables the network to be deployed in a real-time and flexible manner according to actual needs [9].

However, UAV communication also faces significant limitations. Since UAVs are often used for temporary and dynamic coverage, they frequently cannot obtain a stable and powerful power supply [10]. Therefore, UAVs are unable to sustain high signal transmission power, and as a result, they often operate at lower flight altitudes to provide better network services by approaching users closely. Given their relatively low flight altitudes, UAVs are often deployed in the gaps of obstacles' shadowing, casting frequent blockage of line-of-sight (LoS)

UAV-user link [11]. Unfortunately, due to the limited transmission power of UAVs, if the LoS is obstructed by blockages such as trees, the received signal at the user is unstable and experiences significant attenuation. The above reasons make terrain one of the most critical factors affecting UAV deployment [12].

B. CHALLENGES OF TERRAIN INFORMATION UTILIZATION

Except for a few scenarios in remote areas with expansive visibility, a large amount of literature on UAV communication networks has taken the influence of terrain into account. In summary, terrain-based UAV deployment is a complex problem that primarily involves the following three challenges.

Firstly, due to the highly complex topology of buildings, the UAV deployment should be fine-grained. Once the UAV or user has a few meters of movement, they may disappear within each other's LoS region [31]. Secondly, as UAVs approach users by reducing their altitude, the distance to obstacles also decreases accordingly [23]. In other words, UAVs often incur a higher probability of being blocked in exchange for reduced path loss. Lastly, when UAVs prioritize providing better service to a few selected users by altering deployment, it can potentially result in a degradation of communication performance for other users. In summary, relevant studies focus on scenarios with different levels of terrain information completeness and address different challenges.

There are several surveys and tutorials delving into a wide range of topics related to UAV communication, including channel modeling [12], integration with 5G and future networks [32], [33], [34], and enhancements through artificial intelligence [35]. However, none of these studies comprehensively explore UAV deployment issues from the perspective of terrain information completeness. Due to the widespread interest in terrain-based UAV deployment, it is necessary to provide a comprehensive tutorial of the diverse research conducted on this topic.

C. CONTRIBUTION

From the unique perspective of terrain information completeness, this article provides a comprehensive tutorial and bibliographic index for readers interested in the field of terrain-based UAV deployment. The core contents and contributions of the article are outlined as follows:

- In Section II, we categorize the existing studies into three classes from the perspective of prior terrain information completeness.
- In Section III, we review two pivotal aspects of the UAV-aided terrain construction method and the UAV-based trajectory design with complete terrain information. Then, a case study, for the first time, integrates these two approaches, drawing meaningful conclusions based on the interaction between these methods.
- In Section IV, we review the air-to-ground LoS probability model (A2GLPM), summarize how existing studies utilize this model in UAV deployment with incomplete terrain information. Then, a case study is proposed to validate the accuracy of the model.
- In Section V, we review the core concepts of real-time search algorithm, which can be implemented without prior terrain information. Additionally, in the case study, we have advanced the algorithm's capability from serving a single user with one UAV to serving multiple users.
- In Section VI, we discuss several factors that can not be ignored in terrain-based UAV deployment but have received limited attention.

II. CLASSIFICATIONS OF EXISTING LITERATURE

In this subsection, we classify the existing terrain-based UAV positioning studies from different perspectives. Table 1 displays the categories to which the existing studies belong under different classifications. The classification based on terrain information completeness determined the main framework of this paper. The correspondence between this classification and the other classification approaches is also a key focus in this subsection.

A. TERRAIN INFORMATION COMPLETENESS

As mentioned, terrain information completeness is classified into complete, incomplete, and no terrain information.

1) COMPLETE TERRAIN INFORMATION

Complete terrain information means the available terrain information enables the terrain construction to a certain degree of granularity [31]. This information should at least include the positions, heights, and shapes of obstacles such as buildings. In such situations, the most critical issue is how to acquire and periodically update three-dimensional (3D) terrain maps at a relatively lower cost.

2) INCOMPLETE TERRAIN INFORMATION

Due to the high cost of getting and updating complete 3D maps, a compromise solution is to record the features of occlusions with a few parameters. For instance, we can characterize the building density by the ratio of the building footprint area to the total area of the region [36]. Undoubtedly, since the available terrain information is compressed as characteristic parameters, UAVs are unable to accurately verify occlusion, resulting in a coarse-grained deployment. In this case, the most critical task is to map these characteristic parameters onto the blockage probability of the UAV-user link.

3) NO TERRAIN INFORMATION

No terrain information refers to the condition that prior information can not provide direct assistance or does not have a direct impact on the UAV deployment. Without relying on prior terrain information, UAVs have to collect terrain information during networking to achieve terrain-based deployment. Due to the limitations on power, UAVs have a restricted search trajectory length during real-time networking. Finding the optimal deployment position that avoids obstacles' occlusion has

TABLE 1. Summary of Terrain-Based UAV Networking Studies

Ref.	Completeness	Topology	Stage	Research objective	Application scenario
[13]	Complete	Single-hop	Hybrid	Optimize channel parameters learning	UAV-aided wireless network
[14]	Complete	One-to-many	Hybrid	Minimize the distances between UAVs and targets	Monitor moving targets
[15]	Complete	One-to-many	Hybrid	Optimize coverage and reduce overload	Cover irregular terrain surface
[16]	Complete	One-to-many	Hybrid	Improve the coverage and capacity	Establish links from a BS to users
[17]	Complete	One-to-many	Hybrid	Optimize the performance of localization	Localizing outdoor ground users
[18]	Incomplete	Single-hop	Offline	Predict the geometric LoS probability	Different urban environments
[19]	Incomplete	Single-hop	Offline	Evaluate the performance of UAV network	Finite interference nodes
[20]	Incomplete	Relay	Offline	Enhance system performance analysis	Hybrid cellular networks
[21]	Incomplete	Relay	Offline	Optimize the placement of relay UAVs	UAV swarm application
[22]	Incomplete	One-to-many	Offline	Maximize coverage and energy efficiency	Centralized town
[23]	Incomplete	One-to-many	Offline	Maximize wireless coverage on the ground	Rapid deployable relief networks
[24]	Incomplete	One-to-many	Offline	Maximize coverage and reduce consumption	Assist the terrestrial network
[25]	Incomplete	One-to-many	Offline	Optimize coverage and connectivity	Provide emergency communication
[26]	No information	Single-hop	Real-time	Maintain communication with base station	Complete flight mission
[27]	No information	Single-hop	Real-time	Ensure link quality on the shortest path	Anti-jamming communication
[28]	No information	Relay	Real-time	Boost capacity with linear search length	Provide coverage extension
[29]	No information	Relay	Real-time	Develop search strategies for UAV placement	Densely obstructed areas
[30]	No information	Relay	Real-time	Optimize the performance of relay links	Construct relay links to two users

become the most critical issue, achieved through searching the shortest possible distance [26].

B. NETWORK TOPOLOGY

In terms of network topology, there are three types of transmission modes: single-hop transmission, relay transmission, and one-to-many transmission.

1) SINGLE-HOP

Single-hop communication is the fundamental communication structural unit, thus it has been mentioned in all three cases of terrain information completeness [13], [19], [26]. The most extensively discussed aspect of single-hop communication is the issue of blockage detection. This involves determining the blockage probability based on the relative positions of the UAV and the user, as well as designing a moving trajectory when blocked to re-establish the LoS link.

2) RELAY

In the no terrain information scenario, researchers have simplified the complex study of one-to-many transmission by focusing on relay transmission scenarios to optimize UAV deployment [28]. Due to the absence of a direct LoS link between the transmitter and receiver, they need to perform relay transmission through a UAV located in their common LoS area. In relay transmission, the key issue is how to find the common LoS region and simultaneously optimize the performance of both links.

3) ONE-TO-MANY

One-to-many communication is suitable for scenarios with prior terrain information. When complete terrain information is available, UAVs achieve real-time deployment through fine-grained occlusion assessment [14], [15]. However, in the absence of complete terrain information, UAVs can only resort to statistical models for coarse-grained deployment [24], [25].

C. STAGE

Based on whether UAVs are initiating network services, the acquisition and utilization of terrain information by UAVs can be divided into two stages: real-time and offline.

1) REAL-TIME

In the no terrain information scenario, UAVs acquire terrain information and deploy based on terrain after starting service [26]. Therefore, no terrain information corresponds to the real-time stage.

2) OFFLINE

Some tools can take terrain information as inputs, mapping them to target performance metrics, such as coverage probability and data rate [37]. As the entire process can be completed before networking, the deployment in the incomplete terrain information scenario is done in the offline stage.

3) HYBRID

As for UAV deployment with complete terrain, it is primarily divided into the offline stage of map construction and the

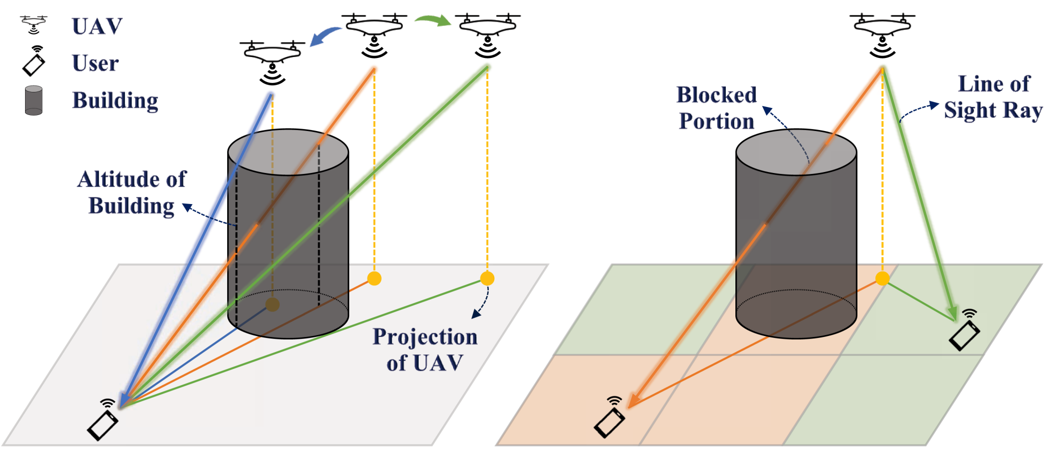

FIGURE 1. Schematic diagram of UAV–aided terrain construction principles.

TABLE 2. Parameters of the Air-to-Ground Channel Model [39]

Meaning	Notation	LoS	NLoS
Average additional loss	η_Q	−35 dB	−48 dB
Path-loss exponent	α_Q	2	2.3
Scale parameter	m_Q	1	2
Transmission power of UAV	ζ	30 dBm	

real-time stage involving UAV flight trajectory design with the assistance of the map [14]. Therefore, it is a deployment method with a hybrid blend of offline and real-time stages.

III. COMPLETE TERRAIN INFORMATION

In this section, we review two crucial aspects in the context of complete terrain information: the UAV-aided terrain construction method and the trajectory design method for UAVs in dynamic scenarios. Then, a case study is proposed as an example of the interaction of two aspects of research content.

A. UAV-AIDED TERRAIN CONSTRUCTION

The UAV-aided terrain construction method is one of the key techniques for obtaining complete terrain information [38]. This method creates a map that records the signal strength at different locations and infers the position and shape of obstacles by map. Its principle is verifying blockage based on the difference in signal strength between LoS and non-line-of-sight (NLoS) links.

According to the air-to-ground channel model proposed in [39], the received power S_Q can be expressed as

$$S_Q = \zeta \, G_Q \, \eta_Q \, d^{-\alpha_Q}, \tag{1}$$

where d is the Euclidean distance between the user and the UAV. G_Q denotes the small-scale fading of the channel, which follows Nakagami-m fading with scale parameter m_Q [40]. The meanings and the recommended values of the remaining parameters are provided in Table 2. Q in (1) is substituted by LoS if a LoS UAV-user link is established, otherwise Q is replaced with NLoS.

The left part of Fig. 1 shows the principle of UAV-aided terrain construction. The link between the middle UAV and the ground user (indicated by the orange line) is blocked by a building, resulting in the user's received power being S_{NLoS}. When the UAV approaches the user and crosses over the upper contour of the building shadow, the UAV-user link (the blue line) becomes LoS, and the user's received power is S_{LoS}. Typically, the received signal power exhibits continuous variations with the continuous movement of the UAV. However, when crossing over the shadow contour of the building, according to (1), the received signal power generally experiences a drastic change exceeding 20 dB. Therefore, the upper contour of the building should be located on the blue line. Similarly, the UAV can detect the right contour of the building shadow by shifting to the right.

Furthermore, there are two remarks worth mentioning. Firstly, to accurately determine the building's position, height, and shape, it often requires the participation of multiple users (or ground signal collectors) in the construction process. In fact, with a larger number of users, the construction can process faster. The right of Fig. 1 provides an example of multi-user-assisted construction, where orange and green squares represent blocked and unblocked areas respectively. Secondly, the segmented propagation model is proposed to describe different degrees of attenuation caused by different types of obstacles, such as solid obstacles (e.g., buildings) and light obstacles (e.g., vegetation blockage). With this model, a greater variety of obstacles can be constructed with more precision and detail [41].

B. TRAJECTORY DESIGN IN DYNAMIC SCENARIO

The design of UAV trajectories is a critical topic in many applications, such as surveying, searching, and monitoring, as it directly influences the effectiveness and performance of UAV mission execution [14], [17]. So far, with the robust computational power of computers, the trajectory planning of UAVs in static scenarios can be simulated through stochastic algorithms in the offline stage. Terrain-based UAV trajectory design typically operates within a small urban area, and in

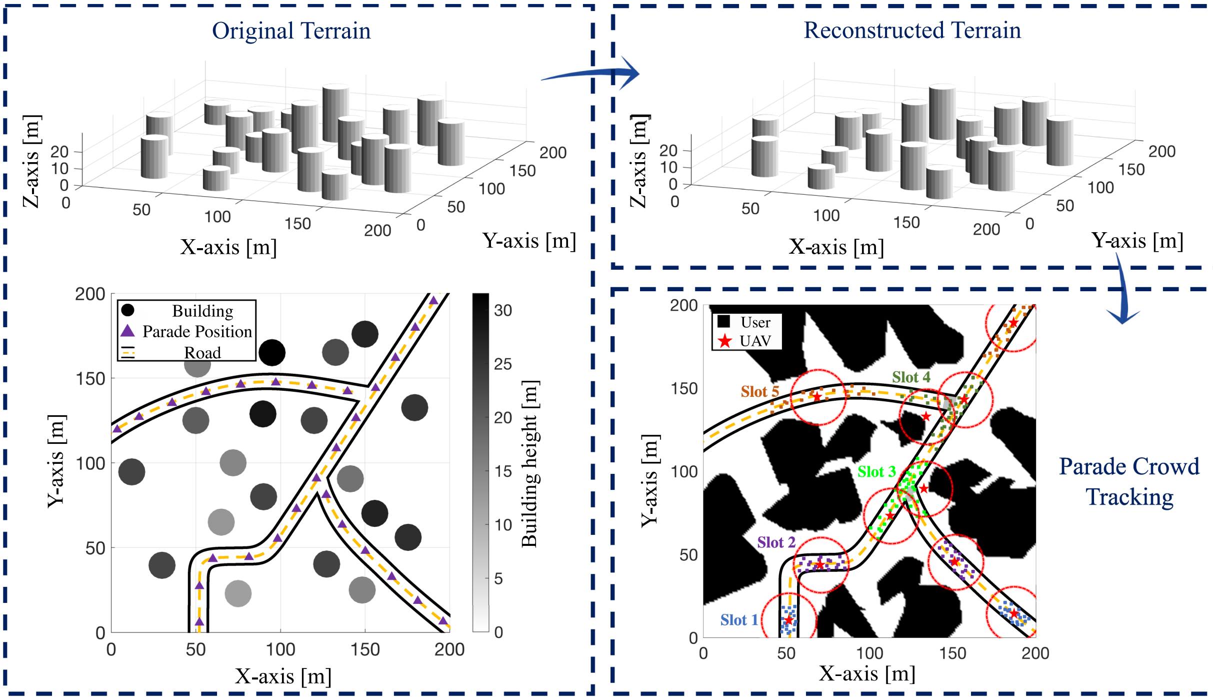

FIGURE 2. UAV-aided terrain construction and parade crowd tracking.

static scenarios with complete terrain information, it can even be accomplished through exhaustive search. Therefore, trajectory design in dynamic scenarios holds greater significance and poses more challenges.

In dynamic scenarios, UAVs need to adjust their deployment positions based on the real-time locations of users. At this point, if the user's movement direction is entirely random, the UAV can not determine its deployment position for the next moment. Therefore, authors in [14] proposed a scenario in which the UAV monitors the parade crowd moving according to a specific trajectory. Given that complete terrain information is available, UAVs attempt to get closer to the crowd to achieve better monitoring effectiveness while avoiding obstruction from buildings.

C. CASE STUDY: UAV TRACKING DURING THE PARADE

1) RESEARCH OBJECTIVE

In existing studies, the topics of UAV-aided terrain construction and trajectory design in dynamic scenario have been discussed separately. However, the two should be closely connected. On the one hand, evaluating the effectiveness of terrain construction in real-world application scenarios is the most direct approach. On the other hand, assuming the availability of complete terrain information for dynamic UAV tracking does not align with practical scenarios in many cases. Therefore, the most important objective of this case study is to explore the interaction between terrain construction and dynamic UAV tracking. Given the known parade route, UAVs can primarily focus on terrain construction in the vicinity of the route to reduce the amount of terrain information collected. Conversely, the impact of errors in terrain construction on UAV tracking can also be studied.

In this case study, we first utilize UAVs for terrain construction, followed by real-time UAV tracking of parade crowds. The constructed terrain assists the UAVs in avoiding blocking from buildings during tracking trajectory design. The algorithm provided in [14] has been demonstrated to effectively track the crowd while avoiding blockage from buildings. However, the scenario is simplified, with users' potential positions restricted to several discrete points along the parade route and the shadow areas of buildings are represented by regular polygon topologies. Therefore, we test the effectiveness of the proposed algorithm in a more general scenario.

2) UAV-AIDED TERRAIN CONSTRUCTION

The left upper and lower parts of Fig. 2 show the 3D and planar city topology, respectively. The buildings are distributed in a square area of 1 km$\times$1 km. To avoid the effect of the building orientation, we refer to the recommendations in [18] and model the building as a cylinder with a radius of 8 m. The center of the cylindrical building follows a homogeneous Poisson point process (PPP) with a density of 500 buildings/km^2. The height of the building obeys log-normal distribution with parameters 3 and 0.4, which are the mean and standard deviation of the height's logarithm, respectively[1].

We only deploy ground signal receivers near the parade route, and UAVs also hover only in these areas, constructing

[1]Note that all of the case studies are performed by MATLAB. The buildings, UAVs, and users' location generations and sampling procedures are implemented through self-written scripts (with "Editor" in MATLAB).

terrain based on the algorithm proposed in [38]. As shown in the upper right part of Fig. 2, the constructed buildings have an acceptable deviation from the original terrain in the vicinity of the route. However, several buildings far from the route have a significant error in terms of altitude, even some buildings have not been successfully constructed.

3) PARADE CROWD TRACKING

As shown in the right lower part of Fig. 2, two sets of crowds are moving at an average pace of 50 m/slot along the predefined parade trajectory on the road. The shaded part provides the blocked area when the UAV is at 30 m height. Each crowd is tracked by one UAV. The positions of each user in the two crowds at different time slots are marked in the right lower part of Fig. 2. The users in the crowd are generated near the preset central position and follow PPP at slot 1. One crowd departs from the bottom right and exits on the left, while another crowd departs from the bottom left and exits on the top right. There is a segment of overlapping routes between two intersections at slots 3 and 4, leading to a certain degree of mixing of the crowds. Furthermore, the coverage is significantly influenced by terrain blockage at slots 3 and 4. With the help of the constructed terrain, the flight path of the UAV can more accurately avoid the blockage of the building and adapt to the more complex movement trajectory during these challenging slots for UAV tracking.

IV. INCOMPLETE TERRAIN INFORMATION

This section reviews the A2GLPM, where the LoS probability is the probability of establishing the LoS link between the transmitter and the receiver. After that, we summarize how existing studies deploy UAV networks and analyze network performance based on this model. Considering that the accuracy of the model has not been fully validated, we propose a case study to analyze the accuracy of the model itself and the accuracy of network performance analysis based on this model.

A. LOS PROBABILITY MODEL

The International Telecommunication Union (ITU) has proposed a standardized model for urban areas based on three simple terrain feature parameters that can describe the general geometric statistics of cities [42]:

- κ represents the ratio of the buildings' footprint area to the total area (dimensionless).
- ι represents the average number of buildings per unit area (buildings / km^2).
- ω is the scale parameter of Rayleigh distribution that describes the height of the building (dimensionless).

Based on these three parameters, the probability of the UAV and user establishing an LoS link $P_{\text{LoS}}(\theta)$ is given by the A2GLPM [23],

$$P_{\text{LoS}}(\theta) = \frac{1}{1 + a\exp\left(-b\left(\theta - a\right)\right)}, \tag{2}$$

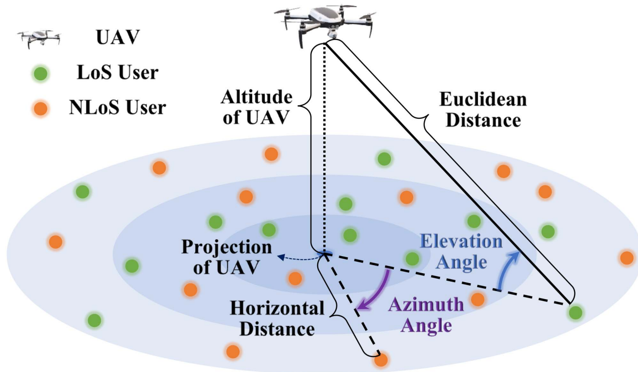

FIGURE 3. Schematic diagram of user distribution and UAV-user relative position.

where $\theta = \arctan(h/\sqrt{d^2 - h^2})$ is the elevation angle, d is the Euclidean distance between the UAV and user, h is the altitude of UAV. An example of the elevation angle is given in Fig. 3. a and b can be presented by the terrain feature parameters:

$$Q = \sum_{j=0}^{3}\sum_{i=0}^{3-j} C_{i,j}\,(\kappa\iota)^i\,\omega^j, \tag{3}$$

where $Q \in \{a, b\}$, $C_{i,j}$ are polynomial coefficients. The values of $C_{i,j}$ can refer to Table 1 and Table 2 in [23].

As a result, the A2GLPM maps the terrain feature parameters to the blockage probability, given the relative positions of the UAV and user.

B. STOCHASTIC GEOMETRY (SG) ANALYTICAL FRAMEWORK

The authors in [39] integrated the A2GLPM into the SG analytical framework, laying the foundation for subsequent extensive research in this field. From the perspective of a typical UAV, users can be categorized into LoS users and NLoS users. Specifically, all of the users are assumed to follow a homogeneous PPP with density λ. Then, the PPP is divided into two sub-PPPs:

- An LoS-PPP with density $\lambda P_{\text{LoS}}(\theta)$ records the positions of users that are not blocked (referred to as LoS users). $P_{\text{LoS}}(\theta)$ is defined in (2).
- An NLoS-PPP with density $\lambda(1 - P_{\text{LoS}}(\theta))$ records the positions of users that are blocked (referred to as NLoS users).

As shown in Fig. 3, when the altitude of the UAV is fixed, the density of LoS users decreases with increasing distance to the UAV.

Then, we take the downlink coverage probability from the perspective of a typical user as an example to illustrate how terrain information influences the SG analyzing process. The typical user is served by the UAV that provides the maximum average received power, while other UAVs are interfering UAVs. The interference power is the cumulative received power at the user side, attributed to interfering UAVs. The coverage probability is defined as the probability that the received signal-to-interference plus noise ratio is larger than a given coverage threshold [43]. From this, it can be observed that coverage probability is closely linked to the distances between users and LoS and NLoS UAVs, and to a large extent, it depends on the accuracy of the A2GLPM.

With the SG analytical framework, coverage probability can be expressed as a function of terrain feature parameters and network distribution parameters, such as UAV deployment density and altitude. Therefore, the derived expression for coverage probability can not only be utilized for performance estimation but also serve as a tool for optimizing the deployment of UAV networks. However, due to incomplete terrain information, the deployment is coarse-grained. Compared to existing deployment algorithms in the complete terrain scenarios, the SG analytical framework also possesses its unique advantage, that is, the capability for interference analysis [39].

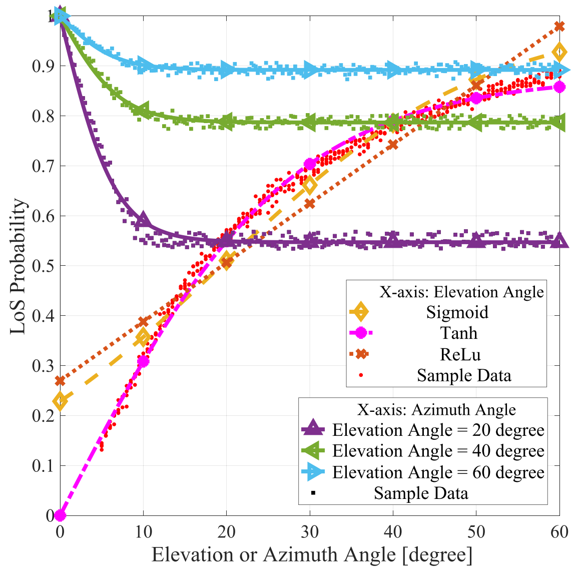

FIGURE 4. LoS probability at different elevation and azimuth angles.

C. CASE STUDY: ACCURACY OF THE MODEL

1) RESEARCH OBJECTIVE

The previous subsection emphasized the importance of model accuracy in performance analysis. Therefore, this subsection has three objectives regarding accuracy verification. First of all, to achieve a concise expression, A2GLPM neglects the correlation of user positions. In other words, the probability of two adjacent users being blocked remains mutually independent in A2GLPM, while two adjacent users are likely to be blocked simultaneously in reality. Therefore, we hope to investigate whether the correlation between user positions can be neglected in the blockage verification. Secondly, the A2GLPM is presented as a modified Sigmoid function containing two degrees of freedom, namely, a and b. An exploratory issue is whether other commonly applied functions involving two degrees of freedom can provide a more accurate description of the relationship between elevation angle and LoS probability. Finally, we aim to find the difference between the approximate coverage probability results obtained through A2GLPM for LoS probability and the accurate coverage probability obtained through simulation with precise blockage verification.

2) MODEL ACCURACY ANALYSIS

In this case study, UAVs and users are distributed in a square area of 1 km × 1 km, forming two homogeneous PPPs. The density of users is fixed as 1000 users/km^2. The height of UAVs is 80 m. The distribution of buildings is the same as in Section III-C In Fig. 4, we plot the sample data obtained by simulation with dots. For a fixed elevation angle, the LoS probability is calculated by the proportion of the number of samples of UAV-user links not blocked by cylindrical buildings in the total number of samples.

The relationship between elevation angle and LoS probability is fitted with three different functions:

- Modified Sigmoid function: $[a, b] = [2.8240, 0.0628]$,

$$P_{\mathrm{LoS}}^{\mathrm{Sig}}(\theta) = \frac{1}{1 + a\exp(-b(\theta - a))}. \tag{4}$$

- Modified Tanh function: $[a, b] = [0.8794, 2.0984]$,

$$P_{\mathrm{LoS}}^{\mathrm{Tanh}}(\theta) = a\,\frac{\exp(2b\theta) - 1}{\exp(2b\theta) + 1}. \tag{5}$$

- Modified ReLu function: $[a, b] = [0.6775, 0.2697]$,

$$P_{\mathrm{LoS}}^{\mathrm{ReLu}}(\theta) = \max\{0, a\theta + b\}. \tag{6}$$

The parameters $[a, b]$ are obtained from the minimum mean square error (MSE) between the sample data and the corresponding value of the fitted curve. The MSEs for Sigmoid, Tanh and ReLu functions are $\{2.12, 0.25, 4.26\} \times 10^{-3}$ respectively. The accuracy of the fitting by the three functions can also be visually observed through Fig. 4. The above results indicate that the improved Sigmoid function in [36] can accurately describe the relationship between LoS probability and elevation angle. However, there might be better alternatives, such as the improved Tanh function.

Next, the correlation between user positions is measured by the azimuth angle. As drawn in Fig. 3 the azimuth angle takes the projection of the UAV on the ground as the endpoint and the rays from the projections to two users (denoted as user A and user B) as the edges. When calculating the LoS probability for azimuth angle in Fig. 4, we verify whether the UAV-user B link is blocked, given that a LoS link is established between UAV and user A. At a fixed elevation angle, the LoS probability is independent of the azimuth angle as long as the azimuth is greater than a threshold, which is around 10 degrees in this case, as shown in Fig. 4. The threshold of independence is related to the footprint area of buildings. Furthermore, under a fixed elevation angle θ_0, the

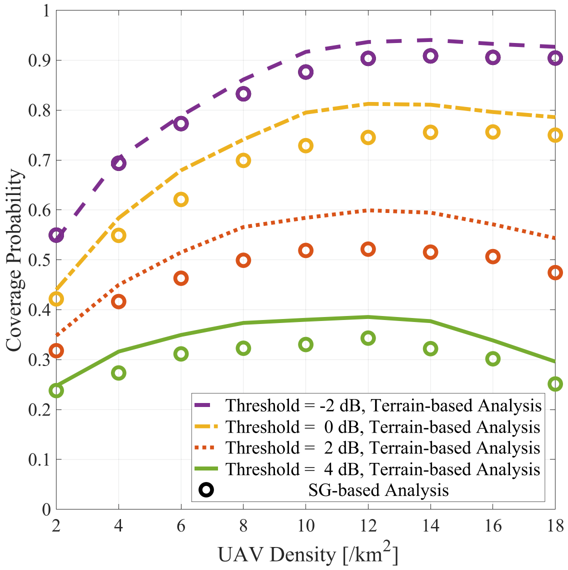

FIGURE 5. **Coverage probability with different UAV densities.**

LoS probability for azimuth angle converges to $P_{\text{LoS}}(\theta_0)$ as the azimuth angle increases.

3) NETWORK PERFORMANCE ACCURACY ANALYSIS

Now, we identify the variance between the approximate coverage probability results obtained by the SG framework and the accurate coverage probability obtained through simulation with accurate blockage verification. Unless otherwise stated, channel parameters are set to their default values given in Table 2. The environmental noise power is $\sigma^2 = -90$ dBm. The points labeled as "SG-based Analysis" in Fig. 5 are obtained by Theorem 2 in [39]. The A2GLPM follows the modified Sigmoid function with terrain related parameters $[a, b] = [2.8240, 0.0628]$. For lines labeled as "Terrain-based Analysis" in Fig. 5, complete terrain information is available for UAVs. Blockage verification is no longer based on any statistical model but is determined through simulation.

Fig. 5 shows that the coverage probability obtained under the SG framework has about a 9% relative deviation compared to the accurate one. Given that the SG-based approach relies on only two parameters to incorporate terrain information, the relative deviation is acceptable, especially when the coverage probability is high. Another interesting observation that can be made from Fig. 5 is that the coverage probability estimated through the SG framework is consistently slightly smaller than the accurate values. The primary reason for this phenomenon is that the A2GLPM underestimates the LoS probability for associated UAV or overestimates the LoS probability for interfering UAVs.

Furthermore, this case study validates the feasibility of optimizing UAV deployment density through SG-based analytical results. Fig. 5 shows the UAVs' density that maximizes the coverage probability is around 12 UAVs / km^2, which is independent of the coverage threshold. When the deployment density of UAVs is low, users may be at a considerable distance from the serving UAV, and there is a possibility of no UAV within the line of sight being available. Conversely, if the deployment density is too high, interference becomes a primary factor limiting coverage probability. It is evident that the optimization of network-level parameters, such as UAV density, relies on the unique interference analysis capability of the SG framework. The optimal value is challenging to attain through the design of UAV tracking or search algorithms mentioned earlier.

V. NO TERRAIN INFORMATION

This section centers on the exploration of the real-time search algorithm. A detailed overview of the algorithm's objectives, principles, and core concepts is provided. Additionally, the specific execution process is illustrated through heat maps. Considering that the existing methods only apply to the relay scenario, we extended the algorithm to one-to-many scenario. Since the real-time search does not require prior terrain information, it is limited by many factors and requires trade-offs between practicability and performance.

A. REAL-TIME SEARCH METHOD

In simple terms, the real-time search method is an online realization of UAV-assisted terrain construction. Real-time search algorithms are typically designed to address a class of max-min problems in the field of wireless communication. The application scenario in [28] is taken as an example to illustrate the optimization problem. In this scenario, the UAV serves as a relay between a user and an aerial base station (ABS). The optimization objective is to identify an optimal UAV deployment position that maximizes the smaller of the two SNRs: the average SNR of the ABS-UAV link and the average SNR of the UAV-user link. It can be mathematically represented as a special case of the following optimization problem when $N = 2$:

$$\arg\max_{x\in\mathcal{X}}\ \min\left\{\frac{\mathbb{E}_G[S_{Q,1}]}{\sigma^2}, \frac{\mathbb{E}_G[S_{Q,2}]}{\sigma^2}, \ldots, \frac{\mathbb{E}_G[S_{Q,N}]}{\sigma^2}\right\} \tag{7}$$

N represents the number of devices simultaneously served by the UAV. x denotes the position of the UAV, and $\mathcal{X}$ is the set recording the locations that are allowed for deployment. $S_{Q,1}$ and $S_{Q,2}$ are receiver power of ABS-UAV link and UAV-user link, where $Q = \{\text{LoS}, \text{NLoS}\}$. Due to the fact that received power is not only dependent on the distance between the UAV and the serviced device but also on whether the link is blocked. Since the terrain is complex and irregular, this problem is non-convex and can only be solved through algorithmic search.

Although the real-time search algorithm can be considered as a specific type of UAV-assisted terrain construction method, there are still distinct differences between the two. Firstly, the search trajectory of real-time search algorithms should be linear, because the limited power supply of UAVs makes it challenging to support search trajectories with quadratic or higher complexity [44]. Linearity is typically in reference to

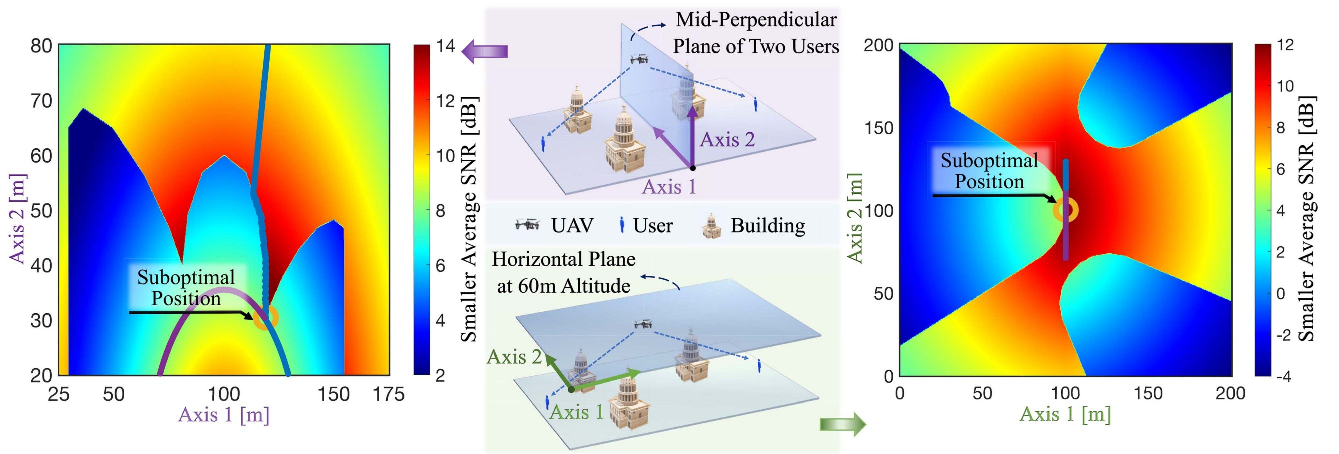

FIGURE 6. **Example of real-time search.**

the distance between the two furthest serviced users. Due to strict limitations on the search trajectory length, the search direction at each iteration needs to be carefully designed based on terrain information gathered through previous searches. In addition, real-time search involves the concept of granularity, which can be understood as the step size of the UAV at each iteration. Due to the need for the UAV to initiate communication with users each time it reaches a new search position to assess whether the link is blocked, larger granularity allows the UAV to search for potential optimal positions more quickly. However, it also increases the probability of missing the optimal position.

B. CASE STUDY: THE EXTENSION OF REAL-TIME SEARCH

1) RESEARCH OBJECTIVE

In this section, we first illustrate the core idea of the algorithm through a relatively simple example to provide an intuitive understanding. Additionally, we will clarify that the algorithm's search trajectory is linear, and how it is designed to search for potential optimal positions. Secondly, since the previous study focuses on a relatively simple relay scenario, and one UAV only serves one user. Therefore, the case study aims to generalize the existing method to a one-to-many scenario. Finally, we will compare the average coverage performance under different levels of terrain completeness.

2) METHOD PRINCIPLE

In this case study, the granularity of UAV search is 0.2 m, and the coverage threshold is set to 4 dB. The optimization objective remains as specified in (7). To facilitate the understanding of algorithmic concepts, we start from a local area on the map and discuss a relatively simple scenario. The scenario involves one UAV, two users, and three buildings, which is shown in the middle part of Fig. 6. The real-time search algorithm is based on two core ideas:

- *(c_1):* When the UAV is not blocked, it moves in the direction where there is a steep increase in the average SNR.
- *(c_2):* When the UAV is blocked, the UAV moves along a trajectory where the average SNR does not change to avoid missing the next LoS region.

The objective of the max-min problem is to emphasize that UAVs can provide equitable service quality for two users. Therefore, a significant portion of the UAV's search trajectory is likely to be along a plane where the optimal deployment position is equidistant to both users, i.e., along the mid-perpendicular plane. In the left part of Fig. 6, we plot a heat map to show the smaller average SNR on the mid-perpendicular plane of two users. In this heat map, the contour of buildings' shadows is quite clear due to the intense changes in SNR.

The UAV starts from above, initially descending rapidly based on the first core idea (c_1) until it reaches the contour of the building's shadow. Then, part of the trajectory overlaps with the contour because the UAV repeatedly enters the NLoS region of one user according to (c_1) and then comes back to the common LoS area according to (c_2) in a bent route. Finally, after reaching the suboptimal position, the UAV follows a left search trajectory (purple curve) and a right search trajectory (blue curve) where the average SNR remains constant on these trajectories according to (c_2). The marked suboptimal position may not necessarily be optimal because the optimal position may not lie within the mid-perpendicular plane[2]. As shown in the right part of Fig. 6, the trajectory from the perspective of the horizontal plane implies the searching trajectory is linear.

3) GENERALIZED ALGORITHM

Next, we generalize the proposed algorithm into a multi-UAV serving multi-user scenario. The buildings follow the same distribution as in Section III-C The user distribution, UAV distribution, and channel model are the same as in Section IV-C.

[2]In fact, a suboptimal position with an elevation angle to the users of less than 45 degrees is a sufficient but not necessary condition for it to be the optimal relay position.

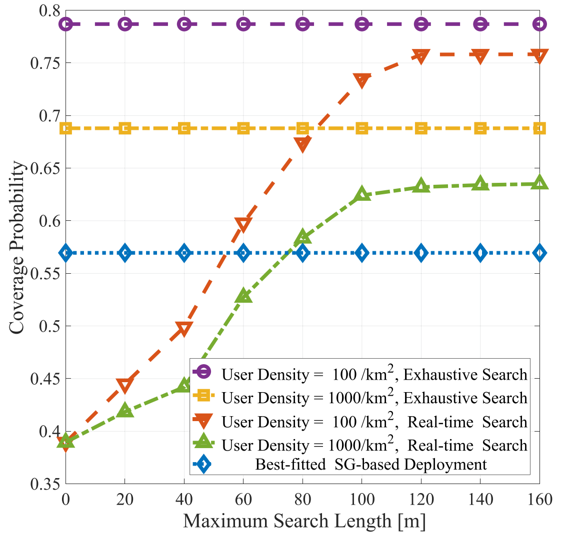

FIGURE 7. Influence of search length on the performance of real-time search.

The density of UAV is set to optimal 12 UAVs / km^2 one obtained in Section IV-C.

The core idea of the generalization is simply described as follows. The UAV focuses on the two most distant associated users to perform the proposed algorithm. Starting from a random position, the UAV takes the shortest path to reach the mid-perpendicular plane and then executes the proposed real-time search algorithm. In this process, the two users farthest from the UAV may undergo changes, thereby causing the algorithm to initiate a repetition of the initial steps. The UAV stops when the maximum search length is reached, or the algorithm finishes.

In Fig. 7, we compare the coverage performance in scenarios with complete, incomplete, and no terrain information. The 3D exhaustive search is executed in the scenario with complete terrain information to serve as an upper bound. In the best-fitted SG-based deployment, UAVs follow a PPP at the optimal altitude that maximizes the coverage probability given the density is 12 UAVs / km^2. This is considered as UAV deployment under incomplete terrain information. In no terrain information, once the search trajectory length reaches the preset upper limit (x-axis in Fig. 7), the search stops, and the UAV is deployed to the position with the maximum coverage probability along the trajectory. The y-axis in Fig. 7) represents the mean coverage probability for all users in the area.

As shown in Fig. 7, with a smaller user density, the coverage performance of the real-time search algorithm is better and closer to the upper bound provided by exhaustive search. However, due to the limitations of a linear search trajectory, the UAV can not achieve complete terrain information through real-time searching. Therefore, regardless of the upper limit set for the search trajectory, the coverage performance of real-time search can never reach the upper bound provided by exhaustive search. The intersection point between the curve corresponding to the real-time search algorithm and the straight line corresponding to the SG-based deployment represents the moment when the terrain information obtained by the UAV through real-time search is equal to the terrain information contained by the terrain feature parameters.

C. TRADE-OFFS BETWEEN PRACTICABILITY AND PERFORMANCE

Without prior terrain information required, the real-time search method can find the optimal position with a linear search distance. It is not difficult to imagine that the method suffers several drawbacks, resulting in trade-offs between practicability and performance.

1) OPTIMALITY AND NUMBER OF SERVED USERS

The real-time search method can ensure optimality when one UAV serves one user. When the UAV is serving two users, the optimality can only be satisfied under certain conditions. In one-to-many network topology, when a UAV approaches one user, the links with other users might be blocked, so achieving optimality is challenging.

2) UPDATE FREQUENCY AND POWER CONSUMPTION

Frequently updating real-time search will lead to a large amount of power consumption, probably resulting in the UAV's inability to maintain high-quality communication. However, a low updating frequency may also cause a degradation of communication quality as whether users enter the shadow of the building is unknown to the UAV.

3) SEARCH LENGTH AND PRIOR TERRAIN INFORMATION

At each update, the determination of the starting search position partly depends on the prior terrain information. More terrain information often leads to a starting position closer to the potential optimal location, thus shortening the search length. Utilizing the terrain information recorded in the search process before updating can be an interesting research direction of real-time search methods.

VI. FURTHER DISCUSSIONS

This section explores three overlooked factors in terrain-based UAV deployment that warrant attention.

A. CHARGING

As mentioned, power supply is an important factor affecting the hovering time and communication quality of UAVs. When charged by wireless laser power beams [45], UAVs should also pay attention to whether the power supply equipment's link is blocked by obstacles, especially in high-rise urban regions. The establishment of aerial power stations with a higher altitude can improve charging efficiency.

B. BACKHAUL

In the one-to-many scenario, the backhaul link between the UAV and the base station from the core network bears the sum of data rates for all users [46]. For base stations with heights lower than buildings, UAVs can also ensure that the backhaul link is not blocked by employing real-time search methods. Additionally, UAVs should promptly reduce the distance to the base station when the backhaul link experiences a significant communication load.

C. ELECTROMAGNETIC FIELD (EMF) EXPOSURE

When lowering EMF exposure is emphasized, UAVs might be deployed below the optimal density to reduce EMF exposure from interference signals [47]. Compared to offline deployment relying on terrain information, real-time search offers greater advantages. The optimal deployment positions identified through real-time search are characterized by lower altitudes, resulting in minimized interference to users.

VII. CONCLUSION

The article classified and discussed terrain-based UAV network deployment methods from the perspective of terrain information completeness. It introduced the core algorithms and models involved, discussed their corresponding application scenarios, and provided case studies as examples. In the first case study, we demonstrated that UAVs could provide stable coverage for regularly moving users using existing local terrain construction methods with UAV sampling. In the second case study, a coarse-grained UAV deployment was performed using a simple set of parameters that characterized the terrain features. A stochastic geometry framework provided general analytical results for the aforementioned coarse-grained UAV networks. In the last case study, the UAV was able to avoid building blockage without prior terrain information through real-time linear-trajectory search.

REFERENCES

[1] S. Ansari, A. Taha, K. Dashtipour, Y. Sambo, Q. H. Abbasi, and M. A. Imran, "Urban air mobility—A 6 G use case?," *Front. Commun. Netw.*, vol. 2, 2021, Art. no. 729767.

[2] A. A. Zaid, B. E. Y. Belmekki, and M.-S. Alouini, "Aerial-aided mmWave VANETs using NOMA: Performance analysis, comparison, and insights," *IEEE Trans. Veh. Technol.*, early access, Nov. 06, 2023, doi: 10.1109/TVT.2023.3330306.

[3] Q. Huang, B. E. Y. Belmekki, A. M. Eltawil, and M.-S. Alouini, "System-level metrics for non-terrestrial networks under stochastic geometry framework," *IEEE Commun. Mag.*, to be published.

[4] M. A. Imran, A. Turkmen, M. Ozturk, J. Nadas, and Q. H. Abbasi, "Seamless indoor/outdoor coverage in 5G," in *Wiley 5G Ref: Essential 5G Reference Online*. Hoboken,NJ, USA: Wiley, 2019, pp. 1–23.

[5] K. B. Letaief, W. Chen, Y. Shi, J. Zhang, and Y.-J. A. Zhang, "The roadmap to 6G: AI empowered wireless networks," *IEEE Commun. Mag.*, vol. 57, no. 8, pp. 84–90, Aug. 2019.

[6] C. Fan, C. She, H. Zhang, B. Li, C. Zhao, and D. Niyato, "Learning to optimize user association and spectrum allocation with partial observation in mmWave-enabled UAV networks," *IEEE Trans. Wireless Commun.*, vol. 21, no. 8, pp. 5873–5888, Aug. 2022.

[7] B. Shang, L. Liu, J. Ma, and P. Fan, "Unmanned aerial vehicle meets vehicle-to-everything in secure communications," *IEEE Commun. Mag.*, vol. 57, no. 10, pp. 98–103, Oct. 2019.

[8] A. A. Zaid, B. E. Y. Belmekki, and M.-S. Alouini, "eVTOL communications and networking in UAM: Requirements, key enablers, and challenges," *IEEE Commun. Mag.*, vol. 61, no. 8, pp. 154–160, Aug. 2023.

[9] C. Fan, B. Li, J. Hou, Y. Wu, W. Guo, and C. Zhao, "Robust fuzzy learning for partially overlapping channels allocation in UAV communication networks," *IEEE Trans. Mobile Comput.*, vol. 21, no. 4, pp. 1388–1401, Apr. 2020.

[10] B. Shang, L. Zhao, K.-C. Chen, and X. Chu, "Wireless-powered device-to-device-assisted offloading in cellular networks," *IEEE Trans. Green Commun. Netw.*, vol. 2, no. 4, pp. 1012–1026, Dec. 2018.

[11] K. Gomez, T. Rasheed, L. Reynaud, and S. Kandeepan, "On the performance of aerial LTE base-stations for public safety and emergency recovery," in *Proc. IEEE IEEE Open J. Veh. Technol. Workshops*, 2013, pp. 1391–1396.

[12] A. A. Khuwaja, Y. Chen, N. Zhao, M.-S. Alouini, and P. Dobbins, "A survey of channel modeling for UAV communications," *IEEE Commun. Surveys Tuts.*, vol. 20, no. 4, pp. 2804–2821, Fourthquarter 2018.

[13] O. Esrafilian, R. Gangula, and D. Gesbert, "Learning to communicate in UAV-aided wireless networks: Map-based approaches," *IEEE Internet Things J.*, vol. 6, no. 2, pp. 1791–1802, Apr. 2019.

[14] H. Huang and A. V. Savkin, "Navigating UAVs for optimal monitoring of groups of moving pedestrians or vehicles," *Trans. Veh. Technol.*, vol. 70, no. 4, pp. 3891–3896, Apr. 2021.

[15] Z. Mou, Y. Zhang, F. Gao, H. Wang, T. Zhang, and Z. Han, "Deep reinforcement learning based three-dimensional area coverage with UAV swarm," *IEEE J. Sel. Areas Commun.*, vol. 39, no. 10, pp. 3160–3176, Oct. 2021.

[16] P. Yi, L. Zhu, L. Zhu, Z. Xiao, Z. Han, and X.-G. Xia, "Joint 3-D positioning and power allocation for UAV relay aided by geographic information," *IEEE Trans. Wireless Commun.*, vol. 21, no. 10, pp. 8148–8162, Oct. 2022.

[17] O. Esrafilian, R. Gangula, and D. Gesbert, "Three-dimensional-map-based trajectory design in UAV-aided wireless localization systems," *IEEE Internet Things J.*, vol. 8, no. 12, pp. 9894–9904, Jun. 2021.

[18] A. Al-Hourani, "On the probability of line-of-sight in urban environments," *IEEE Wireless Commun. Lett.*, vol. 9, no. 8, pp. 1178–1181, Aug. 2020.

[19] C. K. Armeniakos, P. S. Bithas, and A. G. Kanatas, "SIR analysis in 3D UAV networks: A stochastic geometry approach," *IEEE Access*, vol. 8, pp. 204963–204973, 2020.

[20] L. Chen, W. Zhang, M. A. Kishk, and M.-S. Alouini, "Correlation of line-of-sight probabilities in aerial-terrestrial communications: Modeling, analysis, and application," *IEEE Trans. Veh. Technol.*, early access, Nov. 29, 2023, doi: 10.1109/TVT.2023.3337423.

[21] D. Yin, X. Yang, H. Yu, S. Chen, and C. Wang, "An air-to-ground relay communication planning method for UAVs swarm applications," *IEEE Trans. Intell. Veh.*, vol. 8, no. 4, pp. 2983–2997, Apr. 2023.

[22] R. Wang, M. A. Kishk, and M.-S. Alouini, "Resident population density-inspired deployment of K-tier aerial cellular network," *IEEE Trans. Wireless Commun.*, vol. 22, no. 11, pp. 7989–8002, Nov. 2023.

[23] A. Al-Hourani, S. Kandeepan, and S. Lardner, "Optimal LAP altitude for maximum coverage," *IEEE Wireless Commun. Lett.*, vol. 3, no. 6, pp. 569–572, Dec. 2014.

[24] M. Alzenad, A. El-Keyi, F. Lagum, and H. Yanikomeroglu, "3-D placement of an unmanned aerial vehicle base station (UAV-BS) for energy-efficient maximal coverage," *IEEE Wireless Commun. Lett.*, vol. 6, no. 4, pp. 434–437, Apr. 2017.

[25] X. He et al., "Towards 3D deployment of UAV base stations in uneven terrain," in *Proc. 27th Int. Conf. Comput. Commun. Netw.*, 2018, pp. 1–9.

[26] S. Zhang and R. Zhang, "Radio map-based 3D path planning for cellular-connected UAV," *IEEE Trans. Wireless Commun.*, vol. 20, no. 3, pp. 1975–1989, Mar. 2021.

[27] Y. Dong, C. He, Z. Wang, and L. Zhang, "Radio map assisted path planning for UAV anti-jamming communications," *IEEE Signal Process. Lett.*, vol. 29, pp. 607–611, 2022.

[28] J. Chen and D. Gesbert, "Efficient local map search algorithms for the placement of flying relays," *IEEE Trans. Wireless Commun.*, vol. 19, no. 2, pp. 1305–1319, Feb. 2019.

[29] Y. Zheng and J. Chen, "Geography-aware optimal UAV 3D placement for LOS relaying: A geometry approach," 2022, *arXiv:2209.15161*.

[30] Y. Zheng, Y. Wang, and J. Chen, "Online search for UAV relay placement for free-space optical communication under shadowing," *Intell. Converged Netw.*, vol. 4, no. 1, pp. 28–40, Mar. 2023.

[31] D. Gesbert, O. Esrafilian, J. Chen, R. Gangula, and U. Mitra, "UAV-aided RF mapping for sensing and connectivity in wireless networks," *IEEE Wireless Commun.*, vol. 30, no. 4, pp. 116–122, Aug. 2023.

[32] B. Li, Z. Fei, and Y. Zhang, "UAV communications for 5G and beyond: Recent advances and future trends," *IEEE Internet Things J.*, vol. 6, no. 2, pp. 2241–2263, Apr. 2019.
[33] Y. Zeng, Q. Wu, and R. Zhang, "Accessing from the sky: A tutorial on UAV communications for 5G and beyond," *Proc. IEEE*, vol. 107, no. 12, pp. 2327–2375, Dec. 2019.
[34] G. Geraci et al., "What will the future of UAV cellular communications be? a flight from 5G to 6G," *IEEE Commun. Surveys Tuts.*, vol. 24, no. 3, pp. 1304–1335, thirdquarter 2022.
[35] A. O. Hashesh, S. Hashima, R. M. Zaki, M. M. Fouda, K. Hatano, and A. S. T. Eldien, "AI-enabled UAV communications: Challenges and future directions," *IEEE Access*, vol. 10, pp. 92048–92066, 2022.
[36] A. Al-Hourani, S. Kandeepan, and A. Jamalipour, "Modeling air-to-ground path loss for low altitude platforms in urban environments," in *Proc. IEEE Glob. Commun. Conf.*, 2014, pp. 2898–2904.
[37] R. Wang, M. A. Kishk, and M.-S. Alouini, "Ultra-dense LEO satellite-based communication systems: A novel modeling technique," *Commun. Mag.*, vol. 60, no. 4, pp. 25–31, Apr. 2022.
[38] O. Esrafilian and D. Gesbert, "3D city map reconstruction from UAV-based radio measurements," in *Proc. IEEE Glob. Commun. Conf.*, 2017, pp. 1–6.
[39] M. Alzenad and H. Yanikomeroglu, "Coverage and rate analysis for vertical heterogeneous networks (VHetNets)," *IEEE Trans. Wireless Commun.*, vol. 18, no. 12, pp. 5643–5657, Dec. 2019.
[40] D. Wackerly, W. Mendenhall, and R. L. Scheaffer, *Mathematical Statistics With Applications*. Boston, MA, USA: Cengage Learning, 2014.
[41] C.-P. Wu et al., "Learning-based downlink user selection algorithm for UAV-BS communication network," in *Proc. IEEE 17th Annu. Consum. Commun. Netw. Conf.*, 2020, pp. 1–5.
[42] ITU, "Prediction methods required for the design of terrestrial broadband millimetric radio access systems operating in a frequency range of about 20 − 50 GHz," *Draft New Recommendation ITU-R P. [DOC. 3/47], Working Party K*, vol. 3, 2003.
[43] Z. Lou, B. E. Y. Belmekki, and M.-S. Alouini, "Coverage analysis of hybrid RF/THz networks with best relay selection," *IEEE Commun. Lett.*, vol. 27, no. 6, pp. 1634–1638, Jun. 2023.
[44] M. Kishk, A. Bader, and M.-S. Alouini, "Aerial base station deployment in 6 G cellular networks using tethered drones: The mobility and endurance tradeoff," *IEEE Veh. Technol. Mag.*, vol. 15, no. 4, pp. 103–111, Dec. 2020.
[45] B. E. Y. Belmekki and M.-S. Alouini, "Unleashing the potential of networked tethered flying platforms: Prospects, challenges, and applications," *IEEE Open J. Veh. Technol.*, vol. 3, pp. 278–320, 2022.
[46] Z. Lou, B. E. Y. Belmekki, and M.-S. Alouini, "HAPS in the non-terrestrial network nexus: Prospective architectures and performance insights," *IEEE Wireless Commun.*, vol. 30, no. 6, pp. 52–58, Dec. 2023.
[47] Z. Lou, A. Elzanaty, and M.-S. Alouini, "Green tethered UAVs for EMF-aware cellular networks," *IEEE Trans. Green Commun. Netw.*, vol. 5, no. 4, pp. 1697–1711, Dec. 2021.

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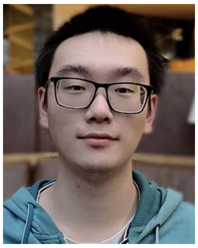

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