Environment-Aware Drone-Base-Station Placements in Modern Metropolitans

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***Abstract*—Unmanned aerial vehicles, i.e., drones, have recently caught attention for providing on-demand capacity to wireless networks as drone-base-stations (drone-BSs). Many studies assume simplified channel models based on average characteristics of the environment to estimate the placement of drone-BSs. However, especially in urban areas, positioning of drone-BSs with respect to intersections and roof-top heights of buildings can severely change the path loss characteristics. To address this issue, we adopt an ITU channel model utilizing more information about the environment, such as the shapes of the buildings. We optimize parameters of the selected ITU model, so that it can be used for altitudes both strictly lower and higher than building roof-tops. Using ray-tracing simulations as a benchmark, we compare the proposed model with a widely used simpler model. Results show that the proposed model can reduce the root-mean-squared error from 35 to 10 dB, which may have critical implications for drone-BS operations, such as planning for the required number of drone-BSs to cover outdoor urban users, as demonstrated with simulations.**

***Index Terms*—5G mobile communication, mobile nodes, wireless networks, radio access networks, channel models, multipath channels, airborne communications, UAV base station, drone base station.**

I. Introduction

AMONG many civillian applications of unmanned aerial vehicles (UAVs), i.e., drones, ubiquitous cellular coverage has recently attracted great attention [1]. Drone-base-stations are moving base stations with wireless backhaul. They are particularly important in modern metropolitans, because population density ensures revenue, and proliferates potential applications, such as improving resilience of smart cities [2], or providing additional coverage [3], to name a few. Since drone-BSs are extremely flexible yet energy-critical devices, issues on their management, and especially drone-BS placement, has gained significant interest [1]–[8]. However, modelling of air-to-ground path loss characteristics is following these developments rather slowly, due to tedious experiments.

Among air-to-ground path loss models, [9] gained popularity due to the consideration of urban environments. In particular, high-rise dense urban environments with buildings of 60 m height on average is represented by adjusting the probability of having line-of-sight (LOS) links in [9]. However, especially cores of modern metropolitans often consist of even higher-rise buildings, with an average height of buildings of 100 m. Urban environments can be classified based on the average heights of the buildings more precisely as follows [10]:

1) *High-rise Urban:* Consists of buildings with several floors ($\leq$ 30 m).
2) *Very High-rise Urban:* Consists of densely located buildings with several tens of floors (30 to 100 m).
3) *Skyscraper Urban:* Consists of densely located skyscrapers ($\geq$ 100 m).

Note that we propose the last case to describe communications with drones in cores of metropolitans such as Hong Kong (553 skyscrapers), New York (799 skyscrapers), and Tokyo (281 skyscrapers) [11]. The particulars of *skyscraper urban* environment are the extreme heights of the buildings, population density, and deep street canyons, which makes it a category of its own with unique propagation characteristics.

In such environments, the altitude of the drone-BSs with respect to building heights can have critical effects. In the literature, drone-BSs are often termed as low-altitude platforms (LAPs), which are platforms lower than 10 km in [9]. Because the operational altitude can vary significantly from tens of meters to kilometres, we would like to describe the drone-BSs lower than 100 m as *ultra-low-altitude* platforms (ULAPs), where 100 m represents the near roof-top level of many skyscrapers. Besides the path loss model, selection of altitude has various effects from the type of drone, to legal permission required, to endurance [1]. For instance, in modern metropolitans, the density of the population may not require serving a larger area, but providing a very good service quality to certain users [8]. In that case, using ULAPs at lower altitudes can be an efficient option.

In this letter, we identify the *skyscraper urban environment* as a scenario where a widely used channel model [9] may be too simple. Since there is no widely accepted channel model for ULAPs, following a similar strategy as [9], we adopt a channel model from [10] to be used with city maps in this environment. The model in [9] is probabilistic in the sense that the probability of a link being (N)LOS depends on the distance between the user and the drone-BS. On the other hand, the proposed model is deterministic, which means that it is known whether a link is LOS or NLOS.

The purpose of this letter is not so much to propose a particular model for the air-to-ground channel. Indeed, many models could be fitted to the data points of various simulation setups. It is rather to propose a particular *type* of model, that is, one that uses basic information about building shapes and city layout, along with blockage, reflection, and around-the-corner-diffraction propagation mechanisms. Indeed, these considerations are necessary to reasonably model the channel in this case.

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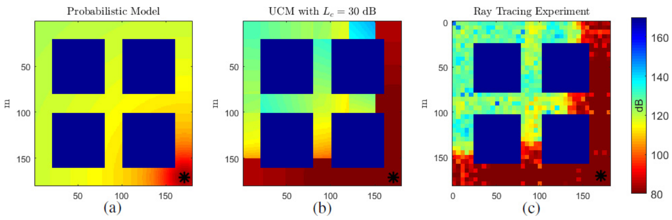


Fig. 1. Path loss patterns for a drone-BS at 50 m altitude.

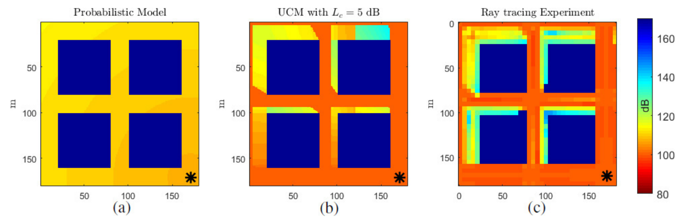


Fig. 2. Path loss patterns for a drone-BS at 1000 m altitude.

II. Channel Models for Low and Ultra-Low Altitude Platforms

One of the main methods to determine whether an air-to-ground link is LOS or NLOS is using probabilistic models based on the averages of the characteristics of the environment (e.g., average height and number of buildings per km^2 etc.), and the location of the drone-BS relative to the user [9].

Probabilistic Model: Recently, a probabilistic model (PM) for air-to-ground path loss is presented in [9], and a similar model for terrestrial links can be found in [12]. The PM depends on combining the free space path loss with excessive loss due to environmental obstacles. Free-space loss is modelled via the Friis equation, which is given as follows for a user located at (x, y) and the drone-BS at (x_D, y_D, h):

$$L_f(h, r) = 20\log(4\pi f_c/c) + 20\log(d)\ [\text{dB}], \tag{1}$$

where $d = \sqrt{h^2 + r^2}$ is the distance between a user and drone-BS in meters, h is the altitude of the drone-BS, and $r = \sqrt{(x_D - x)^2 + (y_D - y)^2}$ is the horizontal distance between the drone-BS and the user. The diffraction and reflection due to environmental obstacles cause excessive loss (η), which is less for a LOS link (η_{LOS}) compared to a NLOS link (η_{NLOS}). The following probability of LOS is used to combine excessive loss with free-space loss:

$$P(h, r) = (1 + a\exp(-b(\arctan(h/r) - a)))^{-1}, \tag{2}$$

where a and b are constant values depending on the environment. Then, the excessive loss can be written as

$$L_e(h, r) = P(h, r)\eta_{\text{LOS}} + (1 - P(h, r))\eta_{\text{NLOS}} \quad [\text{dB}]. \tag{3}$$

Hence, total loss becomes $L_f(h, r) + L_e(h, r)$. Although PM is compact and useful, the imprecise determination of the quality of links can lead to inefficient drone-BS placements. That can be a critical problem for two reasons: First, especially ULAPs are energy-critical UAVs, and inefficient 3D placement can lead to signal transmission with excessive power to ensure service quality. Second, if the drone-BSs are not exploited properly, drone-BSs may not provide any profit to the operator (except critical situations). To combat this problem, more precision can be obtained by making use of information on environment, which can be easily gathered from city maps.

Urban Canyon Model: Note that city maps can be used to determine a *LOS path*, and the remaining NLOS areas, also providing computational efficiency by eliminating the need to calculate $P(h, r)$, which is based on a deterministic approach. The urban canyon model (UCM) investigated in this section depends on a recently released below roof-top path loss model by ITU-R, which requires the knowledge on the locations of the BSs and the users, as well as the street widths, shapes and alignments [10]. This model can also be valid for drone-BSs when ignoring near-field effects of flight and machinery, such as attenuation due to drone's body and effects of turbulence, similar to the approach of the previously presented air-to-ground models [9], [13], [14]. In [10], two-ray plane earth reflection model is utilized for LOS links. In this case, the median of the LOS path loss is given in [10, p. 8] as

$$L_{LOS} = L_b + 6 + K\log(d/R_b) \quad [\text{dB}]. \tag{4}$$

In the above, $R_b \approx \frac{4h_D h_u}{\lambda}$ is the break-point distance, h_D and h_u are the heights of the drone and the user, respectively. If $d \le R_b$, $K = 20$, and $K = 40$ otherwise. For NLOS links, path loss depends on the distance of the drone-BS and the user from the intersections of LOS and NLOS streets, i.e., corners [10, Ch. 4.1.2]. Let C in meters represent effective corner region (CR) from LOS street into NLOS street. A user is assumed to be in CR if distance of the user in NLOS street, r_c^u, satisfies $\frac{w_d}{2} + 1 \le r_c^u \le \frac{w_d}{2} + 1 + d_c$. For this case (in dB),

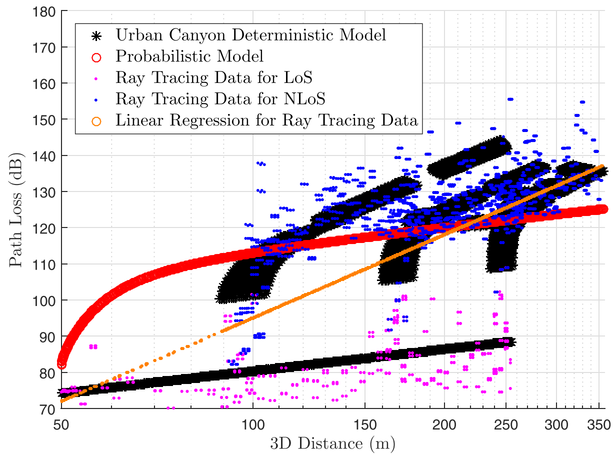
$$L_{cr} = \begin{cases} \dfrac{L_c}{\log(1+d_c)}\log\left(l_{u,c} - \dfrac{w_d}{2}\right), \text{ if } \dfrac{w_d}{2} + 1 \le l_{u,c} \le \dfrac{w_d}{2} + 1 + d_c, & \text{(5a)} \\ L_c, \text{ if } l_{u,c} > 0.5w_d + 1 + d_c, & \text{(5b)} \end{cases}$$

where $l_{u,c}$ represents the user's distance from the corner, w_d is the width of the streets as shown in [10, Fig. 3]. Corner loss region, and corner loss are represented by d_c and L_c, respectively. While (5a) represents strong refraction around corners, (5b) is for the increased loss when proceeded into the street [10, Fig. 4]. Attenuation beyond the corner region is (in dB)

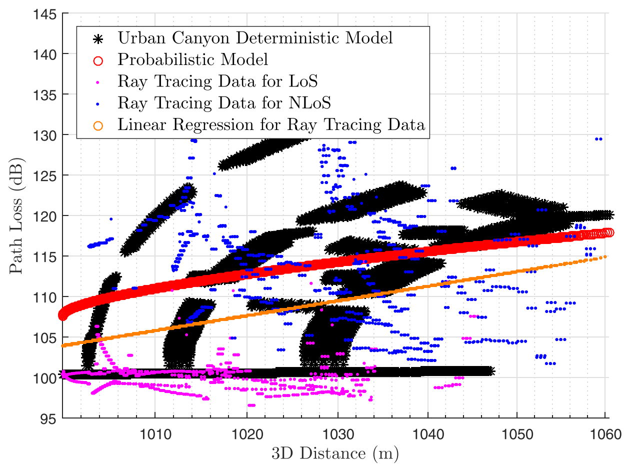
$$L_{att} = 60\left(\log_{10}\left(l_{u,c} + l_{d,c}\right) - \log_{10}\left(l_{u,c} + 0.5w_d + d_c\right)\right). \tag{6}$$

Note that $l_{d,c}$ denotes the distance of drone-BS to the corner region as shown in [10, Fig. 3]. Finally, the path loss for a NLOS link becomes, $L_{NLOS} = L_{LOS} + L_{cr} + L_{att}$. Also, UCM is reciprocal under proper assumptions.

Note that L_c is a critical parameter in determining the path loss, as it determines the average amount of diffraction, and given as 20 dB in [10]. We propose to adjust L_c based on the altitude with the objective of minimizing root-mean-squared error (RMSE) by grid search. We see that L_c decreases with increasing altitude, and the opposite is true for decreasing altitude, due to change in the amount of diffraction. For instance, if the altitude of a LAP is strictly higher than the roof-top level of the buildings, there will be more diffraction. For ULAPs at altitudes strictly lower than roof-top levels of the buildings, diffraction is not likely to occur, and L_c must be higher than the one in the previous case, which is verified by our experiments in the following section. For instance, L_c is determined for certain altitudes in this letter, however, DMS can update L_c values based on the current altitude of the drone-BS. In that



(a) Propagation data at 50 m.



(b) Propagation data at 1000 m.

Fig. 3. Propagation data at different altitudes compared with ray-tracing simulation results.

sense, the proposed UCM can be useful as an easily adjustable path loss model with one single parameter.

III. Simulations and Discussions

The channel models presented in the preceding sections, PM and UCM, are evaluated based on the ray-tracing simulations on a toy map of a Manhattan-grid skyscraper environment with the parameters provided in Table I. The path loss amount is presented as a heat map in Figs. 1 and 2, where h is 50 m and 1000 m, respectively. The drone-BS is hovering on the point marked with a black asterisk, which is the center of the intersection at $(170, 170, h)$. The ray-tracing simulations are conducted via Wireless Insite[1] with 5x5 m pixels. A toy map with fixed building height is preferred to clearly demonstrate the effect of altitude and capability of channel models. Note that varying the height of the buildings does not contribute much to this discussion: If the drone-BS hovers at 50 m, it is lower than majority of the buildings in a skyscraper environment (NLOS except the streets where the drone-BS is located), and at 1000 m, it is significantly higher (mostly LOS). The

[1] http://www.remcom.com/wireless-insite

TABLE I
Parameters for Ray-Tracing and Channel Models

Parameter	Value
Conductivity of walls	150×10^{-4} S/m
Conductivity of ground	5×10^{-4} S/m
Permittivity of walls	15
Permittivity of ground	5.72
Thickness (walls and ground)	0.3 m
Building height (h_B)	100 m
Building width	60 m
Street width (w_d)	20 m
Map area	500 m x 500 m
Carrier frequency (f_c)	2.5 GHz
Receiver height (h_u)	1 m
Altitude (h)	$h \in \{50 \text{ m}, 1000 \text{ m}\}$
L_c (urban)	$L_c \in \{30 \text{ dB}, 5 \text{ dB}\}$
d_c (urban)	30 m [10]
η_{LOS} (high-rise)	2.3 dB [9]
η_{NLOS} (high-rise)	34 dB [9]

TABLE II
RMSE of Propagation Models for Several Building and Drone-BS Heights, h_B and h, Respectively

Model \ RMSE		LOS (dB)		NLOS (dB)		Overall (dB)	
Probabilistic	$\mathbf{h_B}$ \ $\mathbf{h}$	50 m	1000 m	50 m	1000 m	50 m	1000 m
	60 m	34.27	11.20	10.15	10.41	16.97	10.31
	100 m	34.24	11.97	10.33	8.85	17.04	9.73
	Random	34.30	11.40	10.86	10.91	17.30	10.43
Urban Canyon	$\mathbf{h_B}$ \ $\mathbf{h}$	50 m	1000 m	50 m	1000 m	50 m	1000 m
	60 m	7.12	2.24	9.04	13.56	8.40	6.53
	100 m	7.11	1.95	8.82	12.49	8.19	9.07
	Random	7.21	1.44	9.11	13.66	8.47	9.71

200 m x 200 m subsection of the area in Figs. 1 and 2 is sufficient to show main characteristics of PM and UCM, as the map is symmetric. Note that the actual map area in Table I is the repetition of the 2x2 building structure.

According to PM, the probability of having a LOS connection only depends on distance and altitude as given in (2). Therefore, the PM cannot capture LOS on the streets, as seen in Figs. 1a and 2a. On the other hand, PM can be suitable for altitudes much higher than the buildings, as in the case of Fig. 2. In that case, the propagation is dominated by free space loss, as h becomes a much larger quantity than r. In other words, PM is dominated by $L_f(h, r)$ as $L_e(h, r)$ approaches η_{LOS}, and LOS probability approaches 1 for all ground locations. This situation can also be observed in Fig. 3, where the resemblance of PM to the linear regression line of the ray-tracing data is higher for 1000 m compared to 50 m.

There is a significant improvement in following the propagation patterns of ray-tracing simulations via UCM as observed from Figs. 1b and 2b. Figure 3 shows that UCM provides a curve for each street, which coincides with ray-tracing values. Especially, since the proposed UCM can capture no-diffraction (h = 50 m) and strong-diffraction (h = 1000 m) cases by adjusting L_c in (5a) and (5b), it provides better overall RMSE values compared to PM as shown in Table II. For LOS points, environmental awareness provided by UCM leads to more than 25 dB less RMSE compared to PM, which cannot capture LOS links of the points on the same streets (horizontal and vertical) with drone-BS hovering at 50 m. When the drone-BS hovers at 1000 m, RMSE for LOS links is approximately 10 dB better with UCM compared to PM. However, for NLOS links,

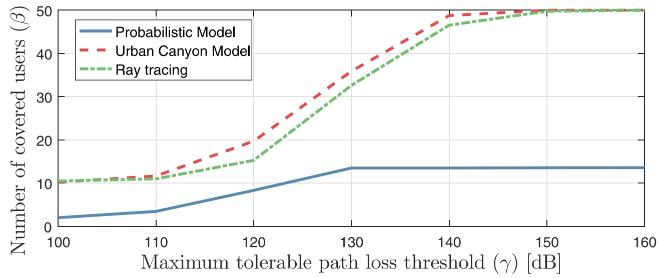


Fig. 4. Number of covered users with PM, UCM, and ray-tracing simulations.

both path loss models perform similarly, and UCM is slightly worse at 1000 m, which is due to adjusting only L_c.

Note that the UCM can be used for many urban environments. To demonstrate the capabilities of the UCM, another set of simulations are conducted with uniformly-distributed random heights, $h_B \in [60, 150]$ m, without changing the parameters of the UCM corresponding to below and above roof-top cases. The similarity of the RMSE values show that UCM can be applicable in different environments with similar urban characteristics.

In order to provide further insights, 50 users are randomly distributed in the area. The number of covered users, β, is chosen as the performance metric, which can easily be used to represent sum rate, revenue, or other key performance indicators. A user is assumed to be covered based on a maximum tolerable path loss threshold, γ, such that a user is covered if the path loss is less than γ at the user's location, and uncovered otherwise. Maximum number of users that can be covered via PM is obtained by the *efficient 3-D placement method* proposed in [4] with the additional constraint of $h \leq 100$ m to enforce the scenario in Fig. 1. High rise urban environment parameters are used for PM, and other simulation parameters can be found in [4, Table I, II]. While the drone-BS is placed at the best location by the algorithm in [4], it is fixed at the center of the environment for ray-tracing and UCM at (252.5 252.5, 50).

Fig. 4 shows β vs γ averaged over 100 Monte Carlo runs. Results show that UCM and ray-tracing have similar coverage, which increase with increasing γ, due to capturing street propagation. However, PM cannot increase coverage after $\gamma = 130$ dB, due to limitation on the altitude, as in (2). Note that PM dramatically underestimates the number of covered users, whereas UCM is very close to ray-tracing simulations.

IV. Conclusion

Inaccurate path loss estimation resulting from probabilistic models (PMs) may cause several problems for the drone-BSs framework in both the planning and operation phases. For instance, network operators may need to determine the number of drone-BSs to be dispatched, their flight durations, coverage area, and potential revenue. In particular, we observed that a widely used PM may not be sufficient to accurately reflect the propagation scenario, and indeed may wrongly estimate the channel path loss by over 34 dB. Consequently, the number of users covered with a drone-BS, and number of required drone-BSs cannot be determined accurately. On the other hand, accuracy in estimating the path loss with deterministic models can enable environment-aware placement methods, and hence, more precise planning for drone-BS operations.

The complex nature of drone-BS operations may require a drone-BS management system (DMS), which is capable of collecting and analysing large amounts of data for operational purposes. Hence, preferring deterministic methods can be acceptable in the presence of such mechanisms. Moreover, a DMS can be useful for integrating drone-BSs with appropriate RATs to the existing terrestrial network [1]. For instance, mmWave-drone-BSs can be preferred over the RF drone-BSs, since the latter ones can cause severe interference.

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