Ray Tracing Based Path Loss Modeling for UAV-to-Ground mmWave Channels in Campus Scenario

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Abstract. In this paper, based on extensive ray tracing (RT) simulation data in campus scenario, a tailored path loss (PL) model for unmanned aerial vehicle (UAV) assisted air-to-ground (A2G) millimeter wave (mmWave) communications is proposed. The new model originates from the classic Close-in (CI) model, but takes the factor of UAV height into account with the help of extensive RT simulated data under the A2G campus scenario. The simulation and analysis results show that the proposed PL model matches better than the original CI model for certain trajectory at any UAV height. This modeling method can also be extended to any A2G scenarios by adjusting the parameters of model with RT simulated data.

Keywords: UAV-assisted mmWave communications · A2G channel · PL model · Large-scale fading · RT method

1 Introduction

Operating as the airborne base stations (BSs) or flying relays, the UAV-assisted communication has attracted great interests to expand the coverage in the fifth and beyond generation (5G/B5G) mobile communications. The mmWave technologies have also been adopted to meet the increasing demand of bandwidth, transmission rate, and massive connectivity. However, the mmWave communications involve very higher PL and have some new features compared with the conventional sub-6 GHz communications [1]. A thorough understanding of PL

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modeling and characteristics is essential for the system design and optimization of UAV-assisted communications.

Some channel models or measurements for the mmWave mobile communications have been done in [2–12] but only limited studies for the UAV scenarios can be found. The authors in [13] conducted field measurements by a UAV flying at five different altitudes in a rural environment and a PL regression curve was extracted. The authors in [14] presented an A2G model based on the measurements of over-water environments and analyzed the correlation of PL. In [15], the authors conducted measurements in the line-of-sight (LoS) and non-line-of-sight (NLoS) scenarios at 900 MHz, 1800 MHz, and 5 GHz and developed a log-distance PL model. Some other PL measurements of UAV channel with different carriers such as 1, 2.585, 4 and 4.3 GHz can be addressed in [17–19], but all of them are only for the sub-6 GHz band.

Note that the field measurement for mmWave UAV channels is difficult and costly. As an alternative option, some propagation models based on the RT simulations have been presented [20–22]. For example, the authors in [23] studied the PL in LoS and NLoS scenarios of mmWave A2G channels at 28 GHz by RT simulation. The authors in [24] proposed a prediction model for PL in A2G mmWave channels based on the machine learning method at 28 GHz and 73 GHz. In [25], a PL model including the factor of elevation angle at 28 GHz was proposed. In [26], an average PL considering LoS probability of mmWave A2G channels was proposed.

The RT simulation method is time consuming and sensitive to the map accuracy. It's more applicable to describe the PL model in a statistical way. However, the study of statistical modeling for the PL of A2G scenario is not sufficient. This paper intends to fill this gap. Based on the extensive RT simulation data in campus scenario, this paper develops a tailored PL model for UAV mmWave communications by considering the factor of UAV height. We compare the 3GPP model and our modified model at three different UAV heights, and validate the modified model by using RT method. This model can be generalized to any other scenes, but the parameter values need to be adjusted according to the RT simulation results.

This paper is organized as follows. Section 2 gives a basic stochastic PL model. In Sect. 3, the computation methods of LoS probability and path loss are developed and analyzed. In Sect. 4, the modified PL model of campus scenarios is evaluated by simulation method. Finally, some conclusions are given in Sect. 5.

2 Stochastic Path Loss Model

The measured-based PL model in a statistical way, i.e., stochastic model or empirical model is more popular. Note that the measured-based path loss modeling method is adopted in most of standardized mobile channel models, such as 3GPP, WINNER +, and ITU-R. A widely used model can be expressed by averaging the path loss in the LoS and NLoS scenarios as

$$L\,[\mathrm{dB}] = P_{\mathrm{LoS}} \cdot L_{\mathrm{LoS}} + (1 - P_{\mathrm{LoS}}) \cdot L_{\mathrm{NLoS}} \tag{1}$$

where P_{LoS} denotes the LoS probability, L_{LoS} and L_{NLoS} are the path losses in the LoS and NLoS scenarios, respectively. It should be mentioned that the UAV propagation scenario is quite different with traditional mobile communications, i.e., three-dimensional (3D) propagation and valid scatterers only around the ground station. Thus, the model parameters provided in the standardized models cannot be used directly and this paper focuses on optimizing these parameters for the UAV mmWave scenarios. Beginning in 90's, the RT methods began to be widely used for the channel modelling, especially for small area and high frequency band [27]. Some well-known software tools based on the RT algorithms can also be found, e.g., Wireless Insite, Volcano, WaveSight, Winpro, and CloudRT. However, it's difficult to calculate all PL by huge number of rays in real-time.

3 Parameter Computation and Modification

3.1 LoS Probability

The UAV-assisted communications have a significant advantage on the mobile communications for having a much higher LoS probability. The LoS probability can be described by a statistical model of distance and environmental layout and it's usually frequency-independent for simplicity. The LoS probability model of rural environments in the 3GPP and ITU-R channel models originates from WINNER's exponential decay model. The NYU and 5GCM model update the parameters based on the 3GPP model. It should be mentioned that most of aforementioned methods are designed for the mobile communication environments. In order to set up a generic A2G PL model, the statistical ITU-R Rec. P.1410 model [28] is adopted in this paper. This model does not need precise information about buildings and is given as

$$P_{\text{LOS}} = \prod_{n=0}^{m} \left[1 - \exp\left(- \frac{\left(h_{\text{UAV}} - \frac{(n+0.5)(h_{\text{UAV}} - h_{\text{V}})}{m+1} \right)^2}{2\gamma^2} \right) \right] \tag{2}$$

where $m = floor\left(d\sqrt{\alpha\beta} - 1\right)$, d is the horizontal distance between the UAV and vehicle, h_{UAV} and h_{V} represent the height of the UAV and vehicle, respectively. α is the fraction of area with buildings to the total land area, β is the average buildings per square kilometer, and γ characterizes the height distribution of buildings.

The simulation results are given in Fig. 1. Different results of LoS probability can be found due to different propagation environments, where the suburban environment has the highest value and the high-rise urban environment has the lowest one. The reason is that the suburban environment is an open area while the high-rise urban environment has more obstacles. Moreover, the LoS probability of high-rise urban is below 40% with the distance over 100 m (Table 1).

Table 1. Parameters of different environments

Environment	α	β	γ
Suburban	0.1	750	8
Urban	0.3	500	15
Dense urban	0.5	300	20
High-rise urban	0.5	300	50

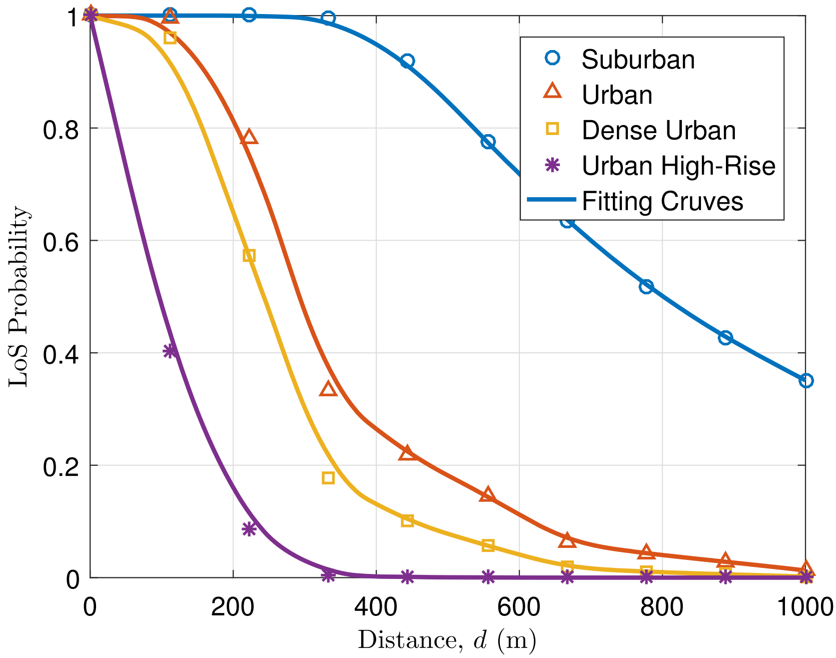

Fig. 1. LoS probabilities under different environments.

3.2 Modified Path Loss

For the mmWave communications, LoS and NLoS conditions are totally different and usually described separately. The PL model of 3GPP channel model and ITU-R model are similar and more suitable for the frequencies below 6 GHz. A well-known terrestrial log-distance PL model, namely CI model, has good parameter stability and is suitable for mmWave band [7]. The CI model bases on the free space path loss and the Friis' law, and accounts for the frequency and distance as

$$L^{\mathrm{CI}}\left(f_c, d\right)[\mathrm{dB}] = 32.4 + 20\log_{10}\left(f_c\right) + 10n\log_{10}\left(d\right) + \chi_\sigma \tag{3}$$

where χ_σ is a zero-mean Gaussian variable to represent the factor of shadow fading, d, f_c are the distance in m and carrier frequency in GHz at 1 m. In (3), n

is the path loss exponent (PLE) and it's recommended as 2.16 and 2.75 by the 3GPP standard in the case of LoS and NLoS.

Note that the factor of flying height is not considered in the above model. In order to make the model fit the UAV communications under the specific area, e.g., the campus scenario, we have conducted tremendous simulations and obtained lots of RT simulated data. In this simulation, we put a vehicle on the ground as a receiver and a UAV as a transmitter. The UAV's height starts from 30 m and increases every 20 m to 500 m, with a total of about 24 layers. For each layer, 1000 positions are selected and they are divided into LoS points and NLoS points. We calculate the path loss for the LoS point and NLoS point separately, and get the relevant data. By fitting these data, we introduce a new parameter with respect to the height of UAV, and upgrade the PL model under the LoS and NLoS scenarios, respectively, as

$$\begin{aligned} L_{\mathrm{LOS}}\left(f_{\mathrm{c}}, d, h_{\mathrm{UAV}}\right)[\mathrm{dB}] = &\ 32.4 + 20\log_{10}\left(f_{\mathrm{c}}\right) \\ &+ 10\left(2.16 + 0.0001 h_{\mathrm{UAV}}\right) \cdot \log_{10}(d) + \chi_{\sigma\mathrm{LOS}} \end{aligned} \tag{4}$$

$$\begin{aligned} L_{\mathrm{NLOS}}\left(f_{\mathrm{c}}, d, h_{\mathrm{UAV}}\right)[\mathrm{dB}] = &\ 32.4 + 20\log_{10}\left(f_{\mathrm{c}}\right) \\ &+ 10\left(2.75 - 0.0001 h_{\mathrm{UAV}}\right) \cdot \log_{10}(d) + \chi_{\sigma\mathrm{NLOS}} \end{aligned} \tag{5}$$

where $\chi_{\sigma\mathrm{LoS}}$ and $\chi_{\sigma\mathrm{NLoS}}$ denote the shadowing in LoS and NLoS scenarios, respectively. In practice, $\sigma_{\mathrm{LoS}} = 5.9\,\mathrm{dB}$ and $\sigma_{\mathrm{NLoS}} = 8.2\,\mathrm{dB}$ is desirable.

In order to compare the difference between the 3GPP model, the CI model, and our modified model, we assume $h_{\mathrm{UAV}} = 100,\ 500$ m, $h_{\mathrm{V}} = 1.5$ m and $f_c = 28\,\mathrm{GHz}$. It is clearly shown that the results of our modified PL model matches the model used in the 3GPP standard, in which the PL increases as the distance increases. The PL is more severe in the NLoS scenario due to the obstacles, and is 30 dB higher than in the LoS scenario when the distance between UAV and vehicle is 5000 m. Moreover, when the UAV height is higher, the difference becomes more obvious, which also means our modified model will be more adapted to different UAV heights (Fig. 2).

4 Simulation and Validation

4.1 Scenario Setup

In this section, we'll analyze the campus tailed PL model in the NUAA campus, which contains 66 buildings with an average height of about 30 m. The surface of buildings is concrete, and the open ground of campus is mostly wet soil. The dimensions of modeled terrain are 1590 m by 1100 m. All the trees, roads, and lake are included in the database. We set six UAV trajectories, each trajectory is simulated at altitudes of 30, 50, 100, 150, 300, and 500 m, and the rest parameters are given in Table 2. Direct, reflection and diffraction are also considered in the simulation (Fig. 3).

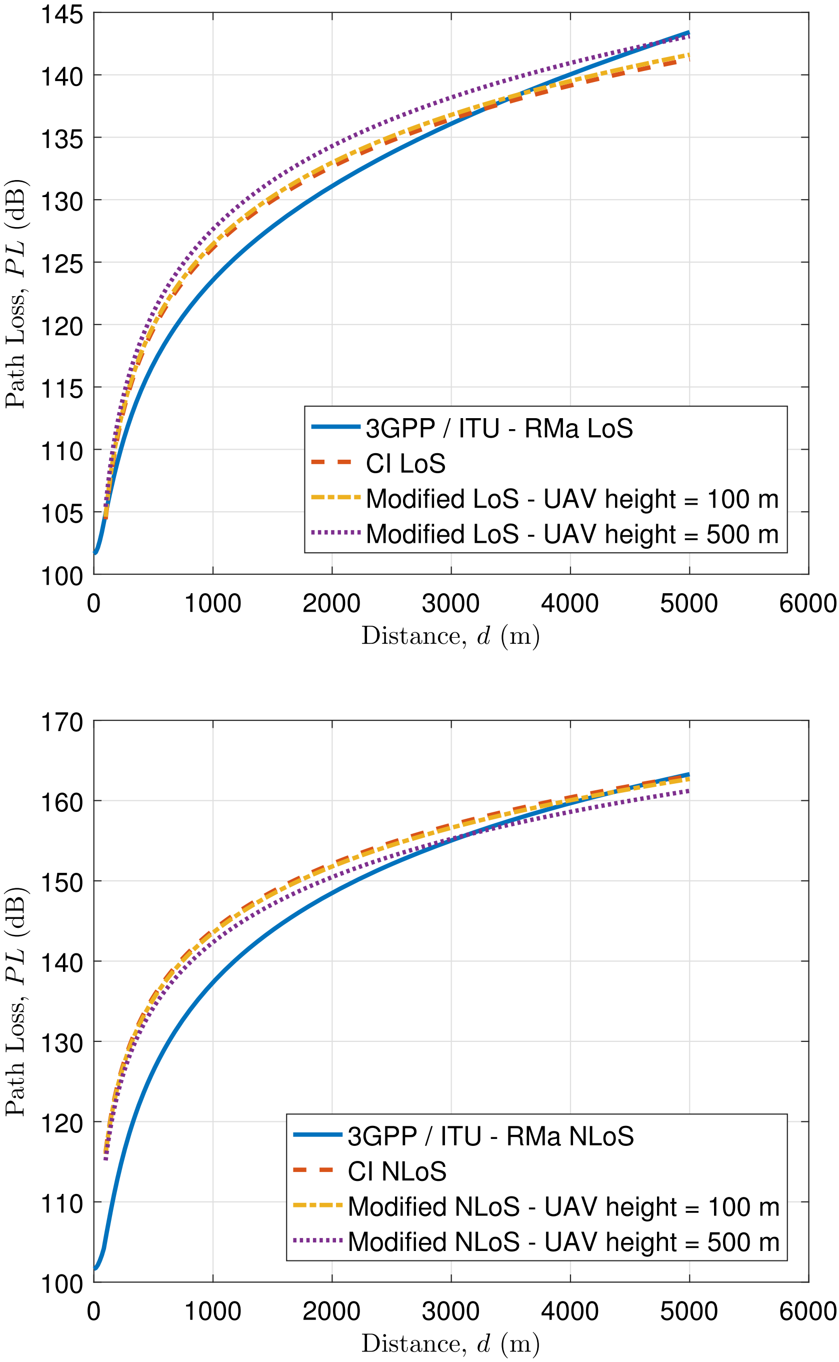

Fig. 2. Comparison of different methods under (a) LoS scenario, (b) NLoS scenario.

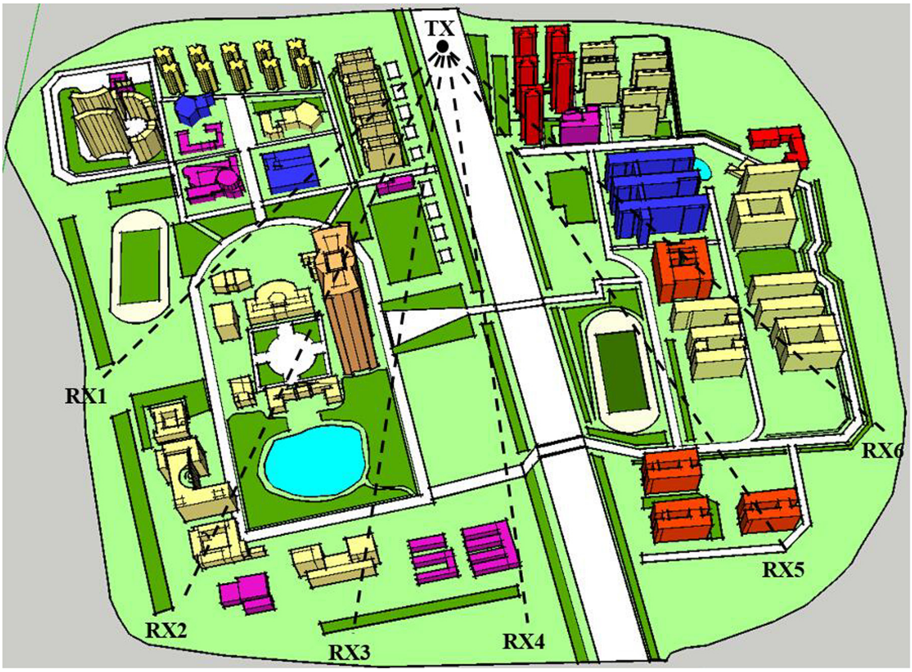

Fig. 3. 3D geographical database of NUAA campus.

Table 2. Simulation parameters

Parameters	Values
Vehicle height	2 m
UAV height	30 m, 50 m, 100 m, 150 m, 300 m, 500 m
Carrier frequency	28 GHz
System bandwidth	500 MHz
Antenna	Omnidirectional antenna
Polarization	Vertical polarization

4.2 Validation and Analysis

Instead of measurement campaign, another way to validate the LoS probability model is by using extensive RT simulations. Actually, a sufficiently large area and enough simulations can ensure that the result is not dependent on the randomly selected cases. In order to compare and analyze the LoS probability, we set $h_{\mathrm{UAV}} = 100$ m, $h_{\mathrm{V}} = 1.5$ m. The simulation results of different methods are given in Fig. 4. As we can see that the LoS probability increases as the elevation angle increases due to the decrease of obstacles. Although they all have a certain deviation from the RT model, we can see that the deviation of the ITU model is smaller than 3GPP model and the method in [29].

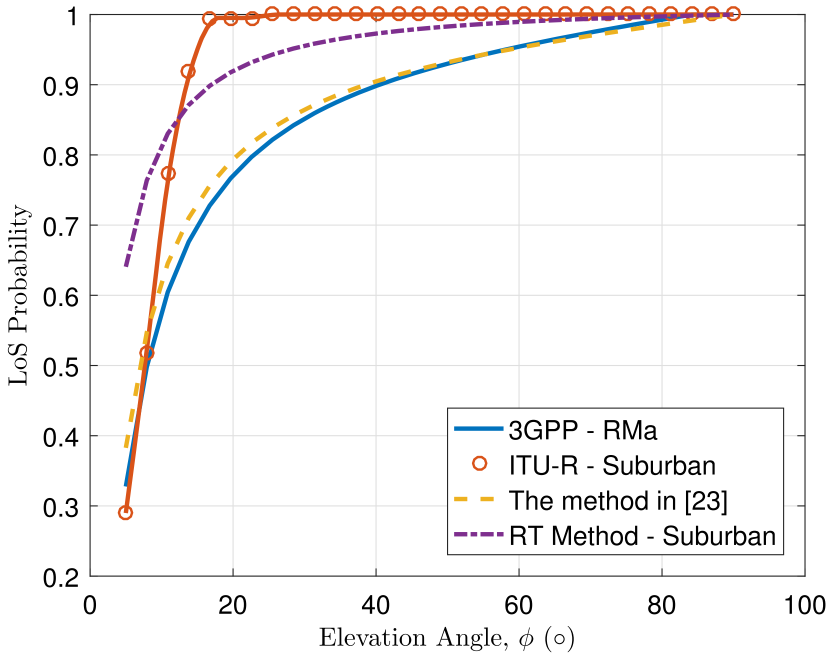

Fig. 4. Comparison of different LoS probability methods.

Then, we use the simulated result by RT method to validate the proposed PL model. Note that the RT method is related to the specific environment and fluctuates greatly. During the simulation, 6 typical trajectories are selected and each trajectory takes six different heights of 30 m, 50 m, 100 m, 150 m, 300 m, and 500 m. Figure 5 shows the path loss results of one typical trajectory, and the UAV height is 50 m. As we can see in the figure, our modified method can fit the path loss trend generated by the RT method and produce reasonable statistics in Table 3 and Table 4.

Moreover, Table 3 shows that in all cases the standard deviation between the PL model and the RT method is lower than 3.5402 dB and the median path loss exponent (PLE) is 2.17. It can be seen that the accuracy of our modified model under the LoS scenario is very high. Table 4 illustrates that the PLE under the NLoS scenario ranges from 2.7000 for the highest height, to 2.7470 for the lowest height and the median path loss exponent is 2.74. The standard deviation between the PL model and the RT method ranges from 6.0998 dB to 10.6271 dB. It is reasonable because the lower the flight altitude, the more the path loss is affected by the obstacle, and the RT method is more accurate.

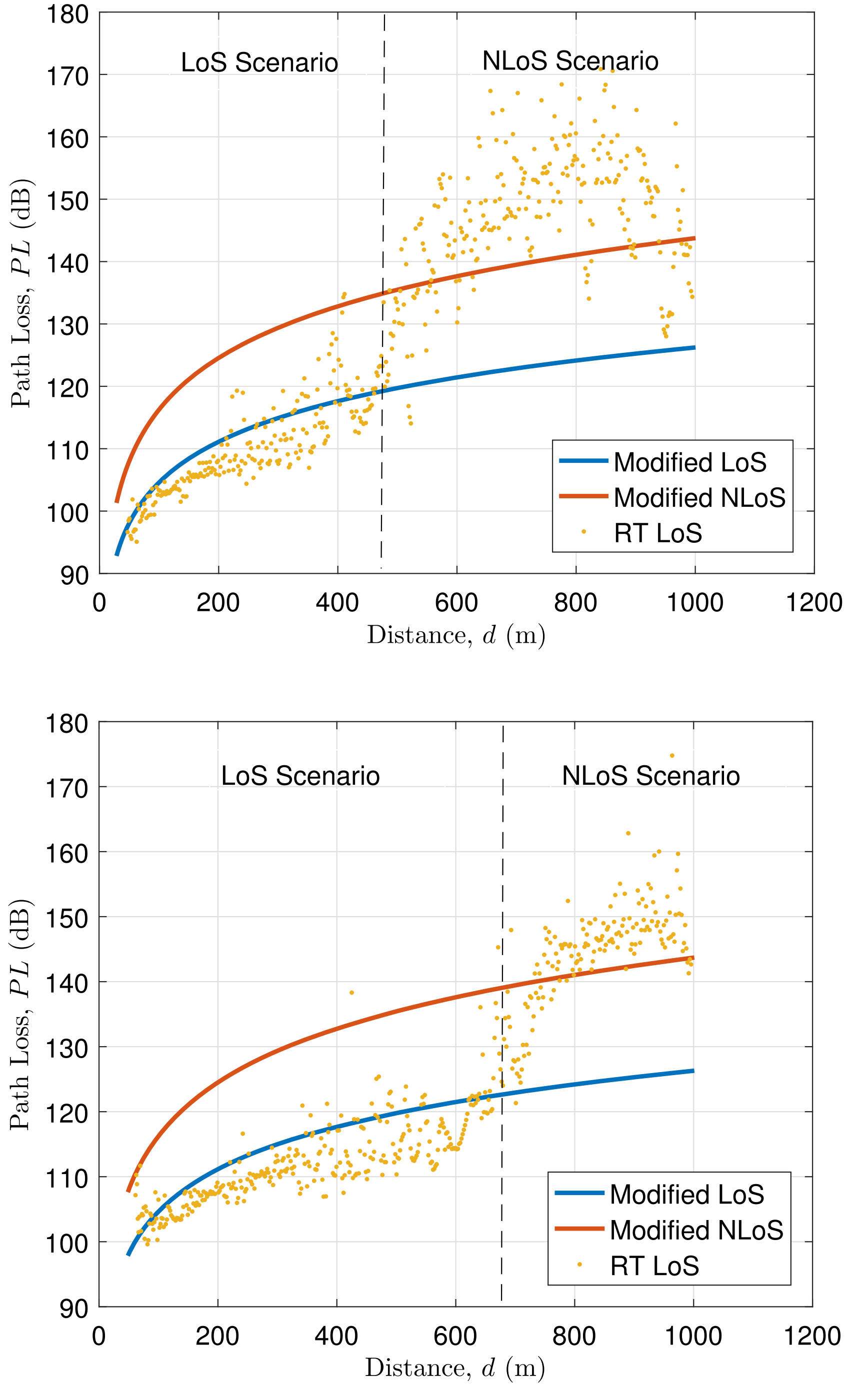

Fig. 5. Path loss results of one typical trajectory (a) UAV height = 30 m, (b) UAV height = 50 m, (c) UAV height = 100 m.

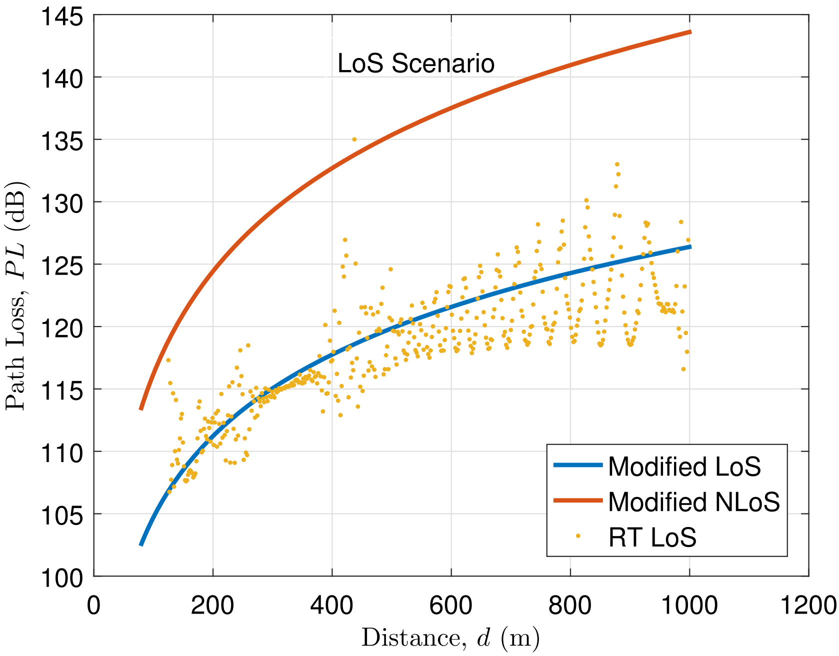

Fig. 5. (*continued*)

Table 3. Statistical properties for RT results (LoS)

UAV height (m)	Path loss exponent	Standard deviation (dB)
30	2.1630	3.4822
50	2.1670	3.4313
100	2.1700	1.4655
150	2.1750	2.0913
300	2.1900	2.9649
500	2.2100	3.5402

Table 4. Statistical properties for RT results (NLoS)

UAV height (m)	Path loss exponent	Standard deviation (dB)
30	2.7470	10.6271
50	2.7450	10.0353
100	2.7400	8.5940
150	2.7350	7.9383
300	2.7200	7.3789
500	2.7000	6.0998

5 Conclusions

In this paper, we have developed a new PL model for UAV mmWave communications by considering the factor of UAV height. For the campus scene, we have obtained extensive RT simulation data and got the tailored parameter value of the new factor by fitting these data. The simulation results have shown that our modified match well with RT method at any UAV height. Moreover, this model is generic for any A2G scene, as long as we adjust the parameter value according to the scene and this's our future work.

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References

1. Rappaport, T.S., MacCartney, G.R., Samimi, M.K., Sun, S.: Wideband millimeter-wave propagation measurements and channel models for future wireless communication system design. IEEE Trans. Commun. Syst. **63**(9), 3029–3056 (2015)
2. Majed, M.B., Rahman, T.A., Aziz, O.A.: Propagation path loss modeling and outdoor coverage measurements review in millimeter wave bands for 5G cellular communications. Int. J. Electron. Comput. Eng. **8**(4), 2254–2269 (2018)
3. Fan, W., Carton, I., Kyosti, P., Karstensen, A., Jamsa, T., et al.: A step toward 5G in 2020: low-cost OTA performance evaluation of massive MIMO base stations. IEEE Antennas Propag. Mag. **59**(1), 38–47 (2017)
4. Zhang, J., Shafi, M., Molisch, A., Tufvesson, F., Wu, S., et al.: Channel models and measurements for 5G. IEEE Commun. Mag. **56**(12), 12–13 (2018)
5. Wang, C.-X., Bian, J., Sun, J., Zhang, W., Zhang, M.: A survey of 5G channel measurements and models. IEEE Commun. Surv. Tuts. **20**(4), 3142–3168 (2018)
6. Hindia, M.N., I-Samman, A.M.A., Rahman, T.A., Yazdani, T.M.: Outdoor large-scale path loss characterization in an urban environment at 26, 28, 36, and 38 GHz. Phys. Commun. **27**(1), 150–160 (2018)
7. Rappaport, T.S., Xing, Y., MacCartney, G.R., Molisch, A.F., Mellios, E., Zhang, J.: Overview of millimeter wave communications for fifth-generation (5G) wireless networks-with a focus on propagation models. IEEE Trans. Antennas Propag. **65**(12), 6213–6230 (2017)
8. Zhou, A., Huang, J., Sun, J., Zhu, Q., Wang, C.X., Yang, Y.: 60 GHz channel measurements and ray tracing modeling in an indoor environment. In: Proceedings of the WCSP 2017, Nanjing, China, December 2017
9. Ji, W., Liu, Y.J., Li, S.D.: Study on the propagation characteristics of indoor millimeter-wave at 37.2 GHz by SBR method. In: Proceedings of the ISAPE, Hangzhou, China, December 2018
10. Zhong, W., Xu, L., Zhu, Q., Chen, X., Zhou, J.: MmWave beamforming for UAV communications with unstable beam pointing. China Commun. **16**(1), 37–46 (2019)
11. Zhu, Q., et al.: A novel 3D non-stationary wireless MIMO channel simulator and hardware emulator. IEEE Trans. Commun. **66**(9), 3865–3878 (2018)

12. Zhu, Q., Wang, Y., Jiang, K., Chen, X., Zhong, W., Ahmed, N.: 3D non-stationary geometry-based multi-input multi-output channel model for UAV-ground communication systems. IET Microw. Antennas Propag. **13**(8), 1104–1112 (2019)
13. Galkin, B., Kibilda, J., DaSilva, L.A.: Backhaul for low-altitude UAVs in urban environments. In: Proceedings of the ICC 2018, Kansas City, MO, USA, July 2018
14. Matolak, D.W., Sun, R.: Air-ground channel characterization for unmanned aircraft systems-Part I: methods, measurements, and models for over-water settings. IEEE Trans. Veh. Technol. **66**(1), 26–44 (2016)
15. Shi, Y., Enami, R., Wensowitch, J., Camp, J.: Measurement-based characterization of LOS and NLOS drone-to-ground channels. In: Proceedings of the WCNC 2018, Barcelona, Spain, April 2018
16. Zhu, Q., et al.: Spatial correlations of a 3-D non-stationary MIMO channel model with 3-D antenna arrays and 3-D arbitrary trajectories. IEEE Wireless Commun. Lett. **8**(2), 512–515 (2019)
17. Cai, X., et al.: An empirical air-to-ground channel model based on passive measurements in LTE. IEEE Trans. Veh. Technol. **68**(2), 1140–1154 (2019)
18. Chen, J., Raye, D., Khawaja, W., Sinha, P., Guvenc, I.: Impact of 3D UWB antenna radiation pattern on air-to-ground drone connectivity. In: Proceedings of the VTC 2018, Chicago, IL, USA, April 2019
19. Cui, Z., Briso-Rodrguez, C., Guan, K., Calvo-Ramrez, C., Ai, B., Zhong, Z.: Measurement-based modeling and analysis of UAV air-ground channels at 1 and 4 GHz. IEEE Antennas Wireless Propag. Lett. **18**(9), 1804–1808 (2019)
20. Chu, X., Briso, C., He, D., Yin, X., Dou, J.: Channel modeling for low-altitude UAV in suburban environments based on ray tracer. In: Proceedings of the EuCAP 2018, London, UK, April 2018
21. Cui, Z., et al.: Analytical modeling of UAV-to-vehicle propagation channels in built-up areas. IEEE Wireless Commun. Lett. (2019)
22. Khawaja, W., Ozdemir, O., Guvenc, I.: UAV air-to-ground channel characterization for mmWave systems. In: Proceedings of the VTC 2017, Toronto, ON, Canada, September 2017
23. Wang, X., Gursoy, M.C.: Coverage analysis for energy-harvesting UAV-assisted mmWave cellular networks. IEEE J. Sel. Areas Commun. **37**(12), 2832–2850 (2019)
24. Yang, G., Zhang, Y., He, Z., Wen, J., Ji, Z., Li, Y.: Machine-learning-based prediction methods for path loss and delay spread in air-to-ground millimetre-wave channels. IET Micro. Antennas Propag. **13**(8), 1113–1121 (2019)
25. Dutta, S., Hsieh, F., Vook, F.W.: HAPS based communication using mmWave bands. In: Proceedings of the ICC 2019, Shanghai, China, July 2019
26. Meng, S., Su, X., Wen, Z., Dai, X., Zhou, Y., Yang, W.: Robust drones formation control in 5G wireless sensor network using mmWave. Wireless Commun. Mob. Comput. **18**(1), 1–7 (2018)
27. Hu, S., Guo, L.X., Liu, Z.Y.: A fast ray-tracing algorithm for rugged terrain. In: Proceedings of the CSQRWC 2019, Taiyuan, China, July 2019
28. ITU-R: Rec. P.1410-2 Propagation data and prediction methods for the design of terrestrial troadband millimetric radio access systems. P Series, Radiowave propagation (2003)
29. Cheng, L., Zhu, Q., Wang, C.-X., Zhong, W., Hua, B., Jiang, S.: Modeling and simulation for UAV air-to-ground mmWave channels. In: Proceedings of the EuCAP20, Copenhagen, pp. 1–5, March 2020