Height-Dependent LoS Probability Model for A2G Channels Incorporating Airframe Shadowing Under Built-up Scenario

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Abstract

The line of sight (LoS) probability is a key factor for the channel modeling of air-to-ground (A2G) communication. However, the existing LoS probability models do not account for the effects of airframe shadowing (AS) and building density, which can cause serious link obstruction and performance loss due to the six-dimensional (6D) mobility and self-body of unmanned aerial vehicle (UAV). In this paper, a new LoS probability model is proposed that considers the AS and building density for different UAV heights. Adding to this, the AS is derived in terms of UAV framework and 6D mobility. Next, the machine learning (ML) based graph neural network (GNN) method is developed to learn the features and structure of the urban environment and predict the LoS probability. Then, the GNN model is trained and evaluated based on the ray tracing (RT) data to establish the relationship between model parameters and UAV heights under the building density and AS factors. The interpretation and explanation of the proposed GNN model and prediction are also discussed in this paper. It is shown from the simulation analysis that the GNN model accurately captures the effects of AS, building height distributions, and UAV heights, with high accuracy compared to the baseline 3GPP, GCM and NYU models.

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The line of sight (LoS) probability is a key factor for the channel modeling of air-to-ground (A2G) communication. However, the existing LoS probability models do not account for the effects of airframe shadowing (AS) and building density, which can cause serious link obstruction and performance loss due to the six-dimensional (6D) mobility and self-body of unmanned aerial vehicle (UAV). In this paper, a new LoS probability model is proposed that considers the AS and building density for different UAV heights. Adding to this, the AS is derived in terms of UAV framework and 6D mobility. Next, the machine learning (ML) based graph neural network (GNN) method is developed to learn the features and structure of the urban environment and predict the LoS probability. Then, the GNN model is trained and evaluated based on the ray tracing (RT) data to establish the relationship between model parameters and UAV heights under the building density and AS factors. The interpretation and explanation of the proposed GNN model and prediction are also discussed in this paper. It is shown from the simulation analysis that the GNN model accurately captures the effects of AS, building height distributions, and UAV heights, with high accuracy compared to the baseline 3GPP, GCM and NYU models.

Introduction: In recent years, unmanned aerial vehicles (UAVs) have become increasingly useful in fields like disaster relief, agriculture, emergency rescue, and are expected to be an emerging technology in future wireless communication systems [1–4]. Unlike terrestrial mobile communications, air-to-ground (A2G) communication operates with three-dimensional (3D) scattering space. Therefore, it is important to consider the communication terminals at different heights and building distributions, including the airframe shadowing (AS) due to six-dimensional (6D) mobility. To ensure reliable communication links between ground users (GU) and UAVs, one way is to increase the probability of a line of sight (LoS) connection [5, 6]. Hence, to better assist A2G mmWave communication networks, it is essential to study the LoS probability model considering the unique features of A2G communications.

In order to improve the reliability of A2G communication channels, limited work has been done so far on LoS probability prediction models. Some researchers utilized accurate digital maps to determine the LoS path through the deterministic method. However, this particular method is only appropriate for a specific scenario and necessitates accurate maps. In this case, stochastic methods [7] are more commonly used and can be broadly classified into measurement-based empirical method, simulation-based empirical method [8], and geometry-based analytical method [9].

The measurement and simulation-based empirical methods establish the stochastic path probability models by analyzing measured and simulation data. There are some representative standard models, including the 5th generation channel model (5GCM) [10], third generation partnership project (3GPP) [11], wireless world initiative new radio (WINNER) II [12] and international telecommunication union-radio (ITU-R) M.21351 models. As obtaining measurement data is complex and costly, several empirical models have been proposed based on simulation data like ray-tracing (RT) and point cloud method. The amount of computations needed and the quality of the original data greatly affect the accuracy of these models.

The LoS probability predictions according to the geometric and electromagnetic wave propagation information of an environment come in the analytical model category. The ITU-R Rec. P.1410 model is a well-known analytical model, which describes the environment stochastically. Researchers have been conducting studies to accurately determine the probability of LoS for dependable A2G communication channels. In [13–15], the authors have proposed an RT-based empirical model with low mean square error, the LoS probability model based on a closed-form empirical LoS probability model using the ITU model. Recently, the application of machine learning (ML) techniques has gained significant attention in channel models and estimation by redefining parameter prediction to accurately find out the internal connection of parameters. The LoS probability model prediction is discussed in [16] using a support vector machine (SVM) at 28 GHz. Similarly, the weighted expectation maximization (WEM) and back-propagation neural network (BPNN) are investigated in [17, 18] for predicting LoS and NLoS paths. However, these proposed models contain several limitations, such as elevation angle, LoS probability blockages because of 6D mobility of UAV known as AS, and practical scenario based building distribution are not considered. In addition, the building structures are assumed to be with same height and equidistant, which is not applicable to a practical environment.

In this paper, a new flexible LoS probability model is introduced based on realistic scenarios. The RT methodology is combined with the virtual scenario concept to conveniently derive AS, building density distribution, and characteristics for a realistic urban scenario such as building height and density and street layout and width, etc. This method offers a cost-effective, accurate, and flexible procedure in comparison to real based scenarios, which typically require substantial amounts of data. The major contributions and novelties of this paper are listed as follows.

1. A new flexible empirical LoS probability model is proposed for A2G mmWave communications that consider the AS due 6D mobility of the UAV and practical scenario based building distribution. The model is compatible with different UAV altitudes and building densities.
2. The interpretation and explanation of the GNN model are presented and model parameters are estimated for LoS probability prediction. The GNN is used to learn the features and structure of the urban environment and classify the LoS and NLoS paths. The proposed GNN model is trained and evaluated via RT simulation data based on the realistic 3D environment.
3. The performance of the model is evaluated in terms of the parameter estimation method under various UAV heights and building densities. The accuracy and generalization of the proposed model are achieved and capture the factors of AS, building distribution, space and width, and UAV heights.

Proposed LoS Probability Model for A2G Channel Scenarios: Figure 1 illustrates the A2G communication scenario utilized for estimating LoS probability. In this scenario, the environment based geometric information is stochastically evaluated. The scenario considers building heights, dispersion, and UAV 6D motion to accurately predict LoS probability. h_{Tx} and d_{Rx} denote UAV height and ground distance between UAV and ground receiver, respectively. Similarly, W, S, and θ_{el} represent building width, building distance, and elevation angle, respectively. The figure depicts UAVs Tx and Rx with MR/MT antennas with ξ_p/ξ_q gaps. Additionally, the Tx and Rx antennas are indicated by A_p^U and A_q^G, respectively. The starting horizontal and vertical distances between Tx and Rx at azimuth and elevation planes are denoted by $\chi(0) = [\chi, 0, 0]$ and $\varsigma(0) = [0, 0, \varsigma]$, respectively. The antenna vectors of A_p^U and A_q^G in local coordination system (LCS) are denoted by $A_p^U = [x_p^U, y_p^U, z_p^U]^T$ and $A_q^U = [x_q^U, y_q^U, z_q^U]^T$ where the $x_p^U = \frac{\mathrm{MT}-2p+1}{2}\xi_p$, $x_p^G = \frac{\mathrm{MR}-2q+1}{2}\xi_q$, $y_p^U = z_p^U = 0$ and $y_p^G = z_p^G = 0$. The $A'^U_p = \Re_o^U A_p^U$, and $A'^G_q = \Re^G A_q^G$ exhibit the antenna vector in ground coordinate system (GCS). Here $\Re_o^U$ depicts the rotation matrix of UAV and $\Re^G$ is the rotation matrix of GU.

Airframe Shadowing and Build-Up Factors: The UAV itself may block the LoS path among UAV and GU due to 6D mobility, which is known as AS. The AS is the main contribution of this letter for the LoS probability

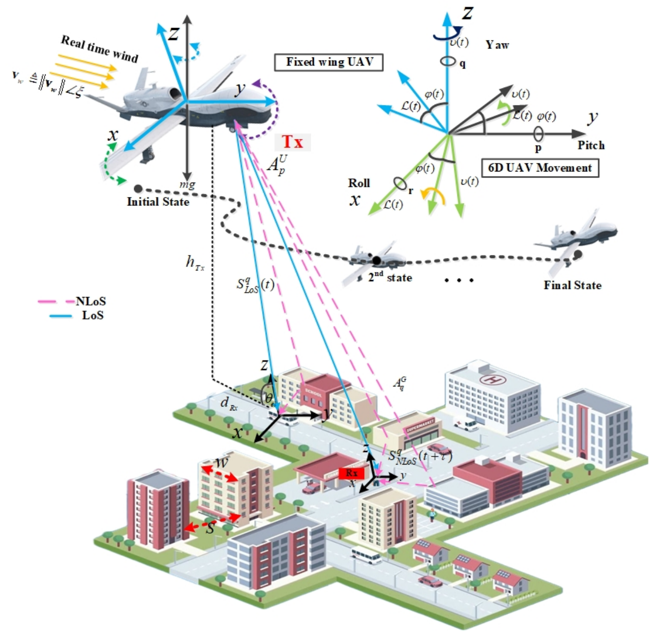

Fig 1 *An illustration of A2G communication channels under built-up scenarios.*

model, which can capture the realistic impact of the UAV 6D mobility on the A2G channel. The angle of departure (AoD) and angle of arrival (AoA) vary in all directions due to the 6D mobility of UAV. Figure 2 explains the main framework of AS and describes that the AoA/AoD and LoS signals can be distorted due to the 6D mobility of UAVs.

To illustrate the AS factor let's consider the UAV is flying over an urban area and communicating with GUs. The AS factor Λ can be modeled as

$$\Lambda(\Phi,\Omega) = k_{sh}.(A_0 + n(\varphi_e - \varphi_0) + \kappa_{i,j}).f(\Phi,\Omega) \tag{1}$$

Where, Φ is further defined as $\Phi = (\nu, \varphi, \mathcal{L})$, k_{sh} is the shadowing constant that depends on the UAV material and design, and $\Omega = (X^L, X^B, w^b, l^b, w^w, v, l^a, o^B, o^L)$, where X^L and X^B denote the leading edge sweep angle and backing edge sweep angle, respectively, w^b, l^b, and w^w denote the width, length of the airframe, and the wingspan of the wing, respectively, v denotes the dihedral angle, l^a denotes the length of the antenna, o^B and o^L denotes the offset distance from the origin. φ_0 denotes the minimum roll angle, A_0 is used for the AS measured at φ_0, n (dB/rad) is the shadowing increasing rate, and $\kappa_{i,j}$ is the zero mean Gaussian random variable. The normal $N'U$ and signal path vector between the UAV antenna and the ground receiver antenna is written as

$$N'U = \begin{bmatrix} -\cos(\phi_e)\sin(\alpha_e)\sin(\hat{\psi}_t) + \sin(\phi_e)c(\hat{\psi}_t) \\ \cos(\phi_e)\sin(\alpha_e)cos(\hat{\psi}_t) + \sin(\phi_e)\sin(\hat{\psi}_t) \\ \cos(\phi_e)\cos(\alpha_e) \end{bmatrix} \tag{2}$$

The distance from the edge of the UAV to the LoS path is expressed as

$$\chi_d^U = \exp||\Lambda.\Re_o^U||\sin\theta \tag{3}$$

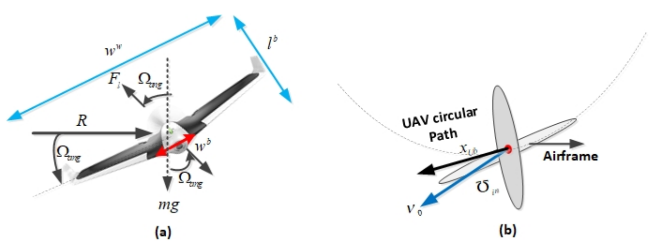

Fig 2 *(a) Steady turn with bank angle and (b) circular movement with angle of incidence.*

Where $\Re_o^U$ is the rotation matrix, which is a function of the UAV attitude angles roll ν, pitch φ, and yaw $\mathcal{L}$. Roll is an x-axis rotation that causes angular acceleration due to torque defined by angle $\nu(t) \in (-\pi, \pi)$. Pitch and yaw represent y and z axis rotations which are denoted by $\varphi(t) \in (-\pi, \pi)$ and $\mathcal{L}(t) \in (0, 2\pi)$, respectively. The rotation matrix $\Re_o^U$ is defined in (4). The trajectory radius of UAV R^U is denoted as $R = \nu/(gtan\varphi_e)$, where the g is the gravitational constant and ν is the tangential speed. At the angle of incidence κ_e the UAV lift force is described as

$$F_l = 1/2g\nu^2 s_w \Upsilon_L \tag{5}$$

Where the Υ_L is the lift coefficient, s_w is the wing area of the UAV. This shows that considering the AS, UAV heights, and built-up scenario factors makes the LoS probability for A2G channels more practical.

The built-up scenario is another key factor that can distort the direct LoS path among the A2G channel. The built-up scenario is described by three parameters $\varsigma_B \in \{\alpha, \beta, \gamma\}$, where α is the area of the covered building in percent, β explains the number of buildings per unit area and random building height with probability density function (PDF) is denoted by γ. The PDF is evaluated in terms of γ, which is given as

$$P(h_a) = \frac{h_a}{\gamma^2}\exp(\frac{-h_a^2}{2\gamma^2}) \tag{6}$$

The building width W and space among buildings S mentioned in Figure 1 are equal to $W = 1000\sqrt{\alpha/\beta}$ and $S = (1000/\sqrt{\beta})(1-\sqrt{\alpha}))$, respectively.

New LoS Probability Equation Description: To simplify the LoS probability model, the authors in [4, 20] have presented the model as

$$P_{LOS}^U(h_u, d_{RX}) = \prod_{n=0}^{M}\left[1 - \exp\left(-\frac{\left[h_b - \frac{(n+0.5)(h_b-h_u)}{M+1}\right]^2}{2c^2}\right)\right] \tag{7}$$

$P_b(\omega, h)\mathbb{P}(\text{blockage} \mid \omega, h)$

$$= e^{-\rho d_R x^2(\omega)} + \sum_{i=2}^{N(\omega)}\left(\prod_{j=1}^{i-1}(1 - e^{-\rho d_R x})\right)e^{-\rho d_R x^2(\omega)} \tag{8}$$

Where the $N = \frac{d_{\mathrm{Rx}}\sqrt{\alpha\beta}}{1000} - 1$, d_{Rx} is used for the horizontal distance between Rx and UAV and c is related to the transmission environments. These models are intended for estimating A2G LoS probability, which takes into account different UAV heights. The models also adhered to the ITU LoS models. However, these models have a number of limitations based on current practical scenarios. For LoS probability among Tx and Rx, perpendicular buildings of the same size are considered. In other words, no alternate buildings or structures are proposed, nor is the AoD assumed. Additionally, the LoS probability formulation produces a product, which restricts its applicability.

In this study, we conducted a more comprehensive examination of the formulation for LoS probability. It involves the Rayleigh distribution H, corresponding to the building height distributions, along with a scaling factor γ. Additionally, we consider AS with built-up scenarios and altitudes, as well as angle of elevation and AoD. The updated suggested model for evaluating LoS probability is discussed in (9), where D_1, D_2, D_3 represent the breakpoints distance, decay parameter, and balance parameter, respectively, depending on the UAV heights h_{Tx}, AS factor Λ, and ζ_B to ensure excellent model performance. A New York University (NYU) LoS probability model is proposed in [19] based on the 3GPP LoS probability model by introducing the square index. The 3GPP and NYU models, on the other hand, have good fitness with measured results only within a small range of altitude (about ten meters). The d_{Rx} parameter specifies the distance between the receiver and the transmitter, while the h_{Tx} parameter specifies the height of various regions from the UAV to the GU. In (9), the shadowing effect due to AS and built-up scenarios are added to make the LoS probability model more realistic and accurate. Current research models were lacking in these insights. The enhanced and accurate LoS probability can be obtained by investigating the combined structure of buildings and the AS to ensure seamless connectivity between GU and UAV.

$$
\begin{bmatrix} \cos\varphi\cos\mathcal{L} & \sin\varphi\sin\nu\cos\mathcal{L}-\sin\mathcal{L}\cos\nu & \sin\varphi\cos\mathcal{L}\cos\nu+\sin\mathcal{L}\sin\nu \\ \sin\mathcal{L}\cos\varphi & \sin\varphi\sin\mathcal{L}\sin\nu+\cos\mathcal{L}\cos\nu & \sin\varphi\sin\mathcal{L}\cos\nu-\sin\nu\cos\mathcal{L} \\ -\sin\varphi & \sin\nu\cos\varphi & \cos\varphi\cos\nu \end{bmatrix} \tag{4}
$$

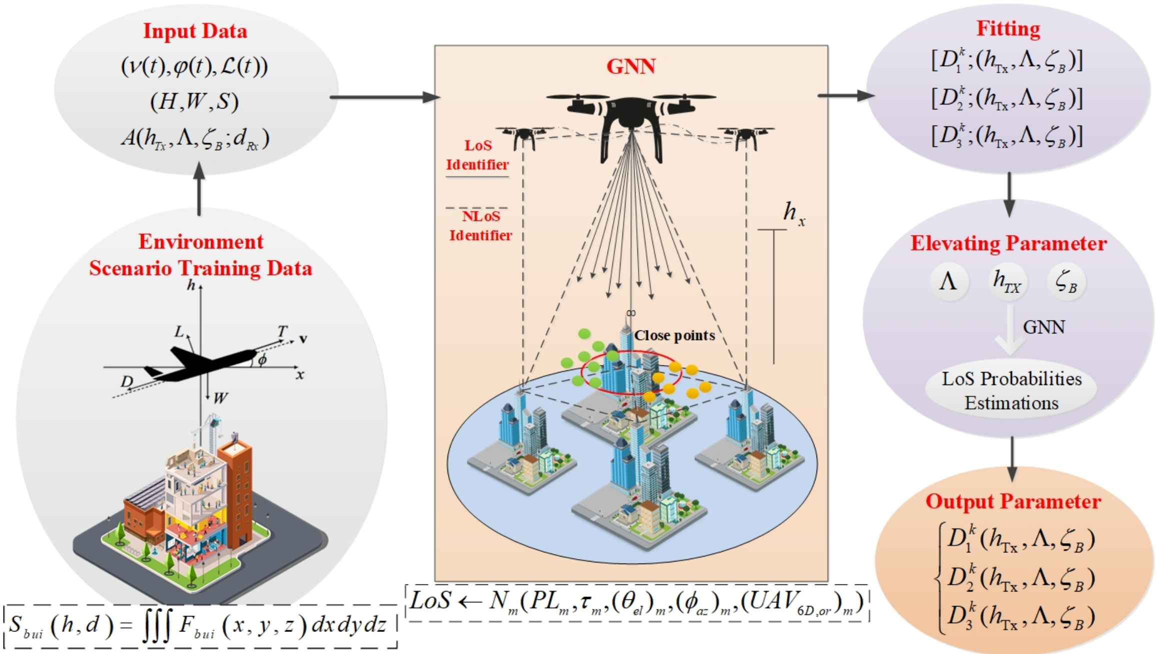

Fig 3 *Flowchart of model parameter computation.*

Machine Learning Based Model Parameters:

Overview of Model Parameter Computation: The impressive capabilities of ML methods for flexible, reliable, and comprehensive data structures are discussed in [14, 15]. Figure 3 depicts the process of parameter estimation using ML. Because field measurements for A2G transmission are difficult and expensive, RT simulation data is used as training data in this paper. The proposed model parameter estimation techniques, on the other hand, can be applied to field measured data.

The presented model's procedure begins with the classification of the input data into LoS and NLoS components. The graph neural network (GNN) algorithm is used for this purpose. The $P_{LoS}^{j,k}$ with j^{th} distance and k^{th} height represents the proportion of the total path and LoS path. The LoS probability at a given height and distance is written as $(P_{LoS}^{j}; d_{Rx}^{j})$, $j = 1, 2, 3.....99$. To estimate the LoS probability of a specific area and distance, the building height and distance distribution, 6D UAV orientation at different heights with AS, and angle of elevation θ_{el} are used. Following that, the least squares (LS) methodology is used to fit D_1, D_2 and D_3 with $(h_{\mathrm{Tx}}, \Lambda, \zeta_B)$ at m different altitudes to obtain the training sets $[D_1^k; (h_{\mathrm{Tx}}, \Lambda, \zeta_B)]$, $[D_2^k; (h_{\mathrm{Tx}}, \Lambda, \zeta_B)]$, $[D_3^k; (h_{\mathrm{Tx}}, \Lambda, \zeta_B)]$. In the final step, a subset of the data set is chosen to test the GNN training procedure and obtain the $(h_{\mathrm{Tx}}, \Lambda, \zeta_B)$-dependent parameters.

Instead of field measurements, the RT simulation now provides high-performance computing and is widely used in channel modeling and verification. The RT technique is based on electromagnetic wave propagation, which includes the processes of direction, reflection, and diffraction. If there is no obstruction between Tx and Rx and the electrical field intensity is high, the direct ray or LoS path is attained. In this paper, a typical urban scenario is proposed, with the statistical parameters ψ chosen according to [10]. For building distributions with random heights and street distances, the Rayleigh distribution method is used.

LoS and NLoS Classification and Parameter Estimation: RT simulation data yields channel metrics including angle of elevation, AoD, delay, path loss, built-up scenario, and 6D UAV mobility. This study uses the GNN mechanism to determine LoS or NLoS data. Pre-labeled training and input data are measured for Euclidean distance to construct this algorithm. Then the nearest points to fresh data are chosen. The data will be LoS if the proportion is maximal. The LoS probability is calculated versus heights, distances, AS due to 6D UAV mobility and built-up scenario.

In addition, the Euclidean distance gives different ranges for different elements; thus, to address this issue, the linear normalization method is used, which is written as

$$
x' = \frac{x - min(x)}{max(x) - min(x)} \tag{10}
$$

where x' denotes the normalized value and x is the input value. The distance for newly input data in terms of different characteristic parameters is calculated in (11), where the parameters PL_u, τ_u, $\theta_{el,u}$ and AoD_u are applied for newly added data, while the above elements with term v present the already labeled data in the GNN network.

In the proposed model to train the GNN network and estimate the average LoS probability, 1000 sets of simulation data are applied at different regions and distances. The data matrix for parameter like τ, PL, θ_{el} and AoD is categorized into training set (80%) and validation set (20%). The error and system performance can be validated and tested after training the network. Judgment error, representing the relation between incorrect judgments and the validated datasets, is formulated as

$$
Jug_{error} = N_i / N_i' \tag{12}
$$

where N_i' is the total number of sets and N_i defines the incorrect judgment.

Following the classification of LoS and NLoS, parameters are further evaluated through the GNN method in terms of d_{Rx}, h_{Tx}, Λ, and

$$
P_{\mathrm{LoS}}(d_{\mathrm{Rx}}, h_{\mathrm{Tx}}, \Lambda, \zeta_B) = \min\left(\frac{D_1(h_{\mathrm{Tx}}, \Lambda, \zeta_B)}{d_{\mathrm{Rx}}}, 1\right) \cdot \left[1 - \exp\left(-\frac{d_{\mathrm{Rx}}}{D_2(h_{\mathrm{Tx}}, \Lambda, \zeta_B)}\right)\right] + \exp\left(-\frac{d_{\mathrm{Rx}}}{D_2(h_{\mathrm{Tx}}, \Lambda, \zeta_B)}\right)^{D_3(h_{\mathrm{Tx}}, \Lambda, \zeta_B)} \tag{9}
$$

$$\Gamma_{new} = \sqrt{(PL_u - PL_v)^2 + (\tau_u - \tau_v)^2 + (\theta_{el,u} - \theta_{el,v})^2 + (AoD_u - AoD_v)^2} \quad (11)$$

Table 1. List of simulation parameters.

Used parameter	Size
Building density(/km^2)	750, 500, 300, 300
α, β, γ	0.8, 300, 20
Transmitter height	5 to 2000 m
Building height distribution	Rayleigh
Building location distribution	random distribution
Receiver height	2 m
Rx distance	0 to 1000 m
Antenna Type	Unidirectional
Building width and spacing	random
Carrier frequency	28 GHz
UAV geometry (length, width, and height)	2, 1, and 0.5 meters
UAV orientation (roll, pi, yaw)	10^0, 20^0 and 30^0

ζ_B. The LS fitting is employed to get the data set $[D_1^k; (h_{\mathrm{Tx}}, \Lambda, \zeta_B)]$, $[D_2^k; (h_{\mathrm{Tx}}, \Lambda, \zeta_B)]$, $[D_3^k; (h_{\mathrm{Tx}}, \Lambda, \zeta_B)]$. In order to obtain the relation among heights, UAV orientation, and model parameters, the GNN is trained and evaluated with an 8:2 ratio. The GNN architecture contains multiple layers and is expressed as

$$h_j^{(l+1)} = \sigma\left(\sum_{i=1}^{N} A_{ij}^{(l)} h_i^{(l)} W_{ij}^{(l)} + b_j^{(l)}\right) \quad (13)$$

$$P_{\mathrm{LoS}}^{(m,n)} = f((D_1^k; (h_{\mathrm{Tx}}, \Lambda, \zeta_B), D_2^k; (h_{\mathrm{Tx}}, \Lambda, \zeta_B), D_3^k; (h_{\mathrm{Tx}}, \Lambda, \zeta_B)) \quad (14)$$

where $h_j^{(l)}$ is the hidden state of node j in layer l, $A_{ij}^{(l)}$ is the adjacency matrix, $W_{ij}^{(l)}$ is the weight matrix, $b_j^{(l)}$ is the bias, σ is the activation function, and f is the final output function. The best fitting results can be obtained by minimizing the loss function L_{ftn}, which is defined as

$$L_{ftn} = \sqrt{\frac{1}{N}\sum_{n=1}^{N}(d_k(h_{\mathrm{Tx}}, \Lambda, \zeta_B)^n - d_k^n)^2} \quad (15)$$

Simulation Results: The accuracy and effectiveness of the LoS probability model based on different heights and AS are assessed in this section. Based on the measured data, the standard LoS probability models such as 3GPP, ITU-R, GCM, and NYM have provided empirical models, which are generally consistent with the real situation. However, they have shortcomings like long testing cycles, high cost of measuring equipment, and limited test scenarios. To overcome these shortcomings of measurement, the composite RT technology under urban, including virtual scenario construction, is applied in this paper. The aim of creating a virtual based built-up area is to replicate the real scenario parameters (α, β, γ) characteristics than the current model. The list of parameters used for simulation analysis with their descriptions is presented in Table 1.

The comparison with the reference models [9, 10] and RT-based models are analyzed to demonstrate the validity of the presented LoS probability model. Figure 4 shows how the LoS probability estimation considering AS improves the realism of scenario prediction. The results also show that the prediction of RT data and LoS probability supports the reference model. Figure 4 also investigates the correlation between the standard models like 3GPP, GCM, and NYU, and the proposed model is satisfactory by applying the GNN algorithm and considering the AS built-up factors.

Our presented model is also capable of high altitudes as the evaluation is performed at 700 m height, determining that the prediction results

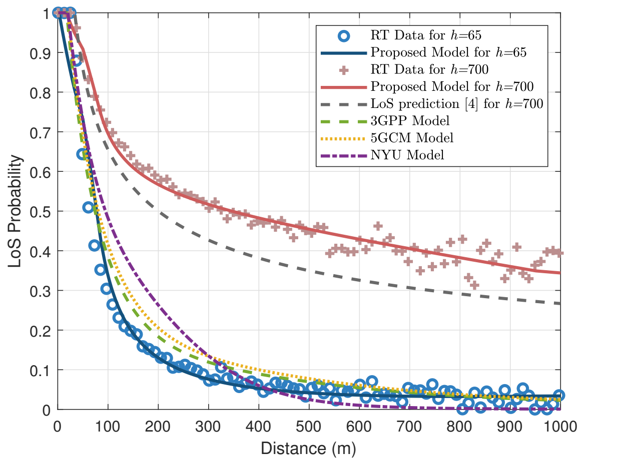

Fig 4 *LoS probability of proposed and previous models.*

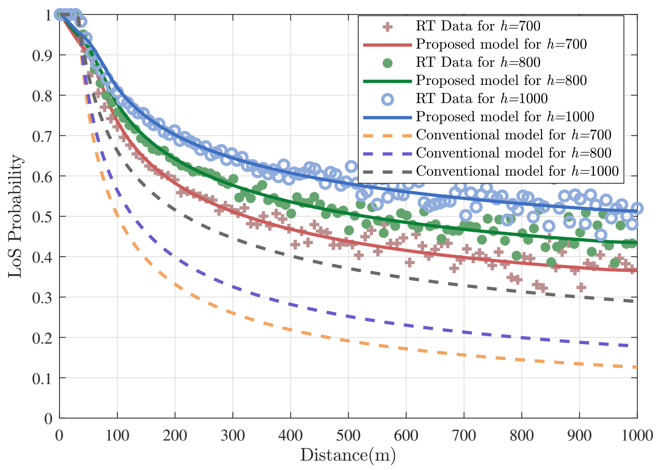

Fig 5 *Comparison of LoS probability at different heights.*

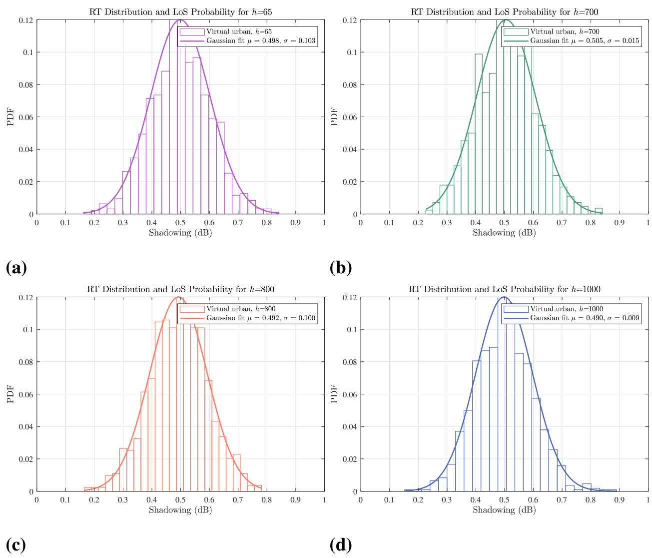

Fig 6 *PDF of LoS probability at different heights of (a) 65 m (b) 700 m (c) 800 m and (d) 1000 m.*

become more practical by considering the AS and built-up scenario factors. The comparison of the proposed model with the existing models in Figure 4 shows that the LoS probability prediction is more accurate.

Figure 5 depicts the validation of RT data with different heights, such as 700 m, 800 m, and 1000 m, which are chosen based on the random distribution of buildings. Furthermore, the comparison investigations are also shown in Figure 5 based on managed AS and without managed AS factor for 700 m, 800 m, and 1000 m altitudes. This explains that the UAV self-body has a key contribution in blocking the LoS path among aerial and ground users. The simulation outcomes also prove that with minimum heights, the building distribution density and AS factors have a significant impact on LoS probability.

For these altitudes, the 0.6 threshold range is chosen, and it can be seen from Figure 5 that the LoS probability model with managed AS factor has outcomes within the threshold. In addition, there is good consistency between the RT data and the proposed model. The PDF of shadowing and corresponding Gaussian distribution fitting results are shown in Figure 6, which shows a good consistency for LoS probability estimation and RT distribution.

Conclusion: In this paper, the understanding of LoS probability has been advanced for the A2G mmWave communication network. A novel LoS probability model has been introduced that integrates critical factors like AS due to 6D mobility, built-up scenarios, and different heights of UAV. A method for combining RT technology with virtual scenarios has been proposed. An ML-based GNN model has been developed, leveraging its capability to learn the features and structures of urban environments. The model has predicted unique LoS probability by considering AS, built-up scenario, and varying heights of UAV. The GNN model has been trained and tested against RT data to establish a strong link between model parameters and UAV heights under AS and built-up scenario factors. The simulation results have shown that the proposed model is superior at representing the complicated effects of AS, built-up scenarios, and UAV altitudes. The accuracy of the GNN model is comparable to that of the baseline 3GPP, GCM, and NYU models, providing a more thorough insight into the A2G communication channel. In order to improve the accuracy, our future efforts will focus on performing more real-world testing scenarios, thoroughly examining additional important elements, and extending the model's applicability to new fields.

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References

1. Mao, K., Zhu, Q., Song, M., Li, H., Ning, B., et al.: Machine-learning-based 3-D channel modeling for U2V mmWave communication. *IEEE Internet of Things Journal* **9**(18), 17592-17607 (2022)
2. Liu, J., Yu, J., Niyato, D., Zhang, R., Gao, X., et al.: Covert ambient backscatter communications with multi-antenna tag. *IEEE Transactions on Wireless Communications* **22**(9), 6199-6212 (2023)
3. Shi, M., Yang, K., Niyato, D., Yuan, H., Zhou, H., et al.: The meta distribution of SINR in UAV-assisted cellular networks. *IEEE Transactions on Communications* **71**(2), 1193-1206 (2023).
4. Mohammed, I., Gopalam, S., Collings, J.B., Hanly, V.: Closed form approximations for UAV line-of-sight probability in urban environments. *IEEE Access* **11**, 40162–40174 (2023)
5. Zhong, W., Xu, L., Zhu, Q., Chen, X., Zhou, J.: MmWave beamforming for UAV communications with unstable beam pointing. *China Communications* **16**(1), 37–46 (2019)
6. Zhu, Q., Mao, K., Song, M., Chen, X., Hua, B., et al.: Map-based channel modeling and generation for U2V mmWave communication. *IEEE Transactions on Vehicular Technology* **71**(8), 8004–8015 (2022)
7. Pan, J., Ye, N., Yu, H., Hong, T., Rubaye, S.A., et al.: AI-driven blind signature classification for IoT connectivity: a deep learning approach. *IEEE Transactions on Wireless Communications* **21**(8), 6033-6047 (2022).
8. Rinaldi, F., Maattanen, H., Torsner, J., Pizzi, S., Andreev, S., et al.: Broadcasting services over 5G NR enabled multi-beam non-terrestrial networks. *IEEE Transactions on Broadcasting* **67**(1), 33–45 (2021)
9. Townend, D., Walker, S. D., Sharples, A., Sutton, A.: Urban line-of sight probability for mmWave mobile access and fronthaul transmission hubs. In: Proc. EuCAP'21, pp. 1–5, Dusseldorf, Germany (2021)
10. 5GCM.: 5G channel model for bands up to 100 GHz. (2016)
11. 3GPP TR. 38.901.: Study on channel model for frequencies from 0.5 to 100 GHz. V17.0.0 (2022)
12. IST-4-027756 WINNER II.: D1.1.2 V1.0 WINNER II channel models. (2017)
13. ITU-R.: Guidelines for evaluation of radio interface technologies for IMT-advanced. *Geneva, Switzerland, Rep.*, ITU-R M.2135-1 (2009)
14. Al-Hourani, A., Kandeepan, S., Lardner, S.: Optimal LAP altitude for maximum coverage. *IEEE Wireless Communications Letters* **3**(6), 569–572 (2014)
15. Pang, M., Zhu, Q., Lin, Z., Bai, F., Tian, Yue., et al.: Machine learning based altitude-dependent empirical LoS probability model for air-to-ground communications. *Front Inform Technol Electron Eng* **23**, 1378–1389 (2022)
16. Gapeyenko, M., Moltchanov, D., Andreev, S., Robert W.H.: Line-of-sight probability for mmWave-based UAV communications in 3D urban grid deployments. *IEEE Transactions on Wireless Communications* **20**(10), 6566-6579 (2021)
17. Zhang, Q., Saad, W., Bennis, M., Li, X., Debbah, M., et al.: Predictive deployment of UAV base stations in wireless networks: Machine learning meets contract theory. *IEEE Transactions on Wireless Communications* **20**(1), 637-652 (2021)
18. Zhu, Q., Bai, F., Pang, M., Li, J., Zhong, w., et al.: Geometry-based stochastic line-of-sight probability model for A2G channels under urban scenarios. *IEEE Transactions on Antennas and Propagation***70**(7), 5784-5794 (2022)
19. Samimi, M. K., Rappaport, T.S., MacCartney, G.R.: Probabilistic omnidirectional path loss models for millimeter-wave outdoor communications. *IEEE Wireless Communications Letters* **4**(4), 357-360 (2015)
20. Wang, Z., Zheng, J.: Performance analysis of location-based base station cooperation for cellular-connected UAV networks. *IEEE Transactions on Vehicular Technology* **72**(11), 14787-14800 (2023)