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Machine learning based altitude-dependent empirical LoS probability model for air-to-ground communications

Key words: Line-of-sight probability model; Air-to-ground channel (A2G); Machine learning; Ray tracing

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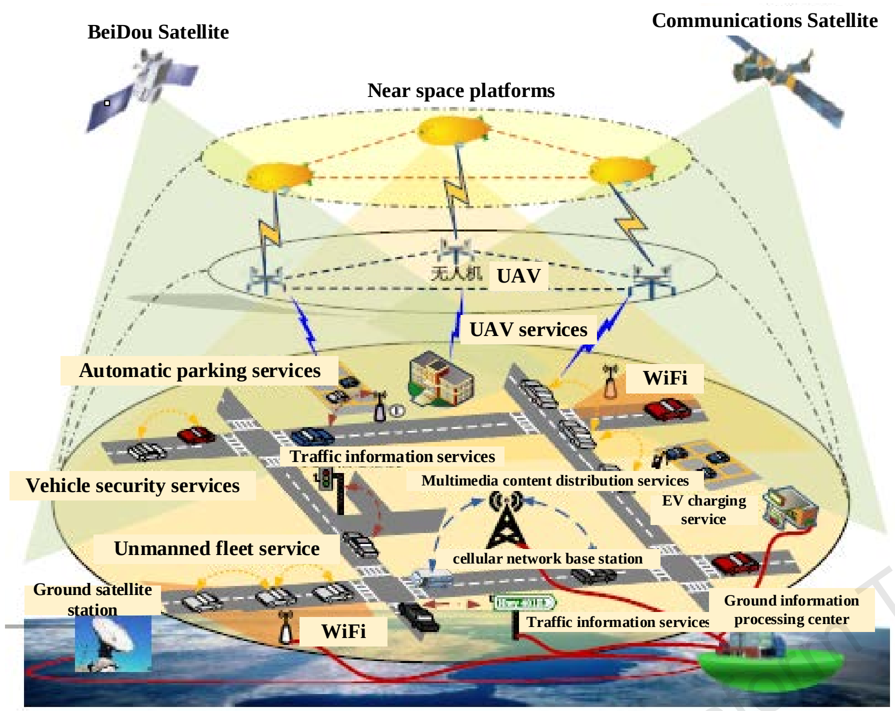
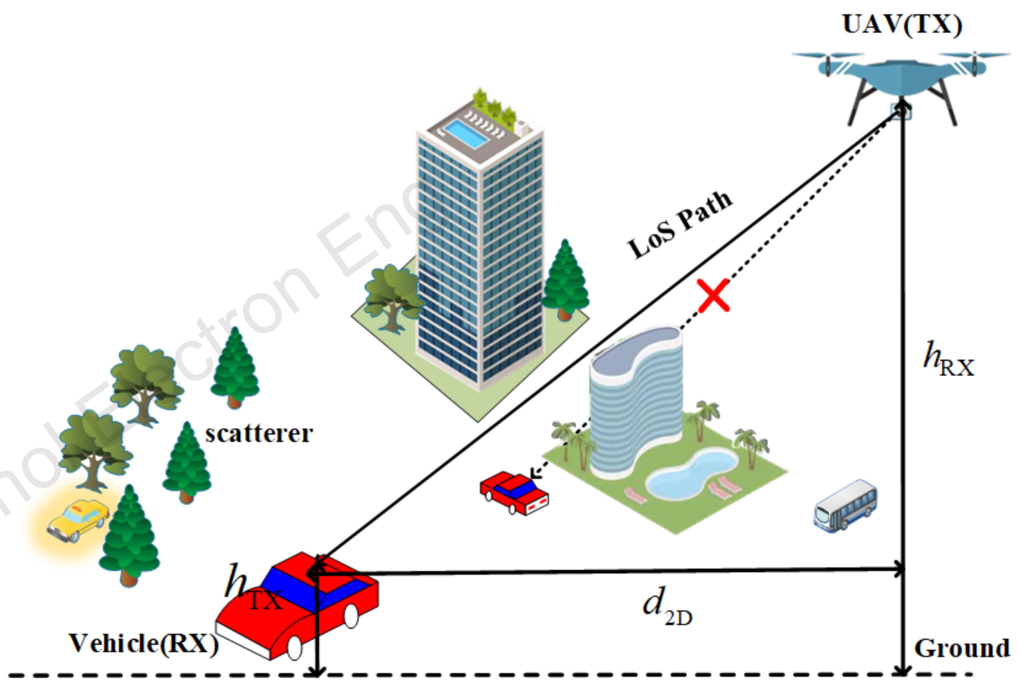
Motivations





- UAV: high mobility, easy operation, easy control
- A2G communication in the communication integrated network
- A2G communication involves 3D scattering space
- The communication altitude needs to be considered
- The connectivity and reliability of A2G mmWave signal transmission depend on the existence of the LoS path

■ **To design and optimize A2G mmWave communication systems, altitude-dependent LoS probability models are necessary.**

Motivations (Cont'd)

■ **Existing stochastic LoS probability models**

- **Analytical models (ITU-R. 1410, Al-Hourani's model…)**

  Improve accuracy - detailed geometry information ❌

- **Measurement-based empirical models (3GPP, WINNER, …)**

  Field-measurement - complex and costly ❌

- **Simulation-based empirical models [NYU** (below dozens of meters), **HAP** (over several kilometers), **Lee's model** (terrestrial communications), …]

…

cannot be employed in air-to-ground (A2G) communication ❌

RT-based empirical model

■ **Existing parameter estimation methods**

- **minimum mean square error (MMSE)**
- **least square (LS) …**

Relationship is uncertain - Ineffective ❌

■ **ML-based parameter estimation**

- ***K*-nearest neighbors (KNN)**
- **Artificial neural network (ANN) …**

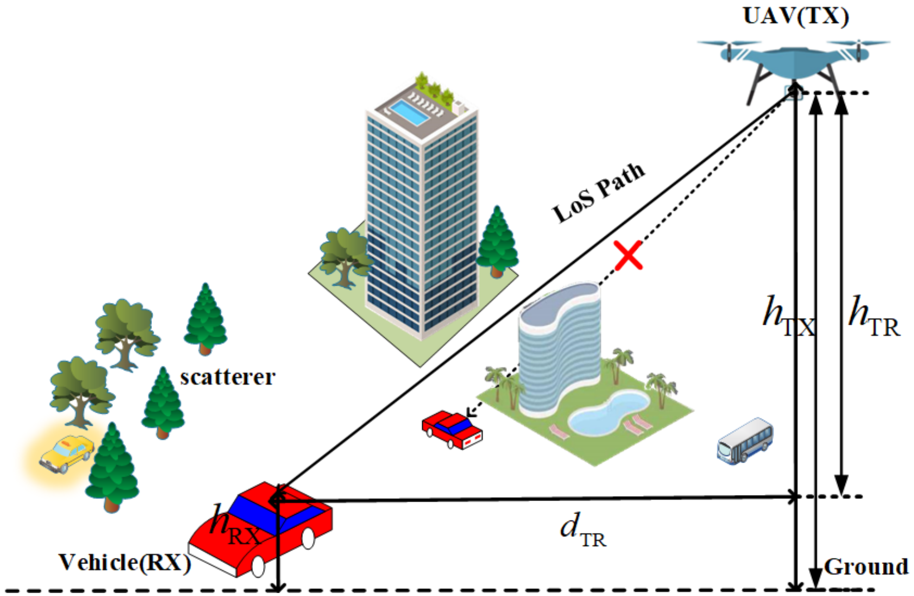
Internal connection of parameters - accurate

Motivation

■ **Multi-height empirical LoS probability models**

■ **Machine learning based model-parameter estimation methods**

New multi-height empirical LoS probability model



3GPP LoS probability model

(18 m) Breakpoint distance at which the LoS probability is no longer equal to 1

$$P_{\mathrm{LoS}}^{\mathrm{3GPP}}\left(\boxed{d_{\mathrm{TR}}}\right)=\min\left(\frac{\boxed{D_1}}{d_{\mathrm{TR}}},1\right)\cdot\left[1-\exp\left(-\frac{d_{\mathrm{TR}}}{\boxed{D_2}}\right)\right]+\exp\left(-\frac{d_{\mathrm{TR}}}{D_2}\right)$$

Distance between RX and TX

A decay parameter (36 m)

New York University LoS probability model

$$P_{\mathrm{LoS}}^{\mathrm{NYU}}\left(d_{\mathrm{TR}}\right)=\left[\min\left(\frac{D_1}{d_{\mathrm{TR}}},1\right)\left[1-\exp\left(-\frac{d_{\mathrm{TR}}}{D_2}\right)\right]+\exp\left(-\frac{d_{\mathrm{TR}}}{D_2}\right)\right]^2$$

New LoS probability model

$$P_{\mathrm{LoS}}\left(d_{\mathrm{TR}},\boxed{h_{\mathrm{TR}}}\right)=\left\{\min\left(\frac{\boxed{D_1\left(h_{\mathrm{TR}}\right)}}{d_{\mathrm{TR}}},1\right)\cdot\left[1-\exp\left(-\frac{d_{\mathrm{RX}}}{\boxed{D_2\left(h_{\mathrm{TR}}\right)}}\right)\right]+\exp\left(-\frac{d_{\mathrm{TR}}}{\boxed{D_2\left(h_{\mathrm{TR}}\right)}}\right)\right\}^{\boxed{D_3\left(h_{\mathrm{TR}}\right)}}$$

Height of TX

Influence of altitude

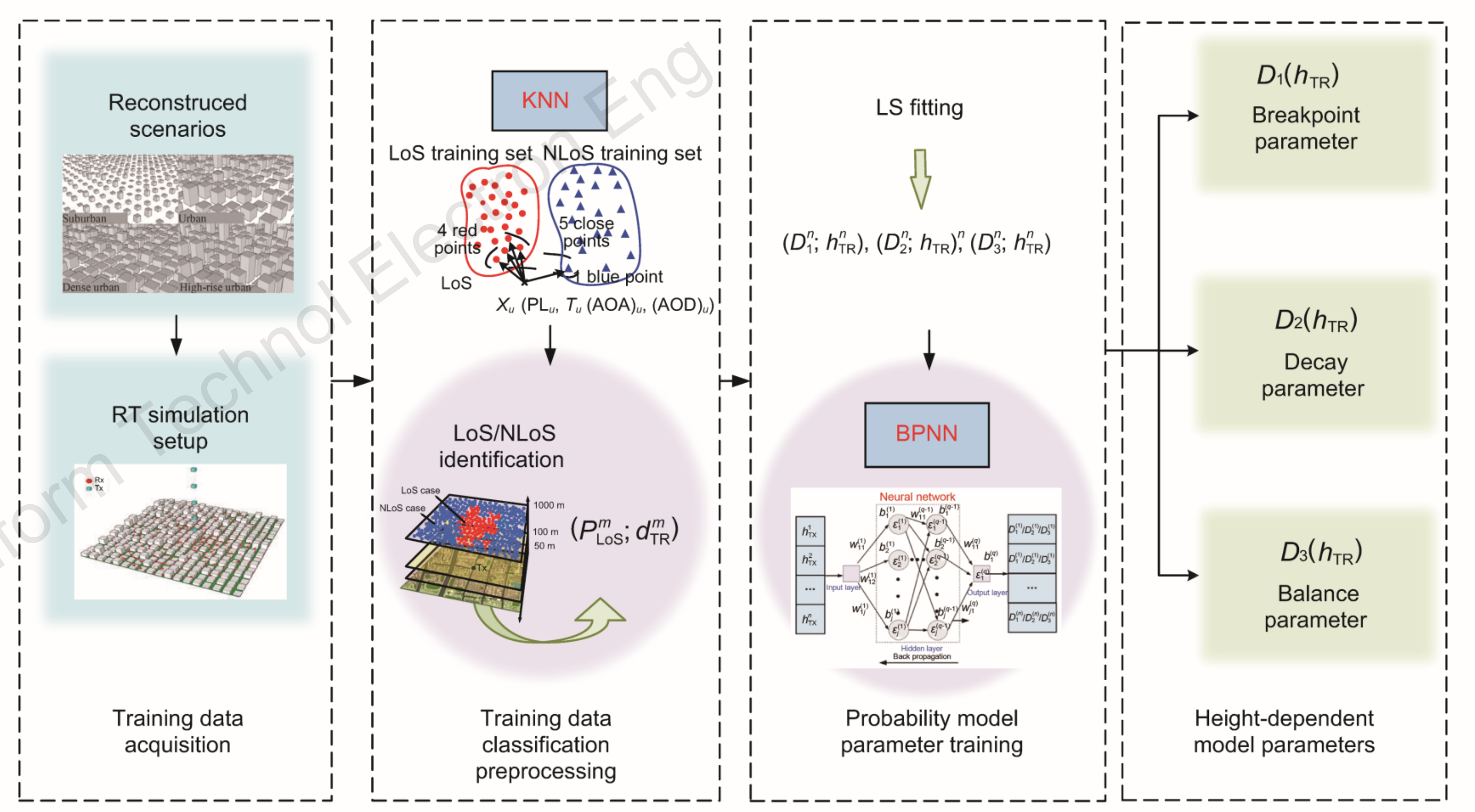
New parameter (balance)

Parameter estimation procedure

■ Flowchart of parameter estimation

Steps:

- ➢ **Scenarios reconstruction**
- ➢ **RT technology (KNN training data)**
- ➢ **KNN-based LoS/NLoS identification**
- ➢ **LS fitting (BPNN training data)**
- ➢ **BPNN-based parameter training**
- ➢ **Introduce the altitude factor**



Flowchart of parameter estimation

RT-based training data acquisition

■ Scenario reconstruction

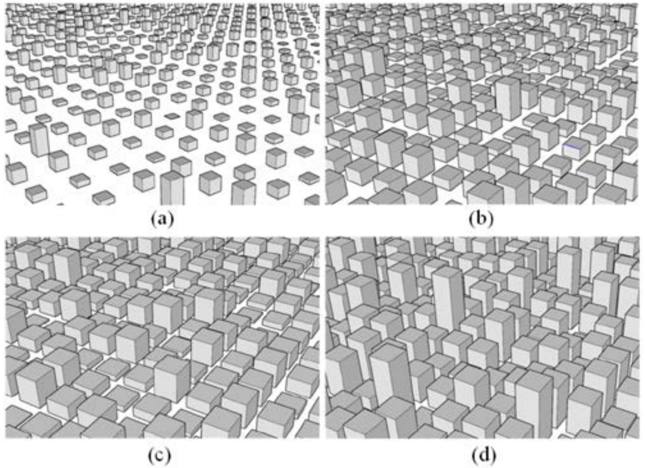


Fig. 2 An illustration of reconstructed scenarios: (a) suburban; (b) urban; (c) dense urban; (d) high-rise urban

Scenario parameters

Parameter	Value
Buildings area ratio	0.3
Number of buildings (/km^2)	500
Building height	Rayleigh distribution (15 m)
Building width	40.8 m
Street spacing	16.91 m

■ RT simulation

Simulation parameters

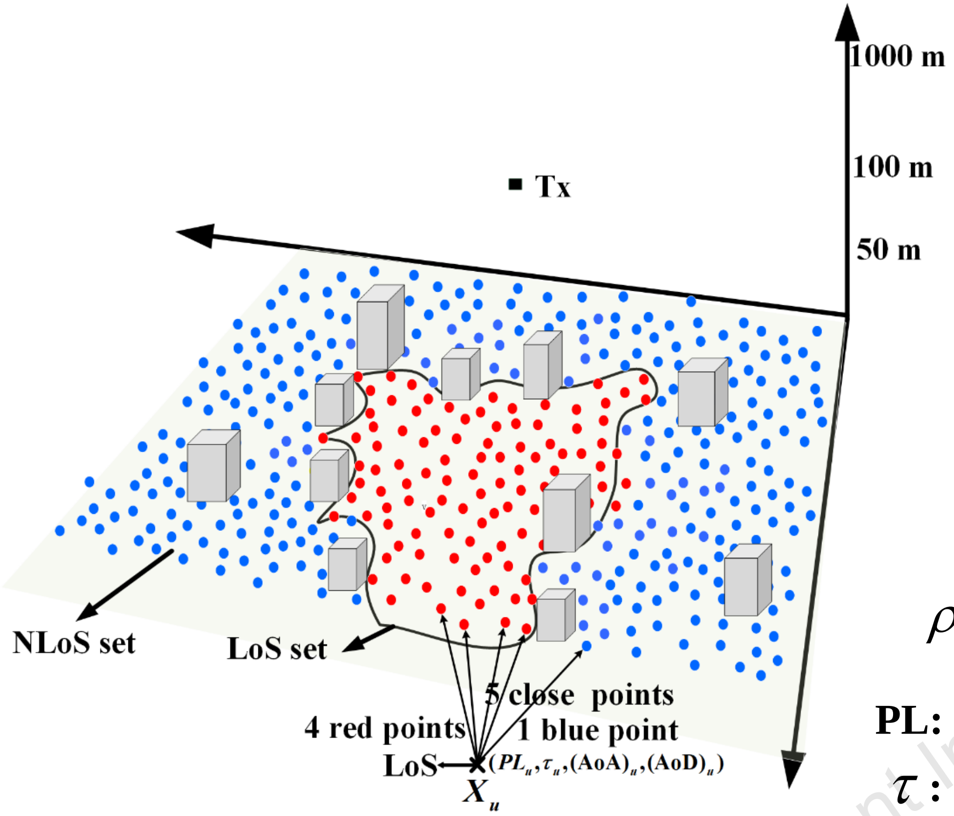
Parameter	Value
Frequency	28 GHz
Bandwidth	500 MHz
Antenna type	Omnidirectional
TX height (interval)	5~1005 m (10 m)
RX height	2 m
RX distance	0~1000 m

■ RT channel characteristic computation

- **Decomposing the ray source**
- **Tracking rays**
- **Intersection operation**

➢ **Calculating the channel characteristics (path loss, delay, angles of arrival, angles of departure)**

KNN-based LoS/NLoS classification



Flowchart of parameter estimation

Linear normalization method

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

Input values of four features   The normalized value

Euclidean distance calculation formula

$$\rho = \sqrt{\left(\boxed{PL_u} - \boxed{PL_v}\right)^2 + \left(\boxed{\tau_u} - \boxed{\tau_v}\right)^2 + \left[\boxed{(AoA)_u} - \boxed{(AoA)_v}\right]^2 + \left[\boxed{(AoD)_u} - \boxed{(AoD)_v}\right]^2}$$

PL: path loss   **AoA: angles of arrival**   **□: new input data**

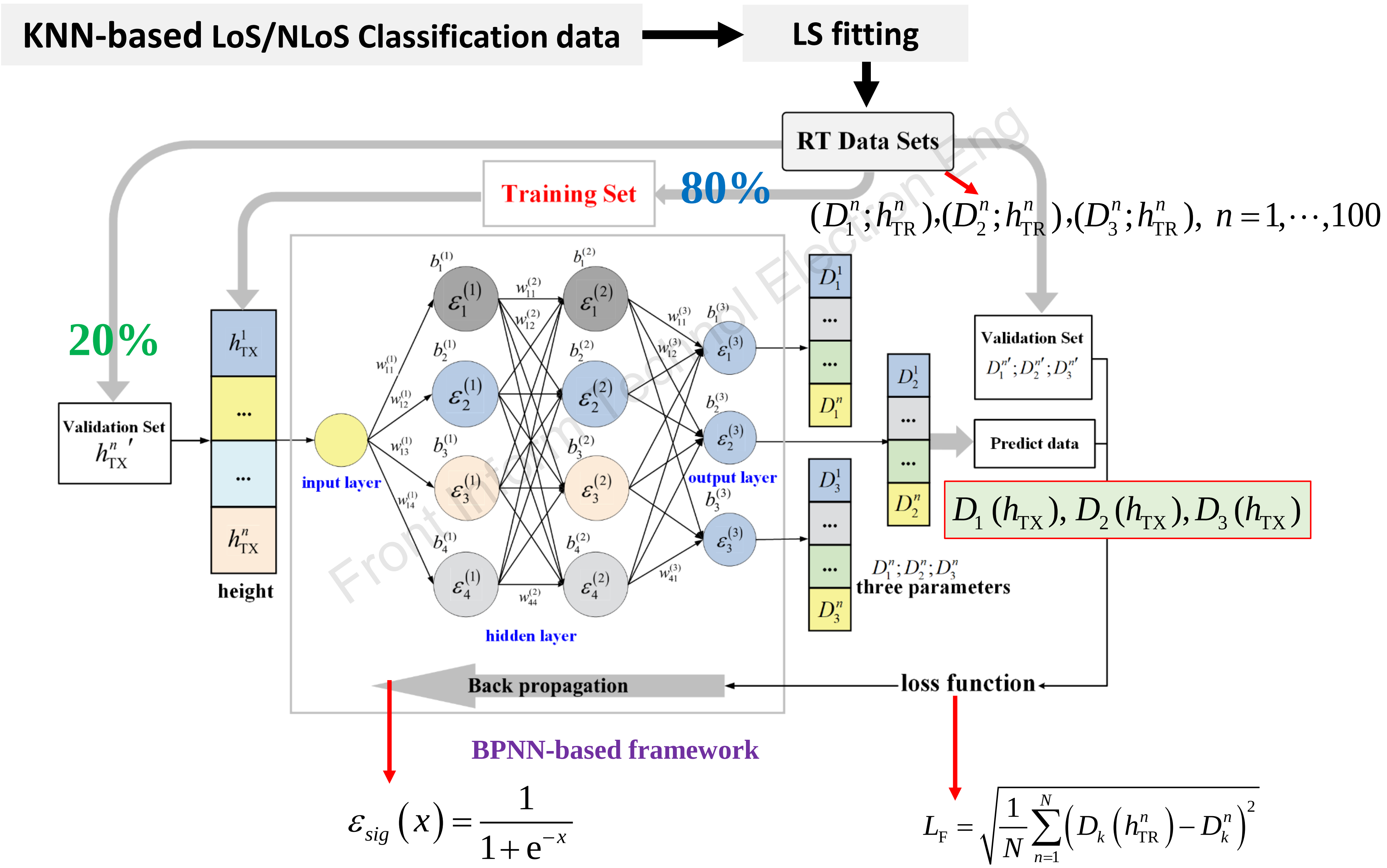
τ : delay   **AoD: angles of departure**   **□: v^{th} labeled data in the KNN network**

Identify LoS/NLoS

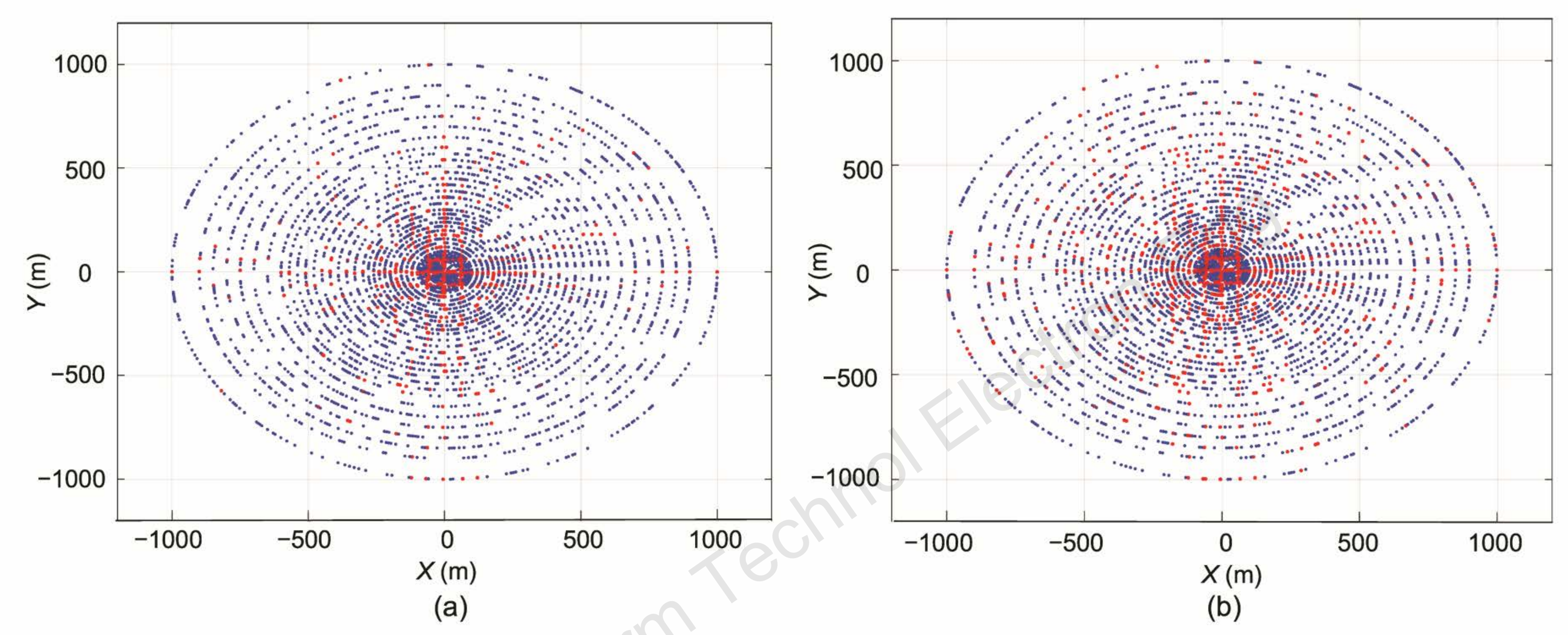
- **Obtain the LoS probability corresponding to each height and distance which can be denoted by** $(P_{\text{LoS}}^{m,n}; d_{\text{RX}}^{m}, h_{\text{TX}}^{n}), m = 1, 2, \cdots, 99, n = 1, 2, \cdots, 100$.

BPNN-based parameter estimation

■ BPNN training



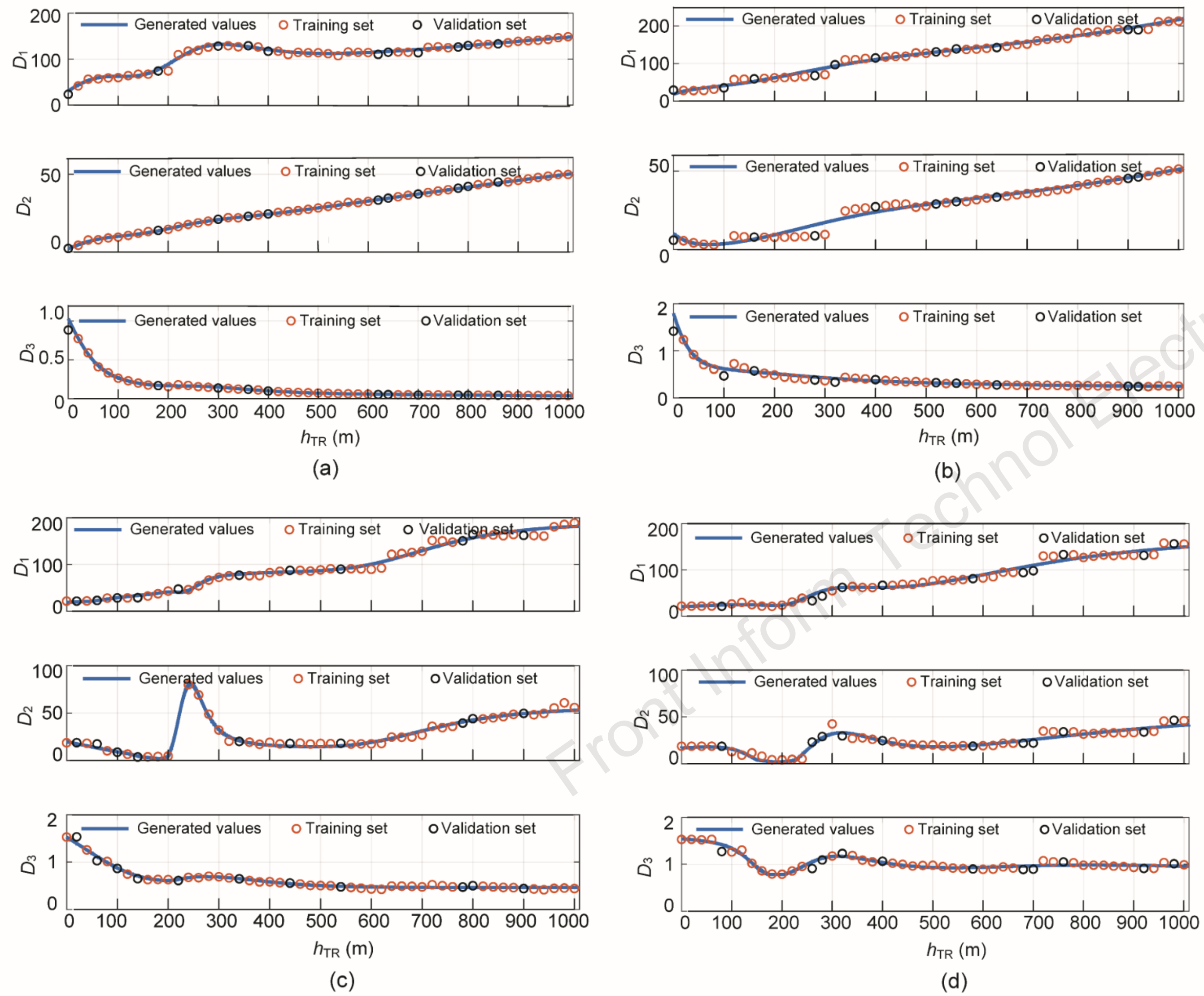
Results of KNN-based classification



Judgment result under dense urban scenario: (a) *h*=200 m; (b) *h*=400 m

- **The red points are the LoS paths while the blue are NLoS paths.**
- **We can see that the number of LoS paths decreases as the distance increases while the number of LoS paths increases when the UAV altitude increases.**
- **Note that some square areas close to the center are still NLoS, because they are blocked by buildings in the scenario.**

Results of BPNN-based estimation

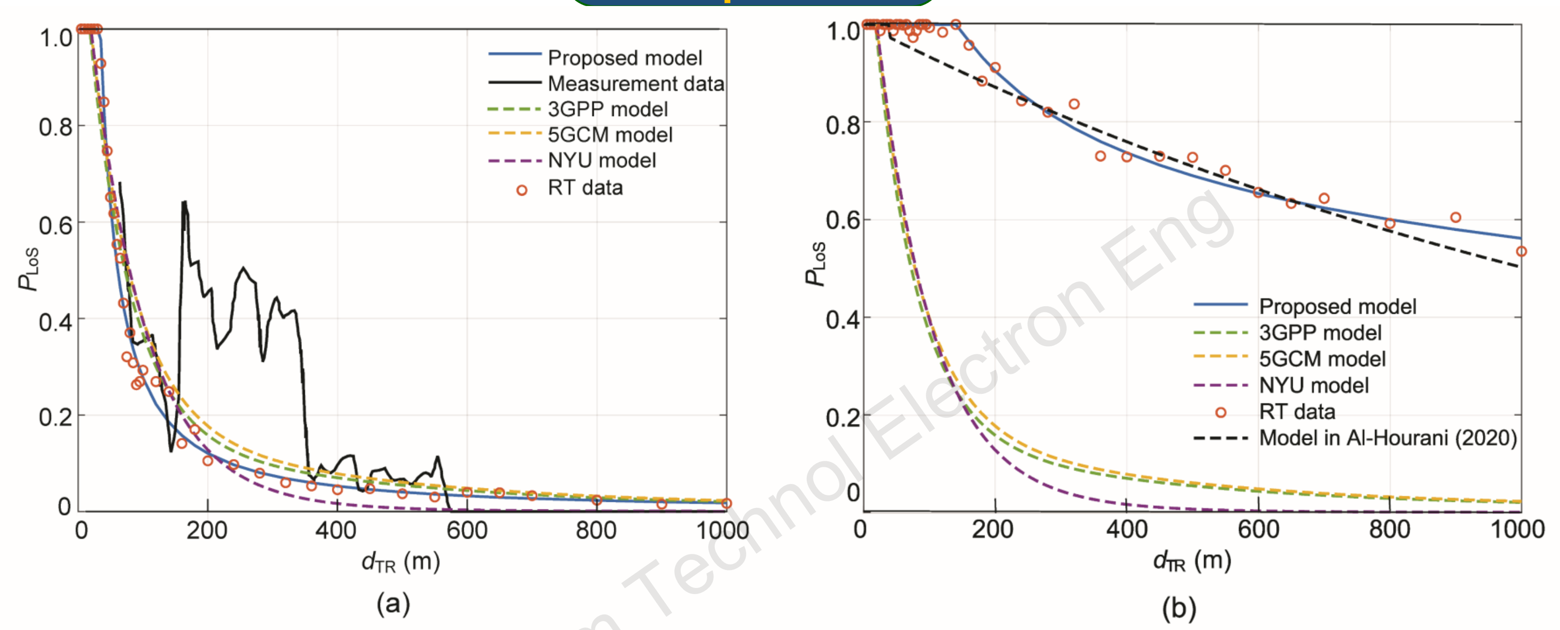


Training results for height-dependent parameters under different scenarios: (a) suburban; (b) urban; (c) dense urban; (d) high-rise urban

- The parameters D_1, D_2, and D_3 increase as the height increases. (When the UAV height increases, the distance range of the existing LoS path becomes larger).
- The prediction values are in good agreement with the original values in the validation set.
- The parameter estimation method can describe the relationship between parameters and height.

Comparison and validation

Comparison



Comparisons of different models at different altitudes: (a) low altitude (h_{Tx}=40 m); (b) high altitude (h_{Tx}=600 m)

- The proposed model's results have good agreement with RT data, and are very similar to those of other representative models (3GPP, 5GCM, NYU). Our model is suitable for low altitude and is compatible with existing low altitude models. The measured data in [2] also agrees with the prediction results.
- Most standard models do not consider the height factor, and the prediction results are unreasonable. Similar to [3], it takes the buildings as random points following the Poisson point process and the heights as a log-normal distribution, so the results are different.

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Conclusions

- The altitude-dependent empirical LoS probability model based on machine learning has been proposed for A2G scenarios.
- The KNN algorithm has been applied to classify the LoS and NLoS paths according to the RT simulation data with the recognition accuracy rate as high as 0.995.
- To introduce the factor of height to the LoS probability, a two-layer BPNN has been developed to estimate the parameters of the proposed LoS probability model, which has better performance than other regression algorithms.
- Simulation results have demonstrated that the prediction results of our proposed LoS probability model can achieve good versatility at both low and high altitudes and have good agreement with RT simulation and measurement data.

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