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Propagation Path Loss Models at 28 GHz Using K-Nearest Neighbor Algorithm

Vu Thanh Quang[1], Dinh Van Linh[1,2], and To Thi Thao[3]

1. Hanoi University of Science and Technology, No. 1 Dai Co Viet road, Hanoi, Vietnam

2. Academy of Cryptography Techniques, 141 Chien Thang Road, Hanoi, Vietnam

3. Post and Telecommunications Institute, Hanoi, Vietnam, Km 10, Nguyen Trai Road, Hanoi, Vietnam

Abstract: In this paper, we develop and apply K-Nearest Neighbor algorithm to propagation pathloss regression. The path loss models present the dependency of attenuation value on distance using machine learning algorithms based on the experimental data. The algorithm is performed by choosing *k* nearest points and training dataset to find the optimal *k* value. The proposed method is applied to impove and adjust pathloss model at 28 GHz in Keangnam area, Hanoi, Vietnam. The experiments in both line-of-sight and non-line-of-sight scenarios used many combinations of transmit and receive antennas at different transmit antenna heights and random locations of receive antenna have been carried out using Wireless Insite Software. The results have been compared with 3GPP and NYU Wireless Path Loss Models in order to verify the performance of the proposed approach.

Keywords: K-nearest neighbor, regression, 5G, millimeter waves, path loss.

1. Introduction

Fifth Generation Mobile Communication System in millimeter waves have been paying attention and investing by the community of scientists and enterprises. In 5G system, radio interface, especially radio frequency channel have had many challenges that need to be solved [1-4]. The millimeter wave band promises a massive amount of unlicensed spectrum at 28 GHz and 38 GHz and these frequency bands are potential for 5G cellular systems [5].

Predicting omnidirectional path loss in dense urban millimeter wave (mmWave) channel is vital for system design and for estimating coverage and capacity of emerging ultrawideband wireless networks [6, 7]. Propagation path loss models that have been synthesized from the collected unique pointing angle (directional) at 28 GHz and 73 GHz mmWave measurements in New York City are reported in [8, 9]. They use both the traditional close-in free space reference distance model, and the floating-intercept least-squares regression model [7, 10].

To study urban cellular propagation, it is necessary to classify the physical environment as being either line of sight (LOS) or non-line of sight (NLOS) between a transmitter (TX) and receiver (RX). In fact, the propagation in the free space is unlikely to occur, a generalized form of path loss model can be built by modifying the free space path loss model with the path loss exponent (PLE) *n* that varies with the environments. NLOS may be further divided into moderately and heavily obstructed environments, where moderate NLOS conditions have small obstructions, such as trees or building edges that partially block the optical path between the TX and RX, while heavily obstructed NLOS conditions have large obstructions fully blocking the optical path.

Machine learning is a method based on an extensive dataset and flexible model architecture to make predictions. Recently, machine learning based methods have been used in self-driving cars, data mining, computer vision, speech recognition, and

Corresponding author: Vu Thanh Quang, Master; research fields: information technology. E-mail: yem.vuvan@hust.edu.vn.

many other fields. These tasks can be classified as supervised learning and unsupervised learning, depending on whether data samples have labels or not. In essence, path loss prediction is a supervised regression problem, so it can also solved by supervised machine learning algorithms, such as artificial neural network (ANN), support vector regression (SVR), and decision tree. It has been reported that the machine learning based models are more accurate then empirical models and more computational efficient than deterministic ones [11, 12]. Here, we investigate one of machine learning methods, named K-Nearest Neighbor (KNN) for regression in pathloss models. KNN uses a weighted average of the *k* nearest neighbors, weighted by the inverse of their distance. The algorithm uses feature similarity to predict the values of any new data points. This means that the new point is assigned a value based on how closely it resembles the points in the training set.

The paper is organized as follows. Section II presents the steps implementing K-Nearest Neighbor for regression-based path loss prediction for collected data. Section III illustrates a number of results obtained by simulating RF transmission model in Keangnam and applied the algorithm above to process the data. The results are compared to theoretical ones. Finally, several conclusions are given in section IV.

2. K-Nearest Neighbor Algorithm for Propagation Pathloss Models

Nearest-neighbor methods use the observations in the training set *T* closest in input space to *x* to form *Y*. Specifically, the *k*-nearest neighbor fit for *Y* is defined as follows [13]:

$$Y(x) = \frac{1}{k}\sum_{x_i \in N_k(x)} y_i \tag{1}$$

where $N_k(x)$ is the neighbor of *x* defined by the *k* closest points x_i in the training sample. Closeness implies a metric, which for the moment we assume Euclidean distance. So, we find the *k* observations with x_i closest to *x* in input space, and average their responses.

The algorithm is performed stepwise as the following:

Step 1: The distance between the new point and each training point is calculated. There are various methods for calculating this distance. The most commonly known methods are Eucidian, Manhattan (for continuous) and Hamming distance (for categorical). Euclidian distance (D) is calculated as square root of the sum of the squared differences between a new point (*x*) and an existing point (*y*).

$$D = \sqrt{\sum_{i=1}^{k}\left(x_i - y_i\right)^2} \tag{2}$$

Manhattan distance (D) is the distance between real vectors using the sum of their absolute difference.

$$D = \sum_{i=1}^{k}\left|x_i - y_i\right| \tag{3}$$

Hamming distance is used for categorical variables. If the value (*x*) and the value (*y*) are the same, the distance D will be equal to 0, otherwise D = 1.

$$\begin{gathered} D_H = \sum_{i=1}^{k}\left|x_i - y_i\right| \\ x = y \Rightarrow D = 0 \\ x \neq y \Rightarrow D = 1 \end{gathered} \tag{4}$$

Step 2: The closest *k* data points are selected (based on the distance calculated in step 1. This determines the number of neighbors and assigns a value to any new observation.

Step 3: The average of these data points is the final prediction for the new one.

From 3 conventional steps in K-Nearest neighbor algorithm, we propose the process for propagation pathloss model regression based on the collected LOS and NLOS data as presented in Fig. 1. The proposed process consists of 6 steps.

Step 1: For preparing learning data, all the measured data divided into two sets, training dataset (80%), test dataset (20%), respectively.

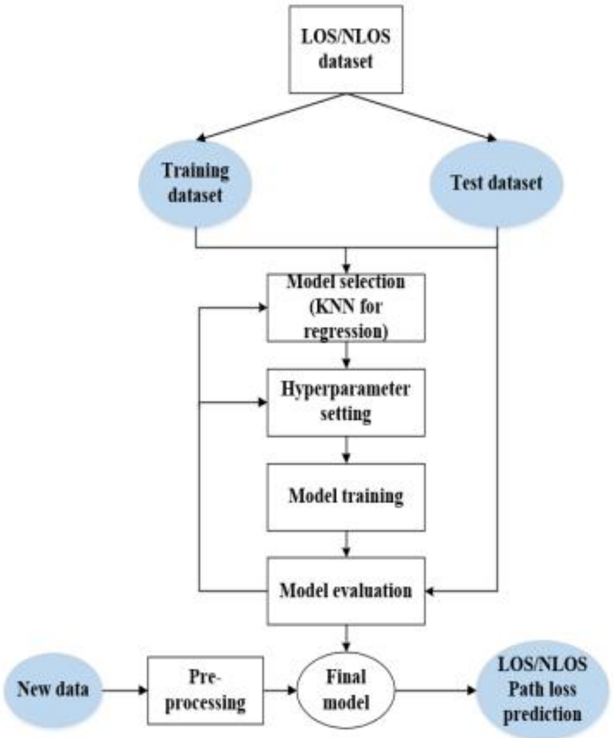

Fig. 1 Procedure of KNN for regression-based path loss prediction.

Step 2: Model selection is K-Nearest Neighbor for regression.

Step 3: Increasing the *k* values from 1 to 19 (only choose odd values).

Step 4: In model training, the distance between the new point and each training point is calculated by Eucidian distance method. The closest *k* data points are selected based on the calculated distance. This determines the number of neighbors and assigns a value to any new observation. Then, the average of these data points is the final prediction for the new point.

Step 5: Based on the k value, the final result tends to change. To optimize the value of k relied on the error calculation for train and validation set. The error rate at $k = 1$ is always zero for the training sample. This is because that the closest point to any training data point is itself. Therefore, the prediction is always accurate with $k = 1$. If validation error curve is similar, $k = 1$ is choosen. Following is the validation error curve with varying value of *k*. At $k = 1$, it is overfitting the boundaries. Therefore, the error rate initially decreases and reaches a minimum value. After the minimum point, then it increases with increasing *k*. To get the optimal value of *k*, it is necessary to segregate the training and validation from the initial dataset. After that, we plot the validation error curve to get the optimal value of k. This value of k should be used for all predictions.

Step 6: From *k* value chosen in step 5, we build optimal final models for LOS and NLOS path loss prediction.

3. Experimental Results

This section simulates RF propagation at 28 GHz in Keangnam area, Hanoi, Vietnam at different TX antenna heights by Wireless Insite software. The collected data, from simulation is processed by the proposed method using K-Nearest neighbor for regression algorithm in section II. The results of path loss model obtained based on Matlab simulation are compared to 3GPP and NYU Wireless experimental results. Keangnam area is a place with the combination of architecture of a large number of tall buildings and highways running through, this is a typical area for a modern urban model (Fig. 2).

Simulation data of this area is taken from google.com/maps and website https://cadmapper.com/ so that the scale of distance in the simulation is identical to real area. In addtion, in order to have accurate data of height of buildings, properties,

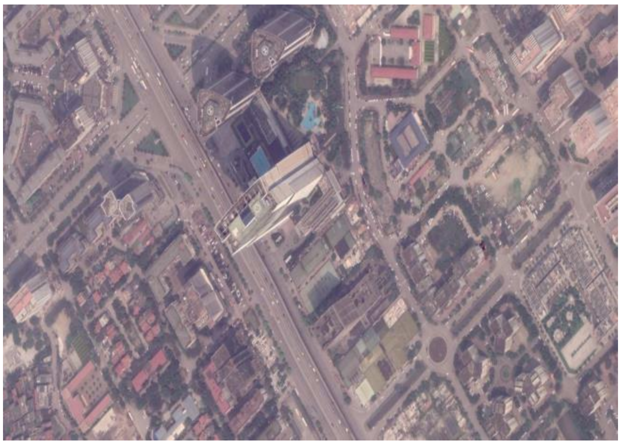

Fig. 2 Keangnam area, Hanoi, Vietnam.

materials…, it must be based on observed reality. The material properties related to reflectance, diffraction, and absorption of wave propagation are either default set up by Wireless Insite tool or could be customized with suitable materials.

The simulation process is performed by the following steps:

1) Simulation model of wave propagation environment is built.
2) On the top of Keangnam Landmark Tower 72, transmit antenna is set up at 7 m and 17 m height with frequency 28 GHz and the input power is 43 dBm.
3) 100 LOS receivers and 100 NLOS receivers are randomly located in simulation model.

The output data is path loss in Wireless Insite and it is given inform of text.txt that aligns for easier latter to form matrix and for data processing. Obtained data set is a form of distance-pathloss with 100 LOS points and 100 NLOS points (Figs. 4-7). With X, Y, Z are the relative distances to the origin of the simulation environment which measure the distance between transmitters and receivers.

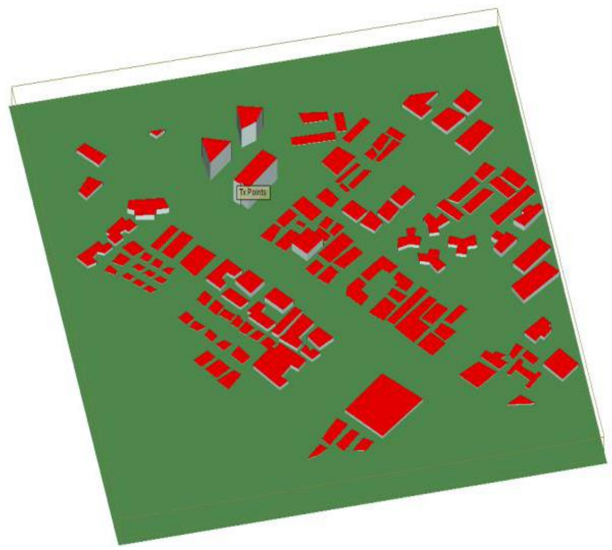

Fig. 3 Omnidirectional transmitter 28 GHz set up in Keangnam area.

Receiver Set: rx_los

# Rx#	X(m)	Y(m)	Z(m)	Distance (m)	Path Loss (dB)
1	0.6912222E-05	-0.2399517E-03	1.500	0.00	127.59
2	0.2251543E+03	-0.4750920E+03	1.500	525.74	124.07
3	0.3927927E+03	-0.6097639E+03	1.500	740.78	125.00
4	0.5567603E+03	-0.8977888E+03	1.500	1072.20	125.29
5	0.7680032E+03	-0.1058296E+04	1.500	1337.51	125.29
6	0.9343555E+03	-0.1274683E+04	1.500	1610.45	125.83

Fig. 4 LOS data is extracted from output with TX antenna at 7 m height.

Receiver Set: rx_nlos

# Rx#	X(m)	Y(m)	Z(m)	Distance (m)	Path Loss (dB)
1	0.1042941E-03	0.2424187E-03	1.500	0.00	131.19
2	0.3217159E+03	-0.3320032E+03	1.500	462.31	175.57
3	0.5441349E+03	-0.5014890E+03	1.500	741.94	184.26
4	0.7016962E+03	-0.6372595E+03	1.500	949.93	159.47
5	0.8546749E+03	-0.8245144E+03	1.500	1191.73	128.11
6	0.8385421E+03	-0.1050604E+04	1.500	1418.39	136.43

Fig. 5 NLOS data is extracted from output with TX antenna at 7 m height.

Receiver Set: rx_los

# Rx#	X(m)	Y(m)	Z(m)	Distance (m)	Path Loss (dB)
1	0.6912222E-05	-0.2399517E-03	1.500	0.00	124.83
2	0.2251543E+03	-0.4750920E+03	1.500	525.74	158.69
3	0.3927927E+03	-0.6097639E+03	1.500	740.78	174.52
4	0.5567603E+03	-0.8977888E+03	1.500	1072.20	172.20
5	0.7680032E+03	-0.1058296E+04	1.500	1337.51	157.27
6	0.9343555E+03	-0.1274683E+04	1.500	1610.45	125.83

Fig. 6 LOS data is extracted from output with TX antenna at 17 m height.

Receiver Set: rx_nlos

# Rx#	X(m)	Y(m)	Z(m)	Distance (m)	Path Loss (dB)
1	0.1042941E-03	0.2424187E-03	1.500	0.00	178.70
2	0.3217159E+03	-0.3320032E+03	1.500	462.31	136.23
3	0.5441349E+03	-0.5014890E+03	1.500	741.94	176.58
4	0.7016962E+03	-0.6372595E+03	1.500	949.93	172.23
5	0.8546749E+03	-0.8245144E+03	1.500	1191.73	186.43
6	0.8385421E+03	-0.1050604E+04	1.500	1418.39	153.66

Fig. 7 NLOS data is extracted from output with TX antenna at 17 m height.

The obtained LOS and NLOS data are processed by K-Nearest Neighbor for regression algorithm and they are divided by 80% training data, 20% test data, respectively as proposed in section II. During the process, increasing the k values from 1 to 19 (only choose odd values), the results obtained based on MATLAB simulation are presented in Table 1 and Table 2. To describe propagation path loss (PL) as a function of distance, the propagation path loss exponent ($\bar{n}$) is a parameter that describes the attenuation of a signal when it propagates in the channel. It can be seen that, both LOS and NLOS of the TX antenna at 7 m and 17 m height, the path loss exponents ($\bar{n}$) are constant, 1.92 and 2.72 in case 7 m antenna height, 1.98 and 2.50 in in case 17 m antenna height respectively. The figure for σ [dB] fluctuates between 12.86 to 26.63 for LOS and 13.20 to 20.37 for NLOS with TX antenna at 7 m height, 15.43 to 25.04 for LOS and 10.98 to 40.25 for NLOS with TX antenna at 17 m height respectively.

Meanwhile, α and β are the intercept and slope of the floating-intercept model parameters in both cases fluctuate dramatically and also appear negative values. In case of TX antenna at 7 m height, in Fig. 8, the line of path loss of the formula CI (LOS) has a slightly lower slope than the path loss line by the formula of free space, due to path loss exponent of free space is 2 and CI (LOS) is 1.92, respectively.

Table 1 The results of processing data by k-nearest neighbor for regression with TX antenna at 7 M.

Tx (m)	Rx (m)	*K*	LOS		NLOS		NLOS (floating-intercept)		
			PLE ($\bar{n}$)	σ[dB]	PLE ($\bar{n}$)	σ[dB]	α[dB]	β	σ [dB]
7	1.5	1	1.92	23.70	2.72	19.81	-174.06	8.99	19.81
7	1.5	3	1.92	12.86	2.72	16.08	-249.58	11.06	16.08
7	1.5	5	1.92	23.68	2.72	17.46	111.17	1.06	17.46
7	1.5	7	1.92	22.78	2.72	16.42	-243.80	11.34	16.42
7	1.5	9	1.92	26.63	2.72	20.37	-324.89	13.59	20.37
7	1.5	11	1.92	18.44	2.72	13.20	-476.86	17.86	13.20
7	1.5	13	1.92	20.14	2.72	18.87	-246.25	11.44	18.87
7	1.5	15	1.92	17.92	2.72	15.86	-766.94	26.15	15.86
7	1.5	17	1.92	18.52	2.72	18.04	-365.39	14.79	18.04
7	1.5	19	1.92	23.27	2.72	15.74	-1188.21	38.24	15.74

Table 2 The results of processing data by k-nearest neighbor for regression with TX antenna at 17 m height.

Tx (m)	Rx (m)	*K*	LOS		NLOS		NLOS (floating-intercept)		
			PLE ($\bar{n}$)	σ[dB]	PLE ($\bar{n}$)	σ[dB]	α[dB]	β	σ [dB]
17	1.5	1	1.98	23.17	2.50	25.35	212.14	-1.47	25.35
17	1.5	3	1.98	21.50	2.50	21.95	66.14	2.33	21.85
17	1.5	5	1.98	22.14	2.50	40.25	-74.45	6.46	40.25
17	1.5	7	1.98	17.54	2.50	19.54	-57.74	5.75	19.54
17	1.5	9	1.98	17.37	2.50	35.95	-542.93	19.79	35.95
17	1.5	11	1.98	15.76	2.50	14.36	-45.65	5.25	14.36
17	1.5	13	1.98	21.01	2.50	16.57	-651.10	22.63	16.57
17	1.5	15	1.98	15.43	2.50	18.88	-1296.91	40.93	18.88
17	1.5	17	1.98	25.04	2.50	10.98	-1304.14	41.43	10.98
17	1.5	19	1.98	20.89	2.50	14.48	1586.30	-40.84	14.48

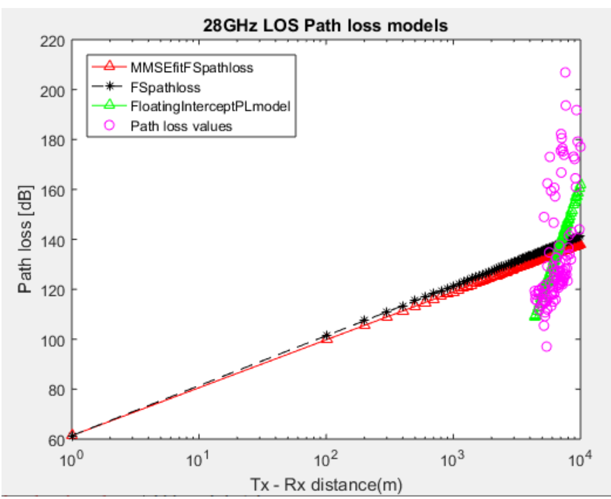

Fig. 8 LOS path loss models at 28 GHz with TX antenna at 7 m height.

Fig. 9 depicts that the slope of NLOS path loss models is much steeper than the one of free space line because path loss exponent in this case is 2.72.

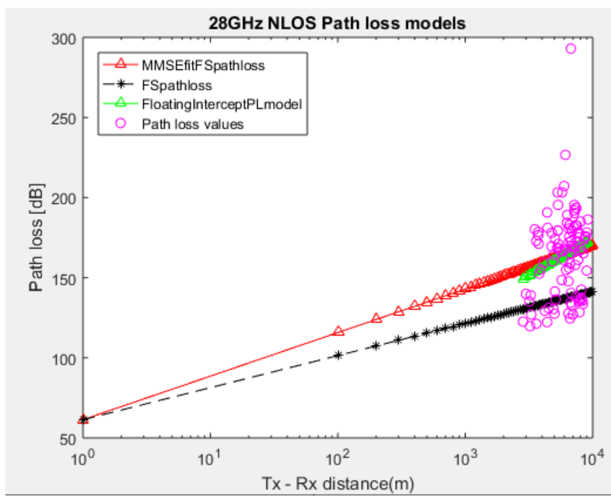

Fig. 9 NLOS path loss models at 28 GHz with TX antenna at 7 m height.

Fig. 10 shows that when increasing k from 1 to 3, the model will underfit and it overfits between 3 to 19. The minimum σ = 12.86 with k = 3, it means that it is the smallest standard deviation of all predictions, so this is the optimal point of pathloss function. Therefore, the path loss at distance d can be described by the path loss exponent $\bar{n}$ = 1.92 using the following equation:

$$PL_{28GHz}(LOS)[\mathrm{dB}](d) = 61.4 + 19.2\log_{10}(d) + X_{\sigma} \quad (\sigma = 12.86) \tag{5}$$

Similar to the LOS situation, Fig. 11 illustrates k = 11 and minimum σ is 13.2 dB. The equation of NLOS is below:

$$PL_{28GHz}(\mathrm{NLOS})[\mathrm{dB}](d) = 61.4 + 27.2\log_{10}(d) + X_{\sigma} \quad (\sigma = 13.2) \tag{6}$$

Considering in the case of TX antenna at 17 m height, in Fig. 12, the line of path loss of the formula CI (LOS) is similar to the path loss line by the formula of free space, due to path loss exponent of free space is 2 and CI (LOS) is 1.98, respectively.

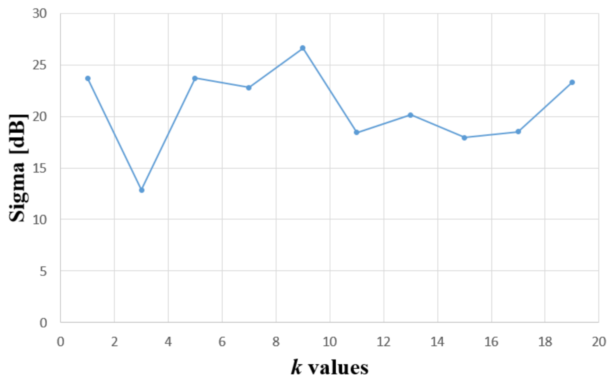

Fig. 10 σ[dB] of LOS when increasing *k* value with TX antenna at 7 m height.

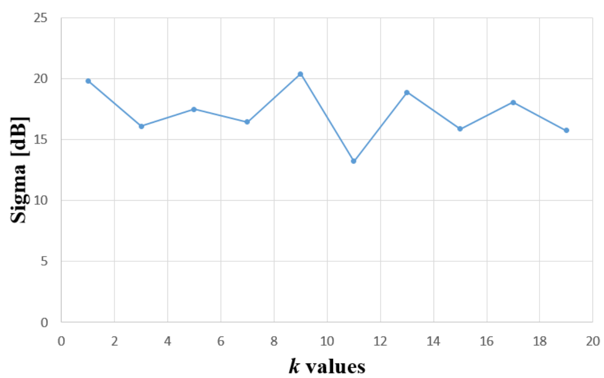

Fig. 11 σ[dB] of NLOS when increasing k value with TX antenna at 7 m height.

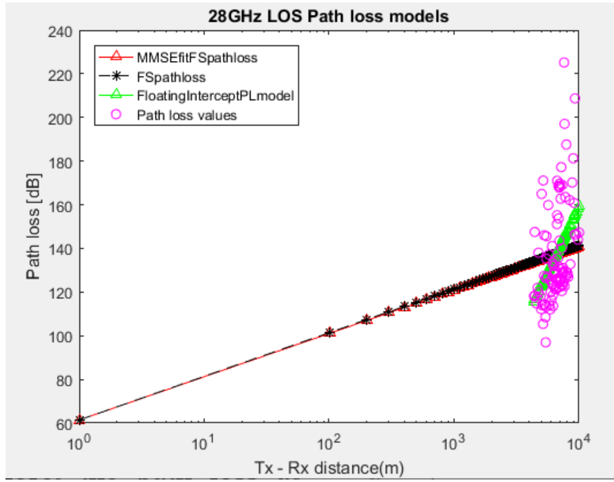

Fig. 12 LOS path loss models at 28 GHz with TX antenna at 17 m height.

Fig. 13 shows that the slope of NLOS path loss models is steeper than the one of free space line because path loss exponent in this case is 2.50.

In addition, Fig. 8, Fig. 9, Fig. 12 and Fig. 13 also show the attenuation lines of FI model that are very steep and there are many measurement data points. But when extending the atenuation lines of FI, they exist the negative attenuation value, this proves that FI model is only used in the measured data range and that does not make sense when extrapolating to the outside.

Fig. 14 and Fig. 15 present σ[dB] of LOS and NLOS when increasing k value with TX antenna at 17 m height. It can be seen that, for LOS the minimum σ is 15.43 dB when k =15 and for NLOS when k =17 the minimum σ is 10.98 dB. So, the equations of LOS and NLOS with TX antenna at 17 m height are the following:

$$PL_{28\mathrm{GHz}}(LOS)[\mathrm{dB}](d) = 61.4 + 19.8\log_{10}(d) + X_{\sigma} \quad (\sigma = 15.43) \tag{7}$$

$$PL_{28GHz}(\mathrm{NLOS})[\mathrm{dB}](d) = 61.4 + 25\log_{10}(d) + X_{\sigma} \quad (\sigma = 10.98) \tag{8}$$

Where *PL28GHz(LOS)* is the LOS free space path loss, *PL28GHz(NLOS)* is the NLOS path loss at 28 GHz computed using the 1m close-in free space reference distance and the floating-intercept models, respectively. $X\sigma$ is the lognormal random variable (normal in dB) with standard deviation σ[dB] to model large-scale shadowing.

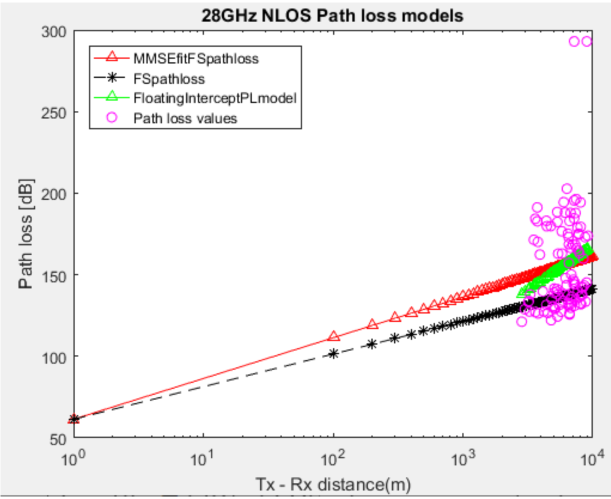

Fig. 13 NLOS path loss models at 28 GHz with TX antenna at 17 m height.

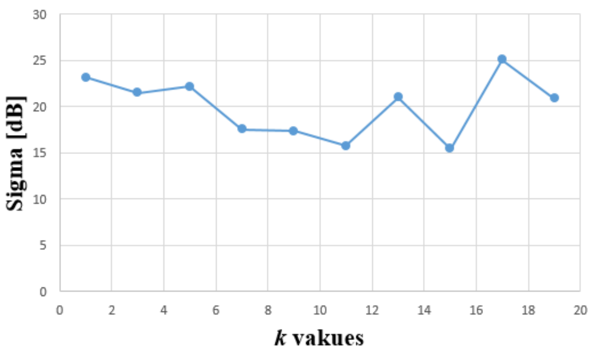

Fig. 14 σ[dB] of LOS when increasing *k* value with TX antenna at 17 m height.

3GPP has presented several propagation path loss formulas for each case and for different environments.

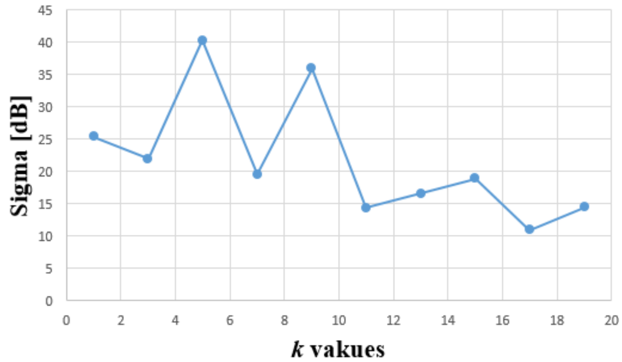

Fig. 15 σ[dB] of NLOS when increasing k value with TX antenna at 17 m height.

From the results presented above, it can be compared with the following formulas [9]:

$$PL_{28GHz}(\mathrm{LOS})[\mathrm{dB}](d) = 61,34 + 21\log_{10}\left(d_{3D}\right)(\mathrm{dB}) \quad (\sigma = 4\mathrm{dB}) \tag{9}$$

$$PL_{28GHz}(\mathrm{NLOS})[\mathrm{dB}](d) = 61.34 + 31.9\log_{10}\left(d_{3D}\right)(\mathrm{dB}) \quad (\sigma = 8.2\mathrm{dB}) \tag{10}$$

The formulas of 3GPP for urban environment have path loss exponent are 2.1 for LOS and 3.19 for NLOS respectively. In our results, at different transmit antenna heights, we obtain a different optimal k values, however the path loss exponents fluctuate in small amplitudes around these two values. Comparing to the results measured by NYU WIRELESS (Table 3), the parameters above for close-in free space reference distance path loss model are quite similar, but σ[dB] is litle bigger, because that the limit of simulation tools as well as choosing receivers randomly cause a great shadowing effect. It also leads to the result of parameters in NLOS (floating-intercept) is so extreme and sloppy.

Table 3 Path loss models of NYU wireless at 28 GHz [10].

Tx (m)	Rx (m)	LOS		NLOS		NLOS (floating-intercept)		
		PLE ($\bar{n}$)	σ[dB]	PLE ($\bar{n}$)	σ[dB]	α[dB]	β	σ [dB]
7;17	1.5	2.1	3.6	3.4	9.7	79.2	2.6	9.6

4. Conclusion

In this paper, we propose a novel approach for pathloss estimation using K-Nearest Neighbor algorithm. The algorithm is performed by choosing *k* nearest points and training dataset to find the optimal *k* value. We observe that, the path loss exponent is a constant while the standard deviation σ[dB] depends on k value. It is necessary to choose an optimal model based on *k* value. Comparing the obtained results with the formulas of 3GPP and NYU Wireless experiments results, the path loss exponent is compatible. Although the standard deviation of the optimal result is rather big due to the shadow fading effect, this value is still acceptable. Therefore, this K-Nearest Neighbor algorithm for regression is suitable for processing data of propagation path loss model in millimeter waves. The proposed approach is applied to impove and adjust pathloss model at 28 GHz in Keangnam area, Hanoi, Vietnam for both line-of-sight and non-line-of-sight scenarios in order to verify the performance.

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