MILLIMETER WAVE PATH LOSS PREDICTION MODEL BASED ON BP NEURAL NETWORK ALGORITHM

Jinke WANG [1] and Zhigang LI [2]

[1]Dept. of Information and Communication Eng., Harbin Engineering University
(Harbin, Heilongjiang, China)
E-mail: wangjk145@hrbeu.edu.cn
[2]Associate Professor, Dept. of Information and Communication Eng., Harbin Engineering University
(Harbin, Heilongjiang, China)
E-mail: lizhigang@hrbeu.edu.cn

In 5g communication, millimeter wave channel modeling is a key technology. First of all, the measurement of 60 GHz and 73 GHz millimeter wave outdoor micro cellular channel is carried out. Then Back Propagation (BP) neural network is used to fit the measured data. Finally, the fitting results were compared with close-in (CI) fitting results. The experimental results show that BP neural network can predict path loss better than CI fitting. At the same time, the path loss model for 60GHz and 73GHz millimeter wave channels in outdoor microcellular line-of-sight and non-line-of-sight scenarios is proposed.

Key words: *millimeter-wave channel; path loss; BP neural network; outdoor microcellular; LOS; NLOS*

1. INTRODUCTION

While 5G wireless mobile communication is commercialized all over the world, many countries around the world have rapidly carried out the research on 6G mobile communication[1)]. In order to improve the experience quality of mobile users in different indoor and outdoor scenarios, all kinds of data-driven services and all-round innovative applications in mobile communication system need ultra-high data rate and ultra-low delay[2)]. In order to solve these requirements, millimeter wave communication is widely used Signal and large-scale multiple input multiple output (MIMO) antenna have become two key technologies[3)].

Millimeter wave communication and large-scale MIMO antenna technology, as an important component of 5G or Beyond-5G communication technology, has been a research hotspot at home and abroad[4)]. In recent years, many scholars have studied the propagation characteristics of millimeter wave channel in different complex indoor and outdoor environments. Compared with the frequency below 6 GHz, millimeter wave has higher free space path loss in the first meter propagation of transmitting antenna[5)]. Using high gain antenna at both ends of the link can overcome the path loss, and beamforming and beam combining technology can be used to improve the link quality and eliminate interference.

Most of the existing literatures use ray tracing method to study the typical indoor environment, but less studying the millimeter band large-scale MIMO channel in dense urban area. Therefore, in this paper, we select 60 GHz and 73 Ghz band to measure the channel in the outdoor environment of the city, then use BP neural network modeling, and compare with the channel model proposed in the previous literature, and give a millimeter wave channel model suitable for this environment.

2. CHANNEL MODEL AND MEASUREMENT

The transmitter (TX) adopts omni-directional antenna with a height of 6.10 m; the receiver (Rx) adopts horn antenna with a height of 1.85 m, and its half power beamwidth (HPBW) is 10°. The horn antenna is controlled by the precision stepping motor turntable, which can make it rotate and scan in the horizontal and vertical planes. In order to obtain the complete three-dimensional information of the angle of arrival of radio waves, and take into account the measurement time and efficiency, the horn antenna rotates horizontally in 5° steps at selected elevation angles, and the elevation angle interval is 10°. For the measurement position close to the transmit-

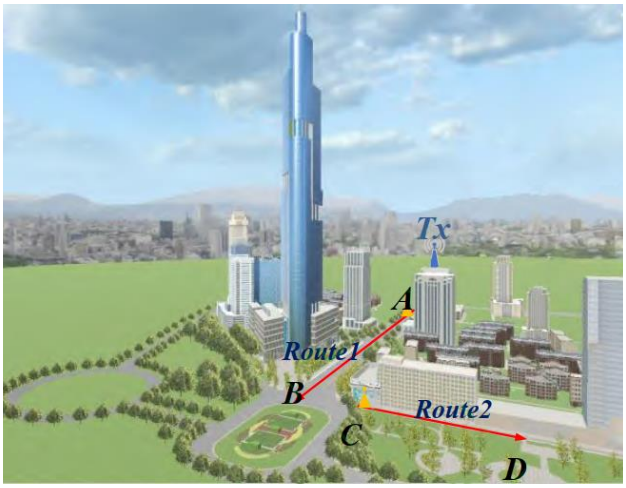

Fig.1 Schematic diagram of the measurement environment

ter, more elevation angles are measured. With the increase of the distance between the transmitter and the receiver, the angle of arrival is mainly concentrated near the horizontal plane, and the number of elevation angles is reduced accordingly. The time domain sliding correlation channel detector developed by keysight is used in the test system.For LOS and NLOS scenarios, signal measurement at 60 GHz and 73 GHz is carried out in vehicular network. In LOS scene, the antennas of transmitter and receiver are aligned on the azimuth and elevation plane of LOS, and the optical path between them is clear; in NLOS scenarios, when the transmitter and receiver antennas are separated by obstacles or the transmitter and receiver antennas are not aligned on the axis of view.

The measurement environment is shown in **Fig.2**. The transmitting antenna with a height of 2 m is placed on the top of the building with a height of 178 M. the receiving antenna moves along the Los (Route1) route and NLOS (Route2) route with an interval of 1 m. the transmitting and receiving antenna adopts omnidirectional antenna. The millimeter band 60 GHz and 73 GHz are selected to study the channel characteristics of single input single output (SISO); Secondly, the 28 GHz band is used to simulate the LOS and NLOS single input multiple output (Simo) channels, and the receiver adopts 4 × 4 antenna array, reflection number is 2, diffraction number is 2, transmission number is 1.

3. CHANNEL MODELING BASED ON BP NEURAL NETWORK

There are a lot of data in the wireless channel. Using the artificial neural network method of machine learning method, we can mine the characteristics of wireless channel parameters, comprehensively analyze the wireless channel from multiple dimensions, more accurately understand the propagation characteristics of the channel, and reduce the high cost of wireless channel measurement.

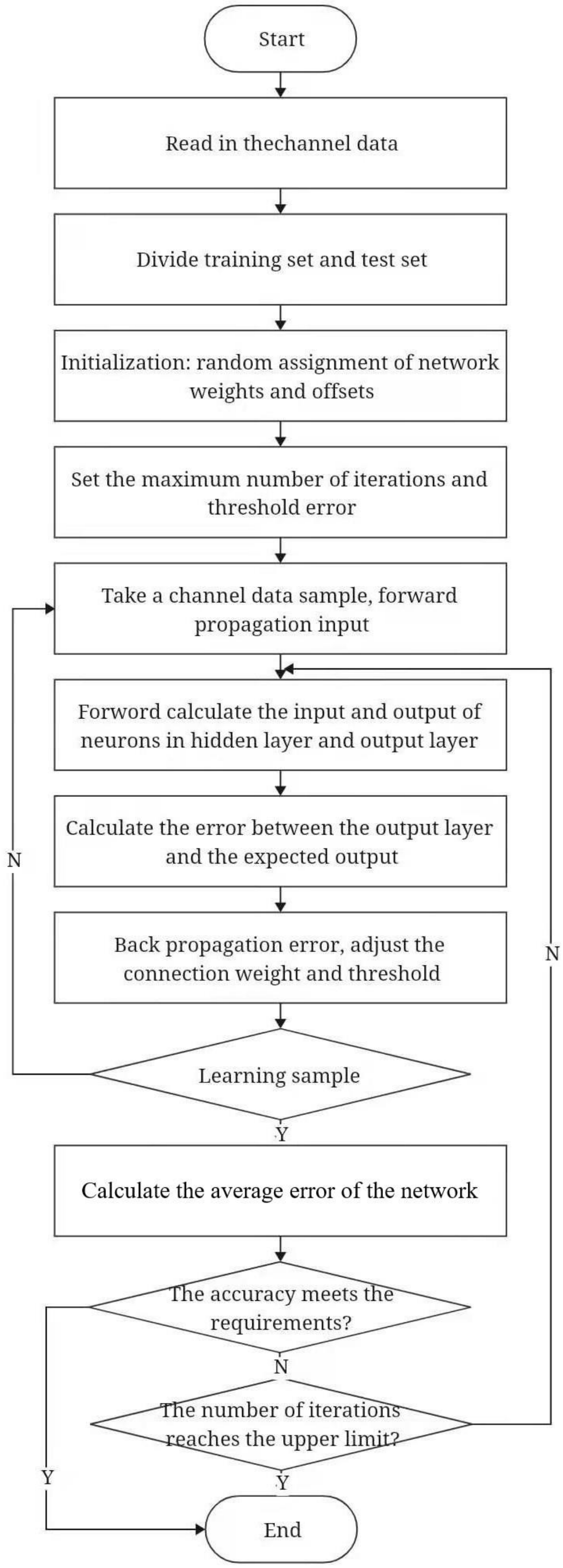

Fig.2 BP neural network modeling process

BP neural network is a kind of multilayer feedforward network trained by error back propagation. Its algorithm is called BP algorithm. Its basic idea is gradient descent method. Gradient search technology is used to minimize the mean square error between the actual output value and the expected output value of the network.

The calculation process of BP neural network consists of forward calculation process and reverse calculation process. In the process of forward propagation, the input mode is processed layer by layer from the input layer to the output layer through the hidden cell layer, and the state of each layer neuron only affects the state of the next layer neuron. If the desired output can not be obtained in the output layer, the error signal is returned along the original connection path by back propagation, and the error signal is minimized by modifying the weights of each neuron.

The flow chart of BP neural network channel modeling is shown in **Fig.2**.

Suppose there are n neurons in the input layer, p neurons in the hidden layer and q neurons in the output layer. Define the input vector of the input layer as $\mathbf{x}=\left(x_1,x_2,\cdots,x_n\right)$, the input vector of the hidden layer as $\mathbf{h_i}=\left(h_{i1},h_{i2},\cdots,h_{in}\right)$, the output vector of the hidden layer as $\mathbf{h_o}=\left(h_{o1},h_{o2},\cdots,h_{on}\right)$, the input vector of the output layer as $\mathbf{y_i}=\left(y_{i1},y_{i2},\cdots,y_{in}\right)$, and the output vector of the output layer as $\mathbf{y_o}=\left(y_{o1},y_{o2},\cdots,y_{on}\right)$. The connection weight from input layer to hidden layer is w_{ih}; the connection weight from hidden layer to output

layer is w_{ho}. The threshold of each neuron in the hidden layer is b_h, and in output layer is b_o The expected output vector is $\mathbf{d_o}=\left(d_{o1},d_{o2},\cdots,d_{on}\right)$, the number of sample data is $k=1,2,\cdots m$, and the transfer function is the function Sigmoid $f\left(\bullet\right)$. It can be divided into the following steps[6]:

As shown in the Fig.1, the details of the principle of BP neural network channel modeling ,from start to the end, are as follows:

(1) The import and partition of data

Firstly, the collected channel data is used as the training data and test data of BP neural network, in which the training data accounts for 70% and the test data accounts for 30%.

(2) Network initialization

When training neural networks, it is very important to initialize the weights randomly. The weights are initialized as (-1, 1) random numbers, which are used to train the expectation of the stochastic optimization algorithm of the model. Given the calculation accuracy ε and the maximum learning times M.

The error function is:

$$e=\sum_{o=1}^{q}\left[d_o\left(k\right)-y_o\left(k\right)\right]^2 \tag{1}$$

(3) Random selection of input samples and corresponding expected output

Randomly select the k-th input sample and the corresponding expected output $x\left(k\right)$ and $d\left(k\right)$.

(4) Calculating the input and output of each neuron in the hidden layer

$$h_{ih}\left(k\right)=\sum_{i=1}^{n}w_{ih}x_i\left(k\right)-b_n,h=1,2,\cdots,p \tag{2a}$$

$$h_{oh}\left(k\right)=f\left(h_{ih}\left(k\right)\right),h=1,2,\cdots,p \tag{2b}$$

$$y_{io}\left(k\right)=\sum_{i=1}^{n}w_{ho}h_{oh}\left(k\right)-b_o,o=1,2,\cdots,q \tag{2c}$$

$$y_{oo}\left(k\right)=f\left(y_{io}\left(k\right)\right),o=1,2,\cdots,q \tag{2d}$$

(5) Calculating the deviation between the output layer and the expected output

$$\begin{aligned}\frac{\partial e}{\partial w_{hn}}&=\frac{\partial e}{\partial y_{in}}\cdot\frac{\partial y_{in}}{\partial w_{hn}}\\&=-\left[d_o(k)-y_{oo}(k)\right]\cdot f^{'}(y_{io}(k))\cdot h_{oh}(k)\\&=-\delta_o(k)\cdot h_{oh}(k)\end{aligned} \tag{3a}$$

$$\begin{aligned}\frac{\partial e}{\partial w_{in}}&=\frac{\partial e}{\partial h_{ih}}\cdot\frac{\partial h_{ih}}{\partial w_{ih}}\\&=\frac{\partial e}{\partial h_{oh}}\cdot\frac{\partial h_{oh}}{\partial h}\cdot x_i\left(k\right)\\&=-\left(\sum_{o=1}^{q}\delta_o(k)\cdot w_{ho}\right)\cdot f^{'}\left(h_{ih}\left(k\right)\right)\cdot x_i\left(k\right)\\&=-\delta_h\left(k\right)\cdot x_i\left(k\right)\end{aligned} \tag{3b}$$

(6) Correction of connection weight $w\left(k\right)$

$$w_{ho}^{N+1}=w_{ho}^{N}+\eta\delta_o\left(k\right)h_{oh}\left(k\right) \tag{4a}$$

$$w_{ih}^{N+1}=w_{ih}^{N}+\eta\delta_h\left(k\right)x_i\left(k\right) \tag{4b}$$

(7) Calculating the network error

$$E=\frac{1}{2m}\sum_{k=1}^{m}\sum_{o=1}^{q}\left[d_o\left(k\right)-y_o\left(k\right)\right]^2 \tag{5}$$

When the error reaches the set threshold or the number of iterations is greater than the set maximum, the algorithm ends; otherwise, the next learning sample and the corresponding expected output are selected for the next round of learning.

The learning rate can't be too fast or too slow. Too fast may lead to the over optimal solution and fall into the local optimal solution; too slow may reduce the efficiency of the algorithm.

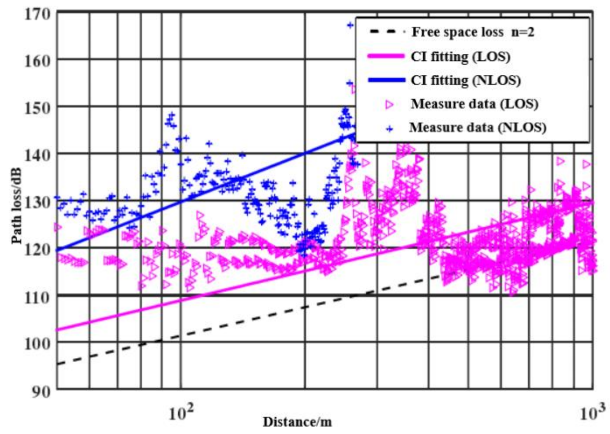

Fig.3 CI fitting on 60GHz

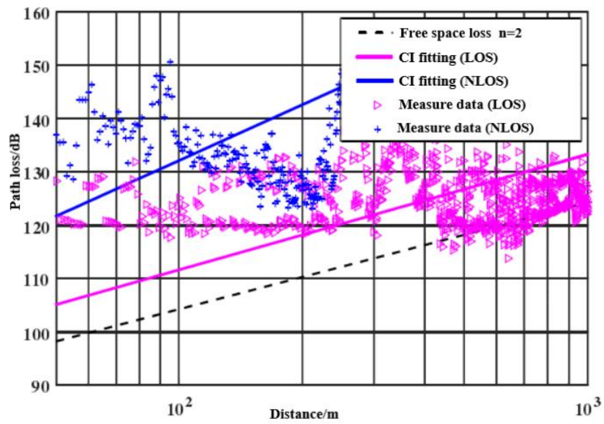

Fig.4 CI fitting on 73GHz

4. RESULTS OF COMPARATIVE ANALYSIS

Large scale propagation model aims at the average loss of signal power between transmitter and receiver in a long distance range of several hundred meters or several thousand meters, which plays an important role in estimating wireless coverage and wireless network planning and optimization. Path loss[7)] is one of the important parameters to characterize the large-scale fading effect of wireless channel propagation, which is very important for base station optimization As a result, a typical path loss model is used, that is, the free space close in (CI) path loss model[8)].

The CI path loss model is

$$PL^{CI}\left(f,d\right)=FSPL\left(f,d_0\right)+10n\log\left(\frac{d}{d_0}\right)+x_\sigma^{CI} \quad (6)$$

Where f is the carrier frequency; d is the distance between transmitter and receiver; d_0 is the relative reference distance; $FSPL\left(f,d_0\right)=20\log\left(\frac{4\pi f d_0}{c}\right)$; n is the path loss index, which is determined by the root-mean-square (RMS) error fitting method, and $n=2$

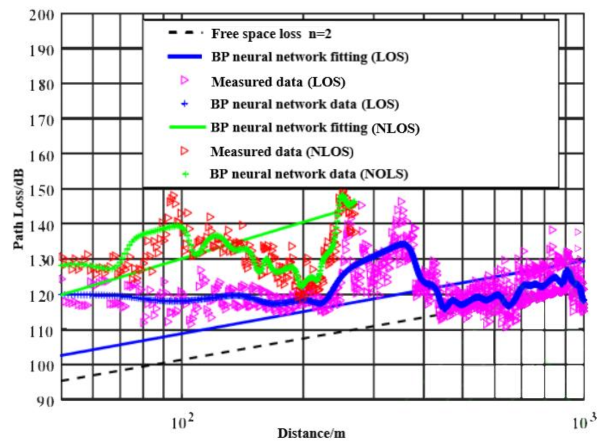

Fig.5 BP neural network on 60GHz

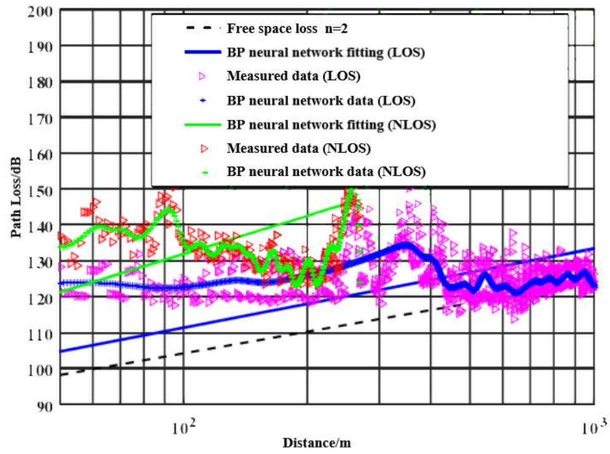

Fig.6 BP neural network on 73GHz

belongs tofree space path loss; x_σ^{CI} is a Gaussian random variable with zero mean.

For outdoor microcell environment, when the receiving antenna moves along LOS path and NLOS path with an interval of 1m, the simulation path loss models of 60 GHz and 73 GHz are obtained by CI and BP neural network algorithm, as shown in **Fig.3** to **Fig.6**.

High buildings and a large number of vegetation lead to greater signal loss in NLOS scenario, so the path loss index of NLOS scenario is larger than that of LOS scenario.

In **Fig.5** and **Fig.6**, the BP neural network data shows the BP neural network fluctuating data at the time of fitting; the BP neural network fitting shows the final regression results.

The parameters n and standard deviations σ of BP neural network and CI fitting are listed in Table.1. Where n ndetermines the size of the parameters in the fitting equation and σ portrays how the model biases the actual data. Generally, the smaller σ, the more accurate the model is. The experimental results show that BP neural network can predict path loss better than CI fitting in longer distance.

Based on the above analysis, we present a general path loss model for 60 GHz and 73 GHz millimeter wave channels in outdoor microcellular line-of-sight (LOS) and non-line-of-sight (NLOS) scenarios.

	LOS/NLOS	Frequency	n	σ
BP	LOS	60 GHz	30.39	1.56
CI	LOS	60 GHz	30.27	3.74
BP	NLOS	60 GHz	32.17	1.26
CI	NLOS	60 GHz	32.04	5.21
BP	LOS	73 GHZ	26.42	4.38
CI	LOS	73 GHz	26.36	4.56
BP	NLOS	73 GHZ	34.19	1.13
CI	NLOS	73 GHZ	33.85	3.12

Table.2 Fitting parameters of BP and CI fitting

When the carrier frequency is 60 GHz, the path loss model of outdoor microcellular LOS environment is:

$$PL(f,d)=20\lg\left(\frac{4\pi f d_0}{c}\right)+30.39\lg\left(\frac{d}{d_0}\right)+1.56 \tag{7a}$$

When the carrier frequency is 60 GHz, the path loss model of outdoor microcellular NLOS environment is:

$$PL(f,d)=20\lg\left(\frac{4\pi f d_0}{c}\right)+32.17\lg\left(\frac{d}{d_0}\right)+1.26 \tag{7b}$$

When the carrier frequency is 73 GHz, the path loss model of outdoor microcellular LOS environment is:

$$PL(f,d)=20\lg\left(\frac{4\pi f d_0}{c}\right)+26.42\lg\left(\frac{d}{d_0}\right)+4.38 \tag{7c}$$

When the carrier frequency is 73 GHz, the path loss model of outdoor microcellular NLOS environment is:

$$PL(f,d)=20\lg\left(\frac{4\pi f d_0}{c}\right)+34.19\lg\left(\frac{d}{d_0}\right)+1.13 \tag{7d}$$

5. CONCLUSIONS

Aiming at the typical outdoor micro cellular scenarios of 60 GHz and 73 Ghz millimeter wave band, this paper studies the channel modeling and simulation based on BP neural network algorithm, and proposes a CI path loss model which is generally applicable to the 60 GHz and 73 Ghz SISO millimeter wave channels of outdoor micro cellular LOS and NLOS scenarios.

The results show that the parameters of path loss model fitted by BP neural network method are in good agreement with those simulated by improved CI method, which indicates that BP neural network algorithm can well predict the large-scale parameters of outdoor micro cellular millimeter wave channel.

REFERENCES

1) ZHANG J. H., TANG P., YU L., et al. Channel meas-ure-ments and models for 6G: current status and future outlook. *Frontiers of information technology & electronic engineering*, Vol. 21, Pt. 1, pp. 39-61, 2020.
2) SHAFI M., MOLISCH A. F., SMITH P. J., et al. 5G: A tu-torial overview of standards, trials, challenges, deployment, and practice. *IEEE journal on selected areas in communications*, Vol.35, Pt. 6, pp. 1201-1221, 2017.
3) RAPPAPORT T. S., MACCART G. R., JR., et al. Wideband millimeter-wave propagation measurements and channel models for future wireless communication system design. *IEEE transactions on communications*, Vol. 63, Pt. 9, pp. 3029-3056, 2015.
4) ZHAO X. W., ABDO A. M. A., XU C, et al. Dimension reduction of channel correlation matrix using CUR-decomposition technique for 3-D massive antenna system. *IEEE access*, Vol. 6, pp. 3031-3039, 2018.
5) Bai T., Heath R. W.. Coverage and rate analysis for millimeter-wave cellular networks. *IEEE Transactions on Wireless Communications*, Vol. 14, Pt. 2, pp. 1100-1114, 2014.
6) SUN X. C.. Study on modeling of 28 GHz millimeter wave channel based on BP neural network. *Nanjing: Nan-jing University of Posts and Telecommunications*, 2019.
7) RAPPAPORT T. S., HEATH R. W., DANIELS R, et al. Millimeter wave wireless communications. *Pearson/Prentice Hall*, 2015.
8) SUN S., RAPPAPORT T. S., THMOTHY T. A., et al. In-vestigation of prediction accuracy, sensitivity, and parameters stability of large-scale propagation path loss models for 5G wireless communications. *IEEE transactions on vehicular technology*, Vol. 65, pp. 2843-2860, 2016.