# Study on Wireless Signal Propagation in Residential Outdoor Activity Area Based on Deep Learning

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***Abstract*—As explosive growth of mobile data traffic brings great challenges to the mobile networks, how to reasonably deploy the latest generation mobile networks to meet the needs of users for communication becomes an urgent technical problem to be solved. Since machine learning technology has shown its superiority in processing big data in recent years, researches on the application of machine learning technology in wireless communication are expanded and explored gradually. In this paper, a wireless signal propagation model based on deep learning neural network is proposed to evaluate the wireless signal propagation characteristics and signal coverage status in different scenarios in the complex and changeable residential outdoor activity areas. The massive data generated in practical applications are reasonably utilized to predict the signal propagation characteristics of each cell with high accuracy and stability. The model has is of good adaptability to different complex scenarios and can providing provide a certain reference value and engineering guidance for further wireless network deployment and optimization development.**

***Keywords-wireless signal propagation; deep learning neural network; feature engineering; residential outdoor activity area***

## I. INTRODUCTION

With the continuous development of the mobile Internet and the increasing demands of users for mobile data, the fifth-generation mobile communication system (5G) comes into being, which has become a research hotspot in the communications industry and academia. However, explosive growth of mobile data traffic will bring great challenges to the network, and for the operators, how to reasonably deploy 5G networks to meet the needs of users for communication will be an urgent technical problem to be solved. The environment in which radio waves propagate is very complex, and many factors on the propagation path may affect or even change the propagation mode and spreading path of electromagnetic waves. The prerequisite for the accurate deployment of 5G networks is to achieve reasonable network planning and efficient network prediction. It is of vital significance to the deployment and implementation to establish a reasonable and efficient wireless propagation model to accurately predict the wireless signal propagation characteristics in the target area.

### *A. Traditional Wireless Propagation Models*

The propagation process of wireless signals is very complicated, as the path loss, shadow effect and multipath effect in the propagation process should be considered when studying its propagation characteristics. The outdoor wireless propagation models commonly used today are still traditional empirical models or theoretical models.

The empirical models mainly include the Okumura-Hata model widely used in Japan and the Cost 231-Hata model developed by the Cost Working Committee based on the Hata model [1]. Some researchers introduced more parameters into the fitting formula to provide an improved empirical model of the calculation model for more finely classified scenes, or applied new optimization methods into the empirical models to improve the performance and accuracy in different application scenarios. The theoretical model was mainly built on the theory of electromagnetic wave propagation whose establishment is mainly implemented by the ray tracing method [2].

Comprehensively, traditional wireless propagation models need to be established through complicated theoretical inferences and artificial fitting and correction of a large amount of data which require great time and labor costs, and most of them have certain limitations in applications. In addition, the empirical model is often not accurate enough in specific application, so it is still necessary to correct the empirical model formula by collecting a large number of engineering parameters and actual measurements in each actual operation.

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## B. Machine Learning in Wireless Propagation Fields

Machine learning technology brings new ideas to break the bottleneck encountered in the development of wireless communication technology, especially in the problems of channel evaluation, resource allocation, decision-making and scheduling in the physical layer, data link layer and routing layer [3]. H. He et al. proposed the LDAMP network to solve the channel estimation in the massive MIMO beam millimeter wave scene [4]; Z. Zhao et al. realized the mapping of received signals to original signals in OFDM systems with DNN [5].

The premise of these researches is to accurately understand and grasp the signal propagation characteristics, therefore it is of great significance to predict the channel propagation path loss in different scenarios with high accuracy and real-time. J. Zhu constructed a wireless propagation prediction model based on XGBoost [6], which shows better prediction accuracy and robustness than those built on long short memory network and linear regression methods. It indicates that machine learning may have certain application prospects and value in wireless propagation characteristics, but current researches are still immature, especially when it faces the complex and dynamic environments in residential activity areas. The propagation characteristics of wireless signals require a more intelligent model with high accuracy and good robustness.

In view of the problems above, a deep learning neural network model is proposed to evaluate the wireless signal propagation characteristics and signal coverage status in different scenarios in the complex and changeable residential outdoor activity areas.

# II. Wireless Signal Propagation Model

Prediction of the wireless signal propagation is actually to forecast the wireless signal strength at arbitrary target location which is characterized by Reference Signal Receiving Power (RSRP)[7], thus the wireless signal propagation can actually be quantitatively evaluated on the RSRP. The deep learning method, one of the machine learning directions, is selected to build a model to predict the corresponding RSRP indicators with given input data. Several hidden layers are added in the deep learning neural networks on the basis of traditional neural networks, as rich network hierarchy and structure enable the optimization of algorithm performance. The model building process includes feature engineering, model structure design, parameter initialization, model training, and model optimization.

## A. Feature Engineering

Firstly, feature engineering including feature selection, correlation analysis and feature filter, is carried out to obtain input features from multiple parameters. From an engineering perspective, it is necessary to characterize the basic parameters of the signal emission. In the downlink wireless transmission process, the wireless signal is sent along a certain direction including the vertical and horizontal directions from a fixed signal source installed on the top of a base station tower, and the signal continuously spreads and radiates to the surroundings, then finally reaches the receiving end. Assuming that the center frequency and transmission power of the signal source are stable, several engineering parameters can characterize the signal transmission status of a single signal source. The specific engineering parameters are shown in Table I.

TABLE I. Engineering Parameters Of Signal Source

| Parameter | Unit | Meaning |
|---|---|---|
| Position(X, Y) | m | Coordinates of the signal source on the two-dimensional map (X, Y) |
| Height | m | Height of the signal source relative to the ground |
| Azimuth | Deg | Horizontal deflection angle of the signal line |
| Downtilt | Deg | Vertical tilt angle of the signal line |
| Frequency Band | Mhz | Center frequency band of the signal source |
| RS Power | dBm | Transmit power of the reference signals |

Theoretically, the RSRP value can be calculated as in

$$RSRP = P - PL \tag{1}$$

where $P$ is transmit power of the reference signal, and $PL$ is the path loss [6]. In the case of a certain transmission power, RSRP depends on the propagation path loss. Combined with the path loss formula of the classical propagation model Cost231-Hata model as in

$$PL = 46.3 + 33.9\log_{10} f - 13.82\log_{10} h_b - \alpha + (44.9 - 6.55\log_{10} h_b)\log_{10} d + C_m \tag{2}$$

where $f$ is the carrier frequency, $h_b$ is the effective height of the base station antenna, α is the user antenna height correction term, $d$ is the link distance, and $C_m$ is the scene correction constant [1].

According to (2) and the basic principle of wireless signal propagation, the link distance between the signal source and the user, the propagation direction of the signal line, the height of the signal source relative to the ground, the effective height of the target end, carrier frequency and application scenarios are taken into consideration in the feature design investigation.

In order to facilitate description and calculation, the two-dimensional map is divided into 5m×5m grids, and the coordinates of the upper left corner of the grid represent the coordinates of the grid to further indicate map information of the signal source and the receiving end. Based on the assumptions that there is only one base station in each unit area, and each unit area is independent of each other in time and space; stable weather conditions without wind and rain, and no interference to signal generation and propagation; no consideration of the distribution of ground objects inside each grid on the map, several parameters that affect the target parameter is initially selected as follows: the spatial position of the site, signal source parameters, spatial position of the receiving end and scene parameters.

In order to improve the training efficiency and performance of the model, it is necessary to perform primitive processing on the parameters initially selected. The processing of the original data mainly includes removing redundant information, reducing data dimensionality, engineering conversion of parameters and coding some parameters with the help of coding models.

The link distance can be determined by the base station grid coordinates (*CX*, *CY*) and the receiving grid coordinates (*X*, *Y*) according to formula as follows:

$$d = \sqrt{(X - CX)^2 + (Y - CY)^2} \tag{3}$$

The vertical distance from the signal line to the user is marked as $H_v$, considering the height of the base station $H_b$, the altitude of the site grid *CA*, the altitude of the receiving grid *A*, the height of the receiving grid building *CB*, and the vertical tilt angle of the signal line $\theta_D$ which can be calculated according to (4) where $\theta_{MD}$ is the antenna vertical mechanical tilt angle, and $\theta_{ED}$ is the antenna vertical electrical tilt angle, can be calculated according to (5).

$$\theta_D = \theta_{MD} + \theta_{ED} \tag{4}$$

$$H_v = H_b + CA - A - CB - d \times \tan\theta_D \tag{5}$$

There may be buildings in the base station grid. If the height of the building is close to or higher than the height of the transmitter, it may have a great impact on the signal propagation method and path. The difference between the two heights is marked as $\Delta H_b$ and it can be calculated by (6) where $H_{cb}$ is the building height of the site grid and $H_b$ is height of the base station.

$$\Delta H_b = H_{cb} - H_b \tag{6}$$

With the help of the 0-1 planning idea, the base station grid height influence factor α is constructed to represent the influence of the building height of the base station grid on the signal transmission, and α can be calculated as in

$$\alpha = \begin{cases} 0, & \Delta H_b < 0 \\ \Delta H_b, & \Delta H_b \geq 0 \end{cases} \tag{7}$$

The directional signal factor is used to characterize the influence of the grid position on the signal propagation, which is denoted as $D_A$, can be obtained as in

$$D_A = \left|\tan^{-1}\left(\frac{X - CX}{Y - CY}\right) - \theta_A\right| \tag{8}$$

where $\theta_A$ stands for Azimuth of the signal line.

Combining classic models and engineering principles, Frequency Band and RS Power with no other processing are considered as two inputs respectively. Moreover, after analyzing the original data set used in the paper, it is found that the frequency band of the signal source center remains basically stable, which suggests little reference significance for model training, so it is excluded from the feature candidate parameters.

Due to the complexity and variability of the scenes of residential activity areas in real life and applications, it is complicated to use specific scenes as feature inputs. The data set used in this paper classifies different scenes, which are characterized by Clutter Index including the Cell Clutter Index and the Clutter Index, but the index has a total of 20 items, which is not suitable as a feature input. Combined with the scene processing method in the Cost 231-Hata model and the analytic hierarchy process, the features of scenes are quantified by 6 levels with the scene coefficient $C_I$. The specific classification of various feature types in the residential activity areas is shown in the Table II. The scene coefficients of the base station grids and the receiving grids are two independent characteristic parameters, so they are respectively recorded as $C_{Ia}$ and $C_{Ib}$, but the quantization and classification methods for the two ones are the same.

TABLE II. SCENE COEFFICIENTS

| Scenes | $C_I$ |
|---|---|
| Oceans, inland lakes, wetlands, open suburban areas, urban open areas, open roads | 1 |
| Vegetation area, shrub vegetation, forest vegetation | 2 |
| High-density buildings in urban areas <20m, multi-storey buildings in urban areas <20m, low-density industrial building areas, suburbs, developed suburban areas, rural areas | 3 |
| Mid-to-high-rise buildings (20m ～ 40m) and high-density industrial buildings in urban areas | 4 |
| Urban high-rise buildings (40m～60m) | 5 |
| Urban super high-rise buildings (>60m), CBD business circle | 6 |

Above all, 8 characteristic parameters are selected as input features of the model, including RS Power, $d$, $H_v$, $H_b$, $\alpha$, $D_A$, $C_{Ia}$, $C_{Ib}$, as shown in Table III.

TABLE III. CHARACTERISTIC PARAMETERS

| Characteristic Parameters | Symbol (unit) |
|---|---|
| Transmitter transmit power | *RS Power*(dBm) |
| Link distance | $d$(m) |
| Effective height of signal line | $H_v$(m) |
| Base station effective height | $H_b$(m) |
| Base station grid height influence factor | $\alpha$ |
| Directional signal factor | $D_A$ |
| Base station grid scene factor | $C_{Ia}$ |
| Receiving grid scene factor | $C_{Ib}$ |

## B. *Correlation Calculation*

After the feature parameters selection, Spearman rank correlation coefficient[8] which is suitable for continuous measurement data is calculated to explore the correlation between the feature parameters and the target RSRP value, that is, to sort and rank the values of the two parameters as in

$$r_s = 1 - \frac{6\sum_{i=1}^{n}(R_i - Q_i)^2}{n(n^2 - 1)} \tag{9}$$

where $r_s$ is the Spearman correlation coefficient between the parameter $x$ and the parameter $y$, $R_i$ represents the rank of $x_i$, and $Q_i$ represents the rank of $y_i$. When two variables have a strictly monotonic functional relationship, they are completely Spearman related. And combined with the statistical characteristics of the original data, six feature parameters suitable for training the model are selected to form the model input feature set, which consist of Link Distance $d$, Signal Line Effective height $H_v$, Signal Direction Factor $D_A$, Receiving Scene Coefficient $C_{Ib}$, Transmitter Transmit Power *RS Power*, Base Station Grid Scene Coefficient $C_{Ia}$.

### C. Model Building

Deep learning neural network is constructed with six input nodes and one output node. By repeatedly adjustment and verification of the numbers of layers and nodes with the cross-validation method which means 5% of the sample data is randomly selected as the verification set, and the rest is the training set for verification, the network is established with 4 hidden layers and the number of nodes in each layer decrease gradually as 15, 10, 8 and 6 respectively. Combining the dynamic range of the input feature data, the hyperbolic tangent function is selected as the activation function of the first three hidden layers, and the linear rectification function (Relu function) is selected as the activation function of the fourth hidden layer to achieve more efficient gradient descent and simplify the calculation process. The basic network structure is shown in Figure 1.

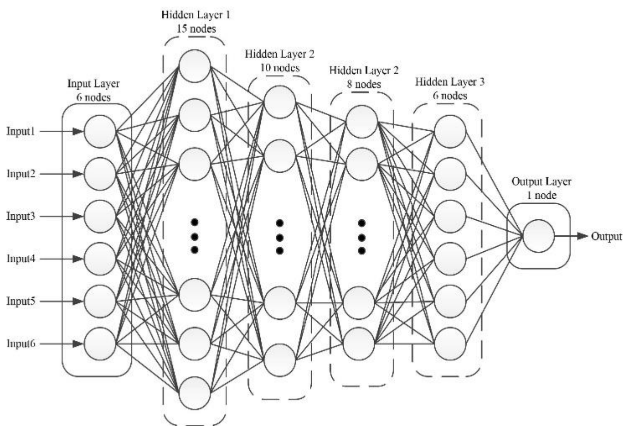



Figure 1. Deep learning neural network model structure.

## III. EXPERIMENTS

The data set used in this article is a measured data set of nearly 4000 residential outdoor activity communities across the country provided by a Chinese mobile operating company. In the data set, each piece of data consists of the index of the community, 8 engineering parameters and 8 geographic parameters as well as the corresponding RSRP, which was obtained from massive mobile users excluding the effects of indoor transmission. Before fed into the model, the data set needs to be preprocessed for better training effect. The data set is cleaned first, and some abnormal data samples such as null values or the actual measurement value does not match the figure index are eliminated with a total of 380,000 valid data left. All values of the feature data fed into the model need to be normalized into the interval [-1, 1] by data preprocessing, otherwise different evaluation indicators with large difference between the values may affect the results unpredictably. The characteristic data need to be standardized by scaling the value proportionally. The Decimal Calibration Standardization is adopted to limit the characteristic data to [-1, 1] by moving the decimal places of the characteristic value.

At the beginning of training, the model assigns weight values randomly. Due to the large amount of training data set, direct training may cause gradient explosion, therefore the mini-batch gradient descent method, one of in the stochastic gradient descent method is applied to divide the training set into smaller subsets named mini-batch for training. The parameters are updated in batches, which are jointly determined by the data in a batch, so that the change in the direction of the parameters is reduced.

In this model, the batch size during training is set to 1024. Because of the large amount of data in the training data set, there is basically no consideration of under-fitting. However, the deep learning neural network has multiple hidden layers, which may cause over-fitting, resulting in unsatisfactory generalization ability. In order to avoid affecting the generalization ability of the model, the maximum epochs is set to 200 times during training. And the Adam Authorization Algorithm, a gradient descent algorithm with adaptive learning rate, is integrated with the mini-batch gradient descent method to optimize the model, that is, an exponentially weighted moving average of small batches of random gradients is performed on the basis of Root mean square propagation algorithm. Compared with the traditional gradient descent algorithm, the adaptive learning rate gradient descent algorithm has the advantages of rapid and accurate convergence with an optimized learning rate for each parameter during the training process.

Root Mean Square Error (RMSE) is selected as the objective function of model training and verification, which can be calculated as in

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{t=1}^{N}(observed_t - predicted_t)^2} \tag{10}$$

where $observed_t$ is the target output value of the training data set and $predicted_t$ is the target output value predicted by the model. The smaller the RMSE values, the better the fitting effect, and vice versa. The RMSE value obtained from the validation set represents the generalization ability of the model. The purpose of model training and debugging is to obtain a model with the best generalization ability. The Early Stopping method [9] is introduced additionally to prevent the occurrence of over-fitting problems during training. More specifically, the early stopping mechanism adopted is to check the generalization result of the model after training several steps, that is, whether the RMSE value of the verification set is better than the average RMSE of the previously specified step, if the generalization performance is found to decrease then stop training.

## IV. EXPERIMENTAL RESULTS AND ANALYSIS

This section presents the experiments results and the analysis of the results to reveal the good performance and reliability of the model.

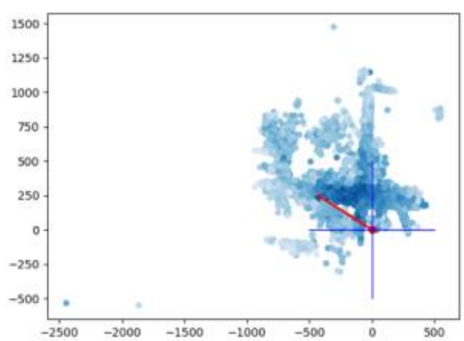
After feature conversion and statistical calculations on the original data, the statistical results of some statistically significant features are obtained as shown in Table IV.

In view of the fact that the feature data that are almost unchanged contribute little to the establishment of the model and will not be recognized and learned during model training, such parameter data can be eliminated from the scope of the final feature input. If the standard deviation is very small or almost unchanged compared to the value of the characteristic parameter itself, it can be discarded as the characteristic parameter has little meaning or contribution to its learning during model training. It can be seen from Table IV that the values of the six characteristic parameters are stable within a certain dynamic range, and the statistical values all meet the basic requirements.

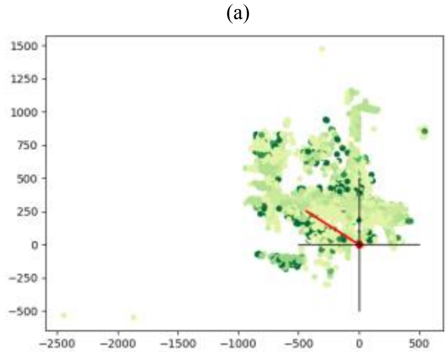
TABLE IV. STATISTICAL RESULTS OF CHARACTERISTIC PARAMETERS

| Characteristic Parameters (Unit) | Mean | Minimum | Max | Standard deviation |
|---|---|---|---|---|
| *RS Power*(dBm) | 11.26919 | 10.2 | 18.2 | 2.51 |
| $d$(m) | 615.13918 | 0 | 5003.30 | 1090 |
| $H_v$(m) | -72.80902 | -3545.82 | 471.04 | 186.78 |
| $H_b$(m) | 23.22668 | 0 | 65 | 9.60 |
| $\alpha$ | 1.06283 | 0 | 83 | 6.25 |
| $D_A$(Deg) | 92.32428 | 0 | 360 | 87.78 |

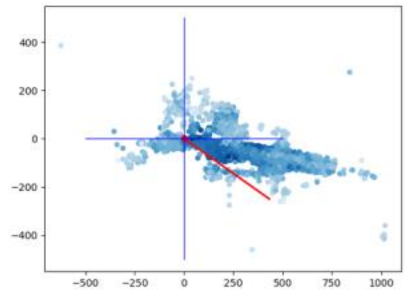
In addition, there are other two scene parameters $C_{Ia}$ and $C_{Ib}$ used to characterize the actual scene, the correlation with the target parameter RSRP of which is shown in Figure 2 after visualization processing. The left pictures show the visual analysis of RSRP values of some randomly selected cells, where the darker color indicates stronger signal coverage. The right ones show the visual analysis of the scene coefficient of the corresponding cell, where the darker color indicates that the scene coefficient is higher. It can be found that the signal coverage strength has a certain correlation with the scene coefficient, the link distance and the signal line direction.



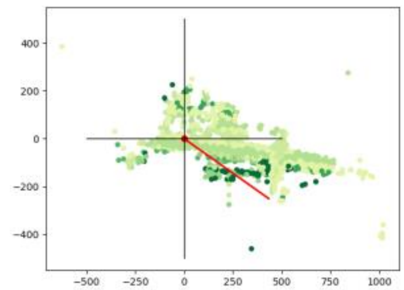

(a)




(b)
Cell A




(a)




(b)
Cell B

Figure 2. RSRP and scene parameters visualization: (a) RSRP of a cell on the two-dimensional map; (b) scene parameters of the cell.

Spearman rank correlation coefficient, which is adopted for quantitative correlation analysis, is calculated with the 8 feature parameters selected and RSRP tag values as variables according to (10). The Spearman correlation coefficients between each characteristic parameter and RSRP are shown in Table V.

TABLE V. CORRELATION RANKING OF CHARACTERISTIC PARAMETERS

| Rank | Characteristic Parameters | Spearman rank correlation coefficient with RSRP |
|---|---|---|
| 1 | $d$ | -0.39431 |
| 2 | $H_v$ | 0.35381 |
| 3 | $D_A$ | -0.11528 |
| 4 | $C_{Ib}$ | -0.03210 |
| 5 | *RS Power* | -0.02025 |
| 6 | $C_{Ia}$ | -0.01167 |

Table V indicates that $d$ and $H_v$ tend to have strong correlations with the RSRP value as the absolute values of the Spearman rank correlation coefficient come at first and second respectively. Secondly, $D_A$ , $C_{Ib}$ and *RS Power* also show a certain correlation with the RSRP value implying a certain learning value for model training. The correlation coefficient between $C_{Ia}$ and the RSRP is relatively weaker compared to the other parameters, but combining the correlation between $C_{Ia}$ and other parameters, it can be found that it is related to building height impact factor and the grid scene coefficient of the base station grid to some extent. The correlation of the base station height and building height influence factor of the base station grid with the RSRP value are rather weak, so the exclusion of these two parameters from the feature candidate parameters is reasonable. In general, by visual analysis and quantitative analysis, the six feature parameters above have a good correlation with the target output, and the data are effective and reliable with certain significance and value for the training of the model.

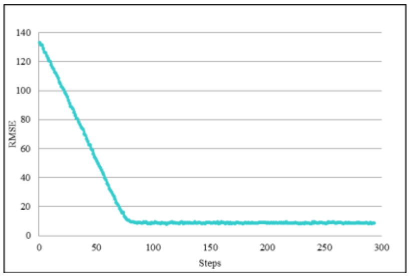



Figure 3. The change trend of RMSE on the validation set.

As mentioned above, 5% of the sample data is randomly selected as the verification set, and then the trained model is verified with the RMSE value of the validation set. The trend of the RMSE value of the validation set with the number of training steps is shown in Figure 3.

As can be seen from the figure above, the model converges quickly as it reaches a relatively stable RMSE value at about 8.843 after a few steps of training. In the subsequent training, the model convergence speed drops, and finally the Early Stop mechanism is triggered when the RMSE reaches at about 8.650. It can be seen from the RMSE value of the validation set that the generalization ability of the trained model is relatively satisfying.

TABLE VI. RMSE OF DIFFERENT MODELS

| Model | RMSE of Training Data Set | RMSE of Validation Data Set |
|---|---|---|
| Deep Learning Neural Networks | 8.472 | 8.650 |
| Linear Regression | 30.652 | 37.233 |
| XGBoost | 9.125 | 10.017 |

The linear regression and the XGBoost-based prediction model are compared with the deep learning neural network model to verify that the model built in this paper shows better generalization performance and higher prediction accuracy. Linear regression aims to fit a linear function [10], while the performance of traditional linear regression might be affected by factor diversity and uncertainty. The XGBoost-based model is put forward for regression or classification by integrated learning methods [11], and requires traversal of data sets. The amount of data in this article is very large, and the space complexity of the pre-sorting process may be too high. The training tests are conducted on the same pre-processed data set, and the model based on deep learning proposed in the paper shows better performance and stronger generalization ability as shown in Table VI, that is, it can predict signal coverage more accurately faced with new complex application scenarios. Additionally, convergence speed of the model in this paper is faster than the existing deep learning wireless prediction models under the premise of similar prediction accuracy and the same training equipment.

## V. CONCLUSION

A wireless signal propagation model based on deep learning neural network is proposed to predict the RSRP value in different scenes of residential outdoor activity areas including different spatial distance and azimuth from the signal source to the receiving end and surrounding features of the receiving end. The comprehensive performance of the deep learning model is better when compared with linear regression methods and the XGBoost-based model. The massive data generated in practical applications are reasonably utilized to predict the RSRP of each cell with high accuracy and stability as the RMSE on the validation set finally stabilized at around 8.650. The model has good adaptability to different complex scenarios, and can provide a certain reference value and engineering guidance for further 5G wireless network deployment and optimization development, yet, the model proposed in this article can still be optimized as follows: the impact of climate on wireless signal propagation is not considered in this model; complicated indoor transmission is not considered in this paper; as model fusion is one of the important methods for model optimization, other model algorithms can be integrated alternatively in subsequent studies for further improvement.

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