Feature engineering based intelligent wireless propagation model for RSRP prediction

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Abstract. Wireless propagation model is of great significance for accurate 5G network deployment. Based on the data set provided by Huawei ModelArts platform, this paper uses the typical method of feature engineering to establish the intelligent wireless propagation model based on back propagation (BP) neural network. The first is feature design, which has designed 12 features from the traditional Cost 231-Hata empirical model and geometric location. Considering the coupling relationship between the features, the angle and distance related features are dimensioned. The second is data processing, using logarithmic transformation, One-Hot coding, missing value processing, etc. Then there is the feature selection, and the final feature set of the model is extracted by the standard deviation, the quantized value of the Pearson coefficient and the feature-reference signal receiving power (RSRP) scatter plot. Finally, the prediction model is built and verified. In order to compare the superiority of the designed features, this paper established and tested three BP neural network models with the same network structure but different inputs to predict the RSRP of different geographical locations. The experimental results verified the superiority of the designed feature set. And a suitable wireless propagation machine learning model was obtained.

1. Introduction

The wireless propagation model predicts the radio wave propagation characteristics in the target communication coverage area, making it possible to estimate the coverage of the cell, inter-cell network interference, and communication rate [1], which is very important for operators to deploy accurate 5G network [2-3].

According to research methods, the existing wireless propagation models can be divided into empirical models, theoretical models and improved empirical models. The most representative ones are Cost 231-Hata, Okumura, Volcano, SPM, etc. [4-6]. Empirical models are often not sufficiently accurate in practical use, so it is necessary to modify the empirical model formula by collecting a large number of engineering parameters and the measured values of reference signal receiving power (RSRP).

Wireless LTE networks have become popular around the world, with billions of users generating vast amounts of data all the time. These data can be used reasonably to assist in wireless network construction [7]. In addition, in recent years, big data-driven AI machine learning technology has made great progress [8]. And with the development of parallel computing architecture, machine learning technology also has the capability of online computing. Its high real-time performance and low complexity make it possible to integrate with wireless communication [9].
Through the data set provided by Huawei ModelArts platform and using machine learning technology, this paper obtains a suitable machine learning model to accurately predict the wireless signal coverage intensity, the RSRP, in the new environment, thereby greatly reducing the network construction cost and improving the network construction efficiency.

2. Introduction to the data set

This paper uses the data set provided by Huawei ModelArts platform, including training set, test set and verification set, for training and testing of AI algorithm model. Because feature engineering mainly uses training data sets, the training data sets are described in detail below.

The training data set contains a total of 4000 files. Each row of each file represents the relevant data of the fixed-size test area in the cell. The number of rows is between 2220-3800, and the number of columns is fixed to 18 columns. The first 9 columns are the engineering parameter data of the site. The middle 8 columns are map data, which records the topography information. The last column is the actual measurement result of RSRP as the tag data for training. In order to facilitate data processing, the map is rasterized, and each grid represents a 5m × 5m area. Table 1 shows one row as an example:

| Engineering parameter data | Meaning description | Map data | Meaning description |
|----------------------------|---------------------|----------|---------------------|
| Cell Index                 | Unique identifier of the cell | Cell Building Height | Building height of the grid where the cell site is located (Cell X, Cell Y) |
| Cell X                     | Grid position of the station belonging to the cell, X coordinate | Cell Altitude | The altitude of the grid where the cell site is located (Cell X, Cell Y) |
| Cell Y                     | Grid position of the station belonging to the cell, Y coordinate | Cell Clutter Index | Feature type index of the grid where the cell site is located (Cell X, Cell Y) |
| Height                     | The height of the cell transmitter relative to the ground (m) | X | Grid position, X coordinate |
| Azimuth                    | Horizontal direction angle of cell transmitter (Deg) | Y | Grid position, Y coordinate |
| Electrical Downtilt        | Vertical electrical downtilt of cell transmitter (Deg) | Building Height | Building height on the grid (X, Y) |
| Mechanical Downtilt        | Vertical mechanical downtilt of cell transmitter (Deg) | Altitude | Altitude on the grid (X, Y) |
| Frequency Band            | Cell transmitter center frequency (MHz) | Clutter Index | Feature type index on the grid (X, Y) |
| RS Power                  | Cell transmitter transmitting power (dBm) | Tag data (RSRP) | Reference signal receiving power of the grid (X, Y) |

3. Feature design

The essence of feature engineering is to convert the parameters from the original data to what best represent the target problem, and make the dynamic range of each parameter within a relatively stable range, thus improving the efficiency of machine learning model training.

In this paper, the feature design is carried out from two aspects: traditional Cost 231-Hata empirical model and geometric location.

3.1. Designing features based on Cost 231-Hata model

The parameters involved in the classic Cost 231-Hata model can be included in the scope of feature engineering, which is defined as follows:

\[
PL = 46.3 + 33.9\log f - 13.82\log h_b - \alpha + (44.9 - 6.55\log h_b)\log d + C_m
\]  

(1)

Where \(PL\) is defined as propagation path loss (dB), \(f\) is carrier frequency (MHz), \(h_b\) is effective height of base station antenna (m), \(\alpha\) is height correction item of user antenna (dB), and \(d\) is the
horizontal distance (km) between base station antenna and user antenna, and $C_m$ is the scene correction constant (dB). The features designed are as follows:

3.1.1. **Feature one: carrier frequency** $f$. The carrier frequency is the same as the cell transmitter center frequency.

$$f = \text{Frequency Band}$$

3.1.2. **Feature two: effective height of base station antenna** $h_b$. The effective height between the base station antenna and the user antenna can be calculated using the relative height of the transmitter and the building on the grid:

$$h_b = \text{Height} + \text{Cell Altitude} - \text{Altitude}$$

3.1.3. **Feature three: the height of the user receiver relative to the ground** $\epsilon h_{ue}$. Considering that the actual range of the user's activity in the actual situation can only be on the ground or in the building, the effective height of the user antenna on the grid $(X, Y)$ does not exceed the height of the building there, so the effective height of the user antenna can be corrected as follows:

$$\epsilon h_{ue} = \epsilon \text{Building Height}$$

Where $\epsilon$ is a continuous variable and $0 \leq \epsilon \leq 1$.

3.1.4. **Feature four: transmitter transmitting power** $P_t$. According to the Cost 231-Hata model, the relationship between RSRP and $PL$ is as follows:

$$\text{RSRP} = P_t - PL$$

The transmitter transmitting power $P_t$ is as shown in equation (6):

$$P_t = \text{RS Power}$$

3.2. Designing features based on geometric location

3.2.1. **Feature five: Euclidean distance** $d$. The Euclidean distance $d$ between $(X, Y)$ and $(\text{Cell X, Cell Y})$ can be used as a feature of the wireless propagation model:

$$d = \left((\text{CellX} - X)^2 + (\text{CellY} - Y)^2\right)^{1/2}$$

3.2.2. **Feature six: the spatial distance between the measurement point and the base station vertex** $D$. Due to the complicated calculation of the spatial distance between the measurement point and the antenna center point, the spatial distance between the measurement point and the highest point of the base station is selected as a feature to approximately replace it, which is shown in equation (8):

$$D = ((X - \text{Cell X})^2 + (Y - \text{Cell Y})^2 + (h_b - \epsilon h_{ue})^2)^{1/2}$$

3.2.3. **Feature seven: the relative height of the grid to the main signal line** $\Delta h_v$. The main signal line can be regarded as the direction with the maximum signal propagation power. The relative height between the grid and the main signal line can qualitatively reflect the strength of the signal. The spatial distance $\Delta h_v$ from the measurement point to the main signal line can be taken as the feature of the wireless propagation model, which has the following two cases:

1) **The target grid is in the direction of propagation of the main signal line.** In the propagation direction of the main signal line, the relative height between the grid and the main signal line is calculated as follows:

$$\Delta h_v = h_b - d \times \tan(\theta_{MD} + \theta_{ED})$$

2) **The target grid is not in the direction of propagation of the main signal line.** For a grid beyond the propagation direction of the main signal line, the propagation power of the signal line (called sub-signal line) propagating to the grid is weaker than the main signal line, and the signal strength is
somewhat weakened. The formula for the distance between the grid in the propagation direction of the sub-signal line and the main signal is as follows, regardless of the height of the measuring point:

\[ \Delta h_v = (\Delta h_v^2 + ds^2)^{1/2} \]  (10)

Where \( ds \) represents the distance between the target grid to the main signal line in the Y-axis direction in the X-Y plane.

\[ ds = ||Cell X - X||(\tan(Azimuth))^{-1} - |Y - Cell Y|| \]  (11)

Where \( \Delta h_v' \) is the relative height between the main signal line and the grid which at the same X coordinate as the target grid, but in the direction of propagation of the main signal line.

\[ \Delta h_v' = h_b - d' \times \tan(\theta_{MD} + \theta_{ED}) \]  (12)

Where \( d' \) is the link distance between the base station and the grid which at the same X coordinate as the target grid, but in the direction of propagation of the main signal line.

\[ d' = ((X - Cell X)^2 + (Y - Cell Y)^2)^{1/2} \]  (13)

3.2.4. Feature eight: vertical distance from the grid to the main signal line \( h_T \). The \( h_T \) is available from the point in space to the straight line distance.

3.2.5. Feature nine: the angle between the measuring point and the signal line in the horizontal direction \( \theta_{TA} \). According to the horizontal direction angles of cell transmitter (Azimuth), (X, Y) and (Cell X, Cell Y), the angle \( \theta_{TA} \) between the measurement point and the signal line in the horizontal direction can be determined.

\[ \theta_{TA} = \arctan((X - Cell X)(Y - Cell Y)^{-1}) - Azimuth \]  (14)

3.2.6. Feature ten: the angle between the measuring point and the signal line in the vertical direction \( \theta_{TD} \). The calculation formula of the angle \( \theta_{TD} \) is as shown in equation (15):

\[ \theta_{TD} = \arctan(|h_b - \epsilon h_{ue}|((X - Cell X)^2 + (Y - Cell Y)^2)^{-1/2}) - \theta_{MD} - \theta_{ED} \]  (15)

3.2.7. Feature eleven: the sum of the vertical mechanical downtilt angle and the vertical electrical downtilt angle of the cell transmitter \( \theta_{MED} \). The calculation formula is as shown in equation (16):

\[ \theta_{MED} = \theta_{MD} + \theta_{ED} \]  (16)

3.2.8. Feature twelve: terrain and climate correction factor \( C_s \). The weather conditions are different, the air density, humidity, and temperature are different in the air, and the efficiency and speed of signal transmission are also different. There is a building in the grid where the cell transmitter is located, and the height of the building has a certain occlusion effect on the signal transmitted by the transmitter, and the above reasons are uniformly expressed as the terrain and climate correction factor \( C_s \).

\[ C_s = k_1 Cell Building Height + k_2 Cell Clutter Index + k_3 Clutter Index + \Delta \]  (17)

Where, \( \Delta \) is the influence of other weather and terrain factors on the signal propagation process.

3.3. Dimension reduction analysis

3.3.1. Angle dimension reduction. The \( \theta_{TA} \), \( \theta_{TD} \), and \( \theta_{MED} \) proposed in the space spherical coordinate system are for describing the positional relationship between the measurement point and the main signal line in the space, considering that the base station to the measurement point and the main signal line are two lines in the space. When the main signal line is a ray, the positional relationship between them can be replaced by the space vector angle \( \theta_{3D} \) between the vectors in the space.
The unit direction vector of main signal line is as follows:

\[(\tan(\theta_{MD} + \theta_{ED}), \cos(\theta_{MD} + \theta_{ED}) \sin(Azimuth), \cos(\theta_{MD} + \theta_{ED}) \cos(Azimuth))\]  

The unit direction vector from the measurement point to the antenna is as follows:

\[\left(\left(X - \text{Cell } X\right)D^{-1}, \left(Y - \text{Cell } Y\right)D^{-1}, (h_b - \varepsilon h_{ue})D^{-1}\right)\]  

The angle between the direction vector of the measuring point and the direction vector of the main signal line is the space vector angle \(\theta_{3D}\).

### 3.3.2. Distance dimension reduction

Considering that the distance between the measurement point and the base station is far, the spatial distance \(D\) is approximately equal to the Euclidean distance \(d\).

\[D \approx d\]

Therefore, only one of the two features is needed, and comprehensively select the spatial distance \(D\) as the feature.

### 4. Data processing

#### 4.1. Abnormal data processing

Abnormal data needs to be cleaned in advance. The following abnormal data was found by consulting relevant data and contacting the actual situation, as shown in Table 2.

| Abnormal situation | Processing method |
|--------------------|-------------------|
| 1 The terrain number (Clutter Index) does not match the building height (Building Height) | Eliminate the entire row of data |
| 2 Cell Building Height > Height, buildings in the grid are higher than the base station | Try both delete and retain |
| 3 The “Height” of 128 cells is zero | Eliminate the entire row of data |

#### 4.2. Data preprocessing

##### 4.2.1. Data transformation

Use the “FunctionTransformer” of the “Preproccessing” library to perform logarithmic transformation on the features proposed by the Cost 231-Hata definition, namely \(\lg f\), \(\lg h_b\), \(\lg d\), and \(\lg D\).

##### 4.2.2. One-hot coding for qualitative features

One-hot coding uses a binary bit to indicate the presence or absence of a qualitative feature, and uses the “OneHotEncoder” class of the “Preproccessing” library to encode the data.

##### 4.2.3. Missing value filling and visualization

As can be seen from the measurement point distribution map of the cell, there are some places in the cell that do not set measurement points to test RSRP. For the area where there is no measurement point, that is, the RSRP missing area, the value of the weak coverage decision threshold \(P_{th} (-103 \text{ dBm})\) is used as the padding. Take the CSV file of a cell (No. 2302410) as an example, its measurement location distribution map is shown in figure 1, and the RSRP thermal map after filling the missing values is shown in figure 2.
In figure 1, the red area is the distribution of target grid measurement points, and the green point represents the location of the signal base station in the cell. In figure 2, the blue background is the value of the weak coverage decision threshold $P_{th}$ (-103 dBm), the deeper the blue, the weaker the signal of the measurement point. And the red area represents that the value of RSRP is strong, and the deeper the red indicates the stronger the RSRP.

5. Feature selection

After the feature design is completed, it is usually necessary to select meaningful feature to input machine learning model for training. For features designed by different methods, it is necessary to judge whether the feature is appropriate from multiple levels.

5.1. Existing feature availability assessment

We evaluated the usability of the designed features from three aspects: data acquisition difficulty, computational difficulty, and universality, and screened out $\Delta h_v$ and $h_T$.

5.2. Divergence analysis

The divergence of features is one of the important criteria for selecting features. The divergence analysis is performed on the designed features by the standard deviation, as shown in table 3.

| Feature | Meaning description                                      | Unit  | Standard deviation |
|---------|----------------------------------------------------------|-------|--------------------|
| $\lg f$ | Carrier frequency logarithm                              | MHz   | 0.001485           |
| $\lg h_b$ | Base station antenna effective height logarithm          | m     | 0.226375           |
| $h_{ue}$ | The height of the user receiver relative to the ground   | m     | 13.265753          |
| $p_t$   | Cell transmitter transmitting power                      | dBm   | 2.582967           |
| $\lg D$ | The spatial distance logarithm of the measurement point to the apex of the base station | m     | 0.457057           |
| $\theta_{3D}$ | The vector angle between the transmitter and the measuring point | Deg   | 49.576319          |

*Because $C_v$ is difficult to calculate with actual values, it does not participate in quantitative calculation.

*The coefficient $\varepsilon$ in $\varepsilon h_{ue}$ is not fixed, so $h_{ue}$ is used instead of $\varepsilon h_{ue}$ for the quantitative calculation.

It can be seen from table 3 that the standard deviation of $\lg f$ is small, because the transmitter power of each cell is at the MHz level, which is not much different. The standard deviation of $\theta_{3D}$ is large,
because $\theta_{3D}$ is in angle system, and the range is distributed between 20° and 180°, indicating a wide distribution between the cell and the measurement points.

5.3. Correlation analysis

The Pearson correlation coefficient $\Upsilon$ is widely used to measure the correlation degree between two variables, with values between -1 and 1.

$$\Upsilon = \frac{1}{n-1} \sum_{i=1}^{n} \left( \frac{X_i - \bar{X}}{\sigma_X} \right) \left( \frac{Y_i - \bar{Y}}{\sigma_Y} \right)$$

(21)

Where $\frac{X_i - \bar{X}}{\sigma_X}$, $\bar{X}$, and $\sigma_X$ are the standard values, mean values, and standard deviations for the $X_i$ samples, respectively. Calculate the correlation between the designed features and the target, and quantify and sort the results, as shown in table 4.

Table 4. Correlation between features and targets.

| The sorting | Feature | Correlation with the target (Pearson coefficient) |
|-------------|--------|--------------------------------------------------|
| 1           | $lgD$  | -0.399144                                       |
| 2           | $p_t$  | 0.128148                                         |
| 3           | $lg h_b$ | -0.119382                                       |
| 4           | $h_{ue}$ | -0.082744                                       |
| 5           | $\theta_{3D}$ | -0.061994                                      |
| 6           | $lg f$ | 0.000339                                         |

It can be seen from table 4 that the correlation between the spatial distance logarithm $lgD$ and the target is more obvious.

5.4. Feature correlation visualization

The visualization of the correlation between the designed features and the target is shown in figure 3.
Figure 3. Feature correlation visualization.

Description: Randomly take 30 files, a total of 91321 rows of data, using uniform sampling to calculate the relationship between the designed features and RSRP. In figure e and figure f, in order to make the results clearer, 1000 random samples were selected for drawing. Figures (a)-(f) are the graphs of relationship between $lgf$, $lh_b$, $h_{ue}$, $p_t$, $lgD$, $\theta_{3D}$ and RSRP, with the horizontal axis representing features and the vertical axis representing RSRP.

It can be seen from figure (a) that although the value of RSRP varies with $lgf$, the samples are concentrated near two logarithmic frequency values. So the correlation between $lgf$ and RSRP is very small. Considering that the standard deviation of $lgf$ is 0.001485 and Pearson coefficient is 0.000339, $lgf$ is deleted.

In figures (b)-(d), it can be seen from the horizontal axis that $lh_b$, $h_{ue}$ and $p_t$ are variables, and their dynamic range is in a relatively stable range. It can be seen from the vertical axis that under the same $lh_b$, $h_{ue}$ and $p_t$, when other factors change, RSRP also changes, but for different $lh_b$, $h_{ue}$ and $p_t$, the range of RSRP changes differently. And the higher the $h_{ue}$, the more concentrated the value of RSRP. It can be seen that $lh_b$, $h_{ue}$ and $p_t$ are correlated with RSRP.

In figures (e)-(f), it can be seen from the horizontal axis that $lgD$ and $\theta_{3D}$ are variables, and their dynamic range is in a relatively stable range. It can be seen from the vertical axis that under the same $lgD$ and $\theta_{3D}$, when other factors change, RSRP also changes, but for different $lgD$ and $\theta_{3D}$, the range of RSRP changes differently. With the increase of $lgD$, the overall RSRP trend is decreasing. Moreover, the decline trend is obvious, indicating that $lgD$ has a strong negative correlation with RSRP. As $\theta_{3D}$ increases, RSRP decreases slightly. It can be seen that $\theta_{3D}$ has a weak negative correlation with RSRP.

In summary, the correlation between the spatial distance logarithm $lgD$ and the target is more obvious, which is consistent with the calculation result of the Pearson coefficient.

5.5. Final feature set

The final selected feature set is shown in table 5:

| Feature | Meaning description | Unit |
|---------|---------------------|------|
| $lh_b$  | Base station antenna effective height logarithm | m   |
| $h_{ue}$ | The height of the user receiver relative to the ground | m   |
| $p_t$   | Cell transmitter transmitting power | dBm |
| $lgD$   | The spatial distance logarithm of the measurement point to the apex of the base station | m   |
| $\theta_{3D}$ | The vector angle between the transmitter and the measuring point | Deg |
6. Model establishment

Based on the feature set established above and the training data set provided by Huawei cloud platform, an AI-based wireless propagation model is established to predict the RSRP in different geographical locations.

6.1. Modeling method

Back propagation (BP) neural network is currently the most widely used neural network, which is a kind of multi-layer feedforward neural network trained according to the error back propagation algorithm [10-11]. In view of the advantages of BP neural network, such as easy operation, strong nonlinear mapping and suitable for engineering problems. BP neural network is selected to train the wireless propagation model.

6.2. Model parameter settings

In order to train a more satisfactory wireless propagation model, we built and tested three BP neural network models. In order to highlight the features designed by feature engineering is more reasonable and useful, the models all use the same network structure (hidden layer is 100, output layer is 1, loss function is mse, learning rate is 0.01), and the model parameters are set as shown in table 6.

| Serial number | Parameter description | The first BP model parameters | The second BP model parameters | The third BP model parameters |
|---------------|----------------------|-------------------------------|-------------------------------|-----------------------------|
| 1             | Input layer neurons  | 17                            | 10                            | 5                           |
| 2             | Hidden layers        | /                             | 1                             | 1                           |
| 3             | Hidden layer neurons | /                             | 100                           | 100                         |
| 4             | Output layer neurons | 1                             | 1                             | 1                           |
| 5             | Learning rate        | /                             | 0.01                          | 0.01                        |
| 6             | Loss function        | /                             | mse                           | mse                         |
| 7             | Optimizer            | /                             | sgd                           | sgd                         |

The first version of the model is the official baseline model, so the model parameters are unknown.

6.3. Training results

Combined with the scores given by the Huawei online scoring system, the training results are shown in table 7 below.

| Model number | Online score | PCRR¹ | RMSE² |
|--------------|--------------|-------|-------|
| 1            | 16.7258      | >20%  | 12.3425|
| 2            | 15.7867      | >20%  | 11.5242|
| 3            | 12.7246      | >20%  | 7.5321 |

¹ PCRR: poor coverage recognition rate, and the threshold is 20%.
² RMSE: root mean squared error.

The first version of the model is obtained by inputting 17 original parameters as features on the officially provided baseline. The second model is trained by using the simple designed features (using 4 highly correlated calculated relative heights, totalling 10 features to input). The third model is trained by inputting five carefully designed and selected features.

The scores of the three model are: 16.7258, 15.7867, and 12.7246. From the results score, it can be seen that the features designed by the typical method of feature engineering are superior, and the model with better effect can be obtained more quickly, which verifies the importance of feature design. Finally, the third version of the training model is selected as the target intelligent wireless propagation model.
7. Summary and outlook
Combining the mechanism of communication propagation loss, this paper uses the typical method of feature engineering to do feature design, data processing and feature selection to reduce the number of input parameters of the neural network model, which reduced the training amount and got more efficient model. It verifies the importance of feature design and also reflects the superiority of the feature set designed. In the experiment, in order to be convenient for calculation, a lot of approximation and simplification were done, and the application scenarios of the final model may be limited.

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