GSM-R wireless field strength coverage prediction algorithm based on GA-BP algorithm

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Abstract. With the opening of multiple railway lines, newly-built routes are adjacent to, close to, and overcoming existing routes. If you do not consider the network coverage of adjacent lines in future planning in the early construction of the lines, you need to adjust the original line network coverage has increased the difficulty of construction and investment costs. In this paper, based on the genetic algorithm and BP artificial neural network, a GSM-R wireless network communication field strength prediction model is established. Combined with the field strength measured data of the base station, the GA-BP neural network model is compared with the traditional HATA model and BP neural network model. The comparison and verification show that the model has greatly improved the accuracy of prediction compared with the HATA model and the BP neural network model. It provides a feasible theoretical basis for the subsequent construction of railway parallel GSM-R wireless network coverage design.

1. Introduction

The key indicator to judge the service quality of GSM-R system is the strength of GSM-R field strength coverage. GSM-R's field-strength propagation path loss is closely related to the propagation environment. Radio waves in different frequency bands are affected by terrain, landforms, artificial buildings, atmospheric environment, electromagnetic interference, and train speed in the propagation environment, showing complex and variable fading characteristics[1]. At present, the GSM-R field strength coverage prediction model mainly uses the Hata model, which is mainly simulated and fitted by scholars based on a large amount of measured data. Literature [2] pointed out that the Hata model is established for certain terrain and terrain conditions, and is not necessarily applicable to railway-specific terrain, such as hills, roads, viaducts, tunnels, etc. Literature [3-4] research on railway typical terrain viaducts pointed out that under the environment of viaduct terrain, the radio wave propagation model is closely related to the viaduct height. It can be known from the above that whether the accuracy of GSM-R field strength coverage prediction has a great relationship with the complexity and particularity of the railway environment. The model must be revised according to different terrain and landforms and measured conditions or a new model must be established based on the measured data. Based on the measured data from a station, the field strength coverage prediction effect of the Hata model correction method, the BP neural network model, and the GA-BP model prediction method is compared, and the data results are analyzed in detail for the subsequent
construction of the railway parallel GSM-R wireless network coverage design. Provides a feasible theoretical basis.

2. Hata correction model

2.1. Test Data
The test data in this article are from the plain area at the base station position K72.9 measured by a test vehicle at a station, and the field strength data between K69.3 to K73. The main test parameters are shown in Table 1:

| Test Data | Pt/dBm | Gt/dBi | Gr/dBi | PLwire/dB | F/MHZ | Hb/m | Hm/m |
|-----------|--------|--------|--------|------------|--------|------|------|
| Data      | 35     | 17     | 4      | 6.8        | 930    | 30   | 3.5  |

Because the measured data contains small-scale fading values, we use Lee's law to perform moving average processing to obtain the median path loss [5].

3. Hata model correction
The Hata model is the most commonly used empirical model in the GSM-R wireless signal communication channel model. It uses urban terrain with low building density as a reference benchmark, and the remaining terrain conditions use urban terrain with low building density as a reference for appropriate corrections. Hata The model predicts the median path loss in three environments (city, suburb, open area) [6].

It can be seen from Figure 1 that the predicted field strength of the Hata model in urban, suburban, and open areas is significantly different from the actual test value. Usually, we use the least squares to fit the predicted field strength and modify the Hata model. The path loss model [7] in the open space environment of the subsequent high-speed railway is shown in equation (1).

$$L_p = 94.07 + 26.16 \log f - 13.82 \log h_b - a(h_m) + \left[32.8 - 6.55 \log h_b\right] \log d - K$$

among them:

$$a(h_m) = (1.11 \log f - 0.7)h_m - (1.56 \log f - 0.8)$$

$$K = 4.78(\log f)^2 - 18.33 \log f + 40.94$$

It can be seen from Figure 2 that the revised Hata model floats within the range of 20 ~ -5 db field strength error, and the field strength error is large; Literature [8] gives the evaluation index of the GSM-R field strength prediction effect, including Mean indicating the predicted value The statistical average difference from the actual drive test value.

$$Mean = \frac{1}{N} \sum_{i=1}^{N} |PL_{ei} - PL_{me}|$$

STD represents the standard deviation of the predicted value and drive test data.

$$STD = \sqrt{\frac{1}{N-1} \left( \sum_{i=1}^{N} |PL_{ei} - PL_{me}| - N \mu^2 \right)}$$

RMS stands for root mean square error.

$$RMS = \sqrt{\mu^2 + \sigma^2}$$

According to the above three GSM-R field strength prediction effect evaluation formulas, the Mean, STD, and RMS indexes are 2.8007, 4.1268, and 4.9870, respectively. Through these three evaluation indicators, we can see that the revised Hata model is The GSM-R field strength prediction effect is not good. Therefore, we use the GA-BP algorithm to establish a GSM-R wireless signal channel model and perform field strength prediction coverage on the GSM-R wireless field strength.
4. **GSM-R field strength prediction model based on GA-BP algorithm**

4.1. **BP neural network algorithm**

BPNN (Back Propagation Neural Neural Networks) structure is composed of input layer, hidden layer and output layer. Input Layer is the input layer, Hide Layer is the hidden layer, and Output Layer is the output layer.

4.2. **The main steps of the BPNN algorithm are as follows**

Step 1: Calculate the forward propagation information from the input layer to the hidden layer. \( Net_{(h_k)} \) the input information of the k-th neuron of the hidden layer, and \( Out_{(h_k)} \) the output information of the k-th neuron of the hidden layer.

\[
Net_{(h_k)} = \sum_{i=1}^{d} i_x * \theta_{w_{i}} - \theta_{(h_k)}
\]  
(7)

\[
Out_{(h_k)} = f(Net_{(h_k)}) = \frac{1}{1 + e^{-Net_{(h_k)}}}
\]  
(8)

Step 2: Calculate the input information of the neurons in the output layer from the hidden layer to the output layer. The output information of the neurons in the hidden layer is the product of the output information of each neuron in the hidden layer and the corresponding connection weight of each pointing, and then compared with the threshold output value.

\[
Net_{(o_j)} = \sum_{y=1}^{q} out_{(h_k)} * \theta_{w_{y}} - \theta_{(o_j)}
\]  
(9)

\[
Out_{(o_j)} = f(Net_{(o_j)}) = \frac{1}{1 + e^{-Net_{(o_j)}}}
\]  
(10)

4.3. **Genetic Algorithm**

Genetic algorithm (Genetic Algorithm) is a random search method based on the law of biological evolution first proposed by Professor Holland J in 1975. The genetic algorithm process is as follows:
The first step: encode the chromosome: the purpose of chromosome coding is to increase the search radius of the network. We encode the chromosome through floating-point encoding, and the chromosome encoding length is:

\[ s = n_1n_2 + n_2n_3 + n_3 + n_4 \] (11)

In the formula, \( n_1, n_2, n_3 \) and are the number of nodes in the input layer, hidden layer, and output layer respectively.

Step 2: Initialize the genetic population: First, randomly generate individuals to form a genetic population, select the most suitable individuals and add them to the initial population, and perform iterative operation until the number of individuals in the initial population reaches the set population size.

Step 3: Calculate fitness: The calculation formula of fitness is:

\[ F = \frac{1}{\sum_{i=1}^{m}|\hat{y}_i - y_i|} \] (12)

In the formula, \( \hat{y}_i \) is the expected output of the network; \( y_i \) is the training output of the network; \( m \) is the number of output nodes of the network. Take \( \sum_{i=1}^{m}|\hat{y}_i - y_i| \) as a function of fitness.

Step 4: Select the operation. Select a certain number of individuals from the current population as the mother and reproduce the offspring. The probability of an individual being selected is:

\[ p_i = \frac{(F_i)^{m}}{\sum_{j=1}^{m}(F_j)^{m}} \] (13)

Step 5: Cross operation. The arithmetic cross method is used to cross-process the individuals in the population, and the chromosome and the gene are cross-calculated. The crossover operator is:

\[
\begin{align*}
  x_{ia} & = (1-a)x_i + ax_j \\
  x_{jb} & = (1-a)x_j + ax_i
\end{align*}
\] (14)

Step 6: mutation operation. The mutation operation has the effect of increasing the diversity of the population. In order to prevent the network from falling into the local optimal value, the genes of the chromosome are selected for mutation. The mutation operator is:

\[
\begin{align*}
  x_i & = \begin{cases} 
  x_i + (x_{i\text{max}} - x_i) & (r_i > 0.5) \\
  x_i + (x_{i\text{min}} - x_i) & (r_i \leq 0.5)
\end{cases} \\
  f(g) & = e^\left(\frac{1 - g}{C_{\text{max}}}\right)
\end{align*}
\] (15)

Step 7: network parameter setting: assign the genetic algorithm and BP neural network related parameters.

In this paper, the GA-BP program is implemented under the MATLAB platform, using the GA-BP design function mapminmax () in the MATLAB neural network toolbox, and the neural network simulation function sim ()

5. Construction of GSM-R field strength prediction model based on GA-BP algorithm

5.1. GA-BP neural network parameter setting

In this paper, the distance between the mobile station and the base station (km), the source transmission power (W), the effective antenna height (h), the base station height (h), and the mobile station height (h) are selected as GA-BP neural network based on data analysis. Input vector, with receiver predicted level value as output variable. Determine the number of nodes in the input layer and output layer of the neural network to be 5 and 1, respectively. According to the empirical formula:
In equation (17), \( P \) is the number of hidden layer nodes; \( n \) is the number of input layer nodes; \( a \) is a constant between 0 and 10. Through trial and error method, the optimal number of nodes in the hidden layer is 4, and a 3-layer BP neural network is established. Since the input layer vector is a variable of different dimensions, the sample needs to be normalized (call the mapminmax() function), that is, the sample data of the input layer and the output layer is mapped between \([0, 1]\), and the most optimal algorithm encodes the chromosomes, sets the fitness function to evaluate the advantages and disadvantages of the new individuals, selects the individuals with higher fitness to select, cross, and mutate to form new populations. The best weights and thresholds. After the training is completed, the output value of the network model is reversely mapped to the original data interval to obtain the prediction result of the network. The specific parameter settings of BP neural network and genetic algorithm are shown in Table 2 and Table 3.

### Table 2. BP neural network parameter settings.

| Maximum training times | Training target error | Learning rate | Number of intervals |
|------------------------|-----------------------|---------------|---------------------|
| 100                    | 0.0001                | 0.1           | 5                   |

### Table 3. Genetic algorithm parameter settings.

| Population size | Number of iterations | Crossover probability | Mutation probability |
|-----------------|----------------------|-----------------------|----------------------|
| 50              | 20                   | 0.4                   | 0.04                 |

In this paper, 40 sets of measured data are used for analysis. Considering the limited sample data of the research model in this paper, in order to improve the prediction accuracy of the network, this paper selects the first 33 sets of data as the training samples of the network, and the last 7 sets of data as the prediction samples of the network.

### 6. Comparison of simulation results of three models

The GA-BP neural network model is compared with the traditional revised GSM-R wireless field strength prediction in the Hata model and the BP neural network model, and the results are compared, as shown in Figure 3 and Figure 4.

**Figure 3.** Comparison of the field strength prediction of the three models.

**Figure 4.** Comparison chart of field strength prediction errors of the three models.
It can be seen from Fig. 6 that the GA-BP neural network model is more accurate than the BP neural network model and the modified Hata model in predicting the field strength, and is more in line with the measured value of the field strength; from Fig. 7 it can be seen that the revised Hata model is between 20 ~ Floating within the 5dbm field strength error range, the field strength error is large; the BP neural network model floats within the range of 18 ~ -5dBm field strength error, which is smaller than the corrected Hata model; GA-BP neural network model The prediction error from the test point to the base station 2 ~ 4KM floats within the range of 10 ~ -5dBm field strength error, and the prediction error is the smallest within the range of 2 ~ 4KM. Comparing the performance of the GA-BP neural network model and the BP neural network model (Table 5), we can see that the maximum relative error of the GA-BP neural network is 8.686%, the average relative error is 3.385%, and the maximum relative error of the BP neural network is 9.468%, with an average relative error of 5.698%. In the comparison between the number of iterations and the average relative error variance, the convergence speed of the GA-BP neural network model is significantly faster, and the average relative error variance is also smaller. It can be seen that the performance of the GA-BP neural network model is superior to the BP neural network model in all aspects. Comparing the field strength predictions of the three prediction models (Table 4), it can be seen that the Mean value, STD value, and Rms value are better than the corrected Hata model and BP neural network model field strength prediction. In summary, the performance of the GA-BP neural network model in GSM-R field strength prediction is superior to the BP neural network model and the modified Hata model.

| The model                        | Number of iterations | Maximum phase error | Minimum relative error | Mean relative error | Mean relative error variance |
|----------------------------------|----------------------|---------------------|------------------------|--------------------|-----------------------------|
| GA-BP neural network model       | 18                   | 8.686%              | 0.236%                 | 3.385%             | 0.0156%                     |
| BP neural network model          | 64                   | 9.468%              | 2.317%                 | 5.698%             | 0.0703%                     |

Table 5. Comparison table of field strength prediction performance of the three models.

| The model                        | Mean  | STD   | Rms   |
|----------------------------------|-------|-------|-------|
| Modified Hata model              | 2.8006| 4.1267| 4.9873|
| BP neural network model          | 2.3667| 3.8765| 4.6433|
| GA-BP neural network model       | 1.4602| 2.2468| 2.8643|

7. Conclusion
In this paper, the genetic algorithm is introduced to improve the BP neural network model, which accelerates the convergence rate and improves the shortcomings of the BP neural network that is easy to fall into the local minimum and the convergence rate is slow. By analyzing the experimental results of GA-BP neural network model, BP neural network model and the modified Hata model, it is obtained that the GA-BP neural network model in the open area of the plains can more accurately predict the field strength and generalize the performance of the predicted field strength. Better and higher accuracy provide a feasible theoretical basis for the design of GSM-R wireless network coverage after the parallel railway.

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