Research on the Handoff for Urban Rail Transit Based on IGM-BP Algorithm

Wei Wei, Xiaojuan LIU* and Yao LI

School of Electronic and Information Engineering, Lanzhou Jiaotong University, Lanzhou, Gansu, 730070, China

*Corresponding author’s e-mail: liuxiaojuan@mail.lzjtu.cn

Abstract. Aiming at the problem that the reference signal received power (RSRP) value received by the urban rail transit train during the handoff fluctuates greatly, which causes frequent occurrence of ping-pong handoff, combined with the A3 event in the TD-LTE standard, the improved grey prediction-BP neural network (IGM-BP) algorithm was proposed to improve RSRP fluctuations. The terminal access unit (TAU) will receive the first four sets of RSRP values at time t to establish a grey model GM(1,1) and get a set of predicted values. Take the average of the predicted value as the expected value, and finally the predicted values, modified by the BP neural network algorithm, are used to obtain the expected RSRP value. The simulation results show that the proposed algorithm, compared with the traditional handoff algorithm and the grey prediction algorithm, decreases the RSRP value fluctuation range, reduces the ping-pong handoff rate and meets the requirement that the TD-LTE system handoff success rate reaches 99.5%.

1. Introduction

With the development of "3C" technologies such as communications, computers, and automatic control, communications, signals, and other technologies in urban rail transit have also been improved, so the fully automatic operation (FAO) system has emerged as the times require [1]. It is a highly centralized control train operation system. It introduces the latest technology in the fields of automatic control, optimization control, human factors engineering, etc. based on the CBTC system, and the degree of automation is further improved, which represents the development trend of future rail transit technology.

In the process of train running, the RSRP value often fluctuates due to Doppler Effect, co-channel interference and other factors, which leads to the problem of frequent occurrence of ping-pong handoff.

Some scholars at home and abroad have also done a lot of research on the issue of handoff. Literature [2] proposed an anchor-based multi-connection architecture. Given a user connected to multiple APs, the best access point is selected as the handoff anchor point to provide a control plane, thereby reducing the handoff probability. Literature [3] proposed a mechanism using train positioning technology to switch, triggering the switch condition after the train reached a specific location, thereby reducing the delay. Literature [4] considered both Reference Signal Received Power (RSRP) and Reference Signal Received Quality (RSRQ), and used the grey prediction model GM (1, N) to predict the next field strength values of two neighbouring base stations at all times, thereby ensuring the quality of service (QoS) of the handoff process.
Aiming at the above problems, this paper proposes an improved GM-BP neural network algorithm, and uses MATLAB as a simulation tool. This algorithm is compared with the traditional algorithm and the grey prediction algorithm to verify the feasibility and effectiveness of the proposed algorithm.

2. Overview of TD-LTE Handoff
The FAO system usually uses TD-LTE technology to realize train-ground communication, which provides a prerequisite for the safer and more reliable operation of trains under the FAO system.

2.1. TD-LTE train-ground communication system
The structure of the TD-LTE train-ground communication system is mainly composed of core subsystems, wireless subsystems, and terminal equipment. The core network subsystem adopts the redundant dual network design of network A and network B. The two networks are completely independent and do not affect each other. The wireless subsystem includes base band unit (BBU) and remote radio unit (RRU) equipment. A single BBU can be connected to multiple RRUs to achieve full-line chain coverage of wireless communication system signals. At the same time, the terminal access unit (TAU) can also implement data transmission with the RRU beside the track.

2.2. Handoff process
The process of handoff is mainly divided into three parts: handoff measurement, handoff decision, and handoff execution. During the handoff decision, the 3GPP LTE protocol standard specifies 7 measurement report trigger events such as A1, A2, A3, A4, A5, B1, and B2 [5], among which the handoff measurement events in the system mainly include A1 - A5 event, the other two types of events are mainly used for trigger measurement events outside the system. The A3 event is often used as a measurement report event in urban rail transit, and its decision formula is shown in equation (1):

$$M_n + O_{fn} + O_{cn} - H_{ys} > M_p + O_{fp} + O_{cp} + O_{ff}$$  \( \text{(1)} \)

Without considering any offset, \( M_n \) and \( M_p \) respectively represent the received RSRP values of the target cell and the serving cell; \( O_{fn} \) and \( O_{fp} \) are the specific frequency offsets of the target cell and the serving cell; \( O_{cn} \) and \( O_{cp} \) respectively represent the specific offsets of the target cell and the serving cell; \( H_{ys} \) is the hysteresis parameter of the A3 event; \( O_{ff} \) is the offset parameter. Because the LTE system uses co-channel networking more often, so \( O_{fn} \) and \( O_{fp} \) do not participate in the calculation, and the neighbouring cell configurations are the same, \( O_{cn} \) and \( O_{cp} \) do not participate in the calculation. Therefore, equation (1) can be reduced to equation (2):

$$M_n - H_{ys} > M_p$$  \( \text{(2)} \)

A3 event handoff trigger diagram is shown in Figure 1. The handoff is triggered only when the difference of RSRP between the target cell and the serving cell is greater than the handoff hysteresis threshold and the trigger delay is met.

![Figure 1. A3 event handoff trigger diagram.](image-url)
3. Improved grey prediction-BP neural network (IGM-BP) algorithm.
The grey prediction algorithm has the advantages of few modelling samples and high short-term prediction accuracy. But it relies heavily on raw data. The BP neural network can perform parallel calculations, making the computing system simple and flexible, and it can also make more accurate predictions when it encounters highly volatile data. But more sample data is needed for learning. When the two are combined, they can give play to each other's strengths and learn from each other's strengths. The BP neural network is used to correct the data error of the grey prediction algorithm. In the case of large RSRP fluctuations, the combined algorithm has higher calculation accuracy than the grey prediction algorithm and BP neural network algorithm. Since the algorithm in this paper is established on this basis, the algorithm in this paper is referred to as the IGM-BP algorithm.

3.1. Grey prediction algorithm and model establishment
Grey system theory was first proposed by Professor Deng in 1982. It is an uncertain system, which is mainly aimed at systems with a small number of samples, some information is known, and some are unknown [6]. The GM (1,1) model is one of the most basic models. It is a model in which the discrete-time response function is approximately exponential. Four data can then be used to build a model for prediction. The modelling steps are as follows:

Step1: \(X^{(0)} = (x^{(0)}(1), x^{(0)}(2), \ldots, x^{(0)}(n))\) is a set of non-negative original data sequences, and the sequence \(X^{(0)}\) is subjected to a first-order accumulation. The cumulative generated sequence is Equation (3):

\[
X^{(1)} = (x^{(1)}(1), x^{(1)}(2), \ldots, x^{(1)}(n))
\]  

Step2: According to the accumulation sequence \(X^{(1)}\) obtained in the first step, a GM (1,1) model is established, and the corresponding whitening differential equation is obtained as equation (4):

\[
\frac{dx^{(1)}}{dt} + ax^{(1)} = b
\]  

Where \(a\) is the development coefficient and \(b\) is the amount of grey development effect. The corresponding grey differential equation is of the equation (5):

\[
x^{(0)}(k) + ax^{(1)}(k) = b, \quad k = 2,3,\ldots,n
\]  

Step 3: Find parameters \(a\) and \(b\). Calculate the parameter sequence \(\Phi = [a, b]^T\) by the least squares method, and the expansion is equation (6):

\[
\Phi = (B^T B)^{-1} B^T Y
\]  

Step 4: Under the initial condition \(\hat{x}^{(1)}(1) = x^{(1)}(1) = x^{(0)}(1)\), the generated data sequence model can be obtained as equation (7):

\[
\hat{x}^{(k)}(k) = (x^{(0)}(1) - \frac{\hat{b}}{\hat{a}})e^{-\hat{a}(k-1)} + \frac{\hat{b}}{\hat{a}}, \quad k = 2,3,\ldots,n
\]  

Step 5: Under the initial condition \(\hat{x}^{(1)}(1) = x^{(1)}(1) = x^{(0)}(1)\), \(\hat{x}^{(0)}(k) = \hat{x}^{(1)}(k) - x^{(1)}(k-1), \quad k = 2,3,\ldots,n\), that is equation (8):

\[
\hat{x}^{(0)}(k) = x^{(0)}(1), \quad \hat{x}^{(0)}(k) = (1 - e^{\hat{a}})(x^{(0)}(1) - \frac{\hat{b}}{\hat{a}})e^{-\hat{a}(k-1)}
\]
Bringing \( k = 2, 3, \ldots, n \) into the above formula can get the fitted value of the initial data; when \( k > n \), the grey model's predicted value for the future can be obtained, and mean value of the predicted value is taken at the same time.

### 3.2. BP neural network and structure design

In the 1980s, scientists such as Rumelhart and McClelland proposed the BP neural network [7] structure, which is a multi-layer feed-forward neural network trained according to the error back propagation algorithm, and is now widely used in various fields. BP neural network structure is divided into three layers, namely the input layer, hidden layer and output layer. Because the purpose of this article is to improve the fluctuation of RSRP, the BP neural network structure is designed as follows:

- **Input layer**: The input value is the predicted value obtained by the grey prediction algorithm, and it is recorded as \( X = [x_1, x_2, \ldots, x_n] \), where \( n \) is the number of neuron nodes in this layer, and the number of nodes in this experiment is 5.
- **Hidden layer**: This paper chooses a hidden layer to meet network performance, and has good real-time performance, which meets the real-time requirements of urban rail transit. For the transfer function, this article will use \( f(x) = 1/(1 + e^{-x}) \) as the transfer function [8]. The selection of hidden layer neuron nodes is generally determined by the empirical formula \( l = \sqrt{n + m + a} \), where \( l \) is the number of hidden layer neurons, \( n \) is the number of input layer neurons, \( m \) is the number of output layer neurons, \( a \) is a constant [9], and the value range is \([1, 10]\), so the range of \( l \) is \(4 - 12\). When the number of selection is too large, it will cause a large amount of calculation and increase the time consuming, resulting in over-fitting the data, and too little will affect the network performance. After many experiments, it is determined that 6 hidden layer neurons will be selected in this experiment.
- **Output layer**: the dimension of this layer is 1, that is, the RSRP prediction value at this moment obtained by the algorithm

#### 3.3. Processing steps

In urban rail transit, the field strength measurement period of the serving cell and the target cell is 50ms, and the reporting period of the train period is 240ms. Therefore, in this process, the RSRP value of the serving cell and the target cell is at most 4 Measurements. In order to make the grey GM (1, 1) model more suitable for the characteristics of urban rail transit, this paper first takes 4 RSRP data to establish a grey prediction model for prediction, and uses the average value of the obtained prediction value [10] as the expected value. The processing steps are as follows:

**Step1**: Since the values of the source data \( M_x \) and \( M_y \) are both negative numbers, all source data need to be taken as absolute values.

**Step2**: Take the first 4 times of the RSRP value of the serving cell received at time \( t \) and form a short sequence of the GM (1, 1) model with the predicted value obtained at the previous time, denoted as \( X_1 = \{X_1(t-4\Delta t), X_1(t-3\Delta t), X_1(t-2\Delta t), X_1(t-\Delta t)\} \). Similarly, record the RSRP value of the target cell. The short sequence is \( X_2 = \{X_2(t-4\Delta t), X_2(t-3\Delta t), X_2(t-2\Delta t), X_2(t-\Delta t)\} \).

**Step3**: Establish a GM (1, 1) model based on the short sequence \( X_1 \), and calculate a new set of prediction sequences \( Y_1 = \{Y_{1,1}, Y_{1,2}, Y_{1,3}, Y_{1,4}, Y_{1,5}\} \); similarly, establish a GM (1, 1) model based on the short sequence \( X_2 \) to obtain a new set of prediction sequences \( Y_2 = \{Y_{2,1}, Y_{2,2}, Y_{2,3}, Y_{2,4}, Y_{2,5}\} \).

**Step4**: Take the average of the prediction sequences \( Y_1 \) and \( Y_2 \) of the serving cell and the target cell obtained after the prediction to obtain an average sequence \( Y_1' = \text{avg}(Y_1), \ Y_2' = \text{avg}(Y_2) \).

**Step5**: Take \( Y_1' \) as the input layer neuron parameters, \( Y_1' \) is the expected value, and use the neural network algorithm to modify the sequence obtained by the grey prediction to obtain the predicted
value $M_n$ at the moment. Similarly, using $Y_2$ as the input layer neuron parameter and $Y_2'$ as the expected value, so get predicted value $M_n'$ at that moment.

Step6: Take the obtained $M_n$ and $M_p$ as negative values, and then replace the $M_n$ and $M_p$ in the judgment condition formula respectively, then the judgment formula becomes equation (9):

$$M_n' - H_{ys} > M_p'$$

(9)

4. Simulation

This paper uses the Beijing Yanfang line as an example. The Yanfang line is 14.431 kilometres in length, all of which are elevated sections, while using wireless channels with a frequency of 1.8GHz.

4.1. Experimental parameter settings

According to the characteristics of urban rail transit, the districts are distributed in a chain shape, so the train handoff process is simulated as shown in the model shown in Figure 2.

![Figure 2. Model of train handoff process](image)

The AB segment indicates that the distance between the two base stations is 1.4 km; the BD segment indicates the handoff overlapping band between the two base stations, and the point C is the midpoint of the handoff band. The specific experimental parameters are shown in Table 1. According to the calculation formula of the handoff zone, the length of the overlapping handoff zone is 188m, and the handoff area is 0.6km - 0.8km.

| Simulation parameters       | Value       |
|-----------------------------|-------------|
| Carrier frequency           | 1.8GHz      |
| Base station transmit power | 44dBm       |
| Base station emission height| 30m         |
| Receiving antenna height    | 1m          |
| Distance between RRUs       | 1.4km       |
| Shadow fading standard      | 4           |
| Path loss model             | $PL(d) = 46.3 + 33.9\log f_c - 13.82\log h_{re} + (44.9 - 6.55\log h_{re})\log d - \alpha(h_{re}) + C_{cell}$ |
| Handoff threshold           | 3dB         |
| Loss of cable per meter     | 4.2dB       |
| Train speed                 | 80km/h      |

4.2. Analysis of results

As shown in Figure 3, the ordinate represents the RSRP value of the target cell and the serving cell obtained by using the traditional handoff algorithm, and the abscissa represents the distance from the base station of the initial serving cell during the train. Figures 4 and 5 represent the changes in the RSRP values of the target cell and the serving cell obtained by the grey prediction algorithm and the IGM-BP algorithm proposed in this paper, as a function of distance. It can be seen from the figure that...
the algorithm proposed in this paper has the best effect in improving the fluctuation of RSRP value, and the fluctuation range is the smallest. It shows that the algorithm in this paper effectively reduces the influence of factors such as co-channel interference and Doppler Effect.

Because the fluctuation of RSRP value is improved in this paper, the success rate of handoff is also improved. The comparison of the handoff success rate of the three algorithms is shown in Figure 6. The success rate of the proposed algorithm at 0.76km reaches 99.6%, which is higher than the traditional algorithms and the grey prediction algorithms here. The success rates are 83.4% and 92.7%.
The highest ping-pong switching rate of the algorithm proposed in this paper is only 3%, which is lower than the success rates of traditional algorithms and grey prediction algorithms by 21% and 14%. It can be concluded that the IGM-BP algorithm can effectively reduce the frequent occurrence of ping-pong switching and improve the stability of the train in the operating environment of the FAO system is improved.

5. Conclusions
With the rapid development of the FAO system for urban rail transit, this paper proposes an IGM-BP algorithm to improve the fluctuations of RSRP values of the serving cell and the target cell received during the train driving process, and improve the handoff success rate. Through experimental simulation of the algorithm, and comparison with the traditional algorithm and the grey prediction algorithm, it is verified that the algorithm can effectively improve the interference of RSRP values due to co-channel interference and multipath effects, and reduce the ping-pong switching rate. Compared with the other two algorithms, it has obvious advantages.

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