

# *Cell base station traffic prediction based on GRU*

Tenglong Xu\*, Yijia Yan

*School of Electronic Engineering, Xi'an Aeronautical Institute, Xi'an 710077, China*

*\*Corresponding author: xu18303907689@163.com*

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**Abstract:** With the expansion of Internet technology and network scale, the data volume of base station traffic also shows explosive growth. Predicting base station network traffic has high practical guiding significance for network research, management and control. Aiming at the problem of accurate prediction of base station traffic, this paper proposes a gated recurrent unit neural network model (GRU model) based on neural network algorithm, which can predict the base station traffic data according to the periodicity and fluctuating characteristics of base station traffic data. After experimental verification, it shows that compared with the traditional time series prediction model AR model, ARIMA model also has the convolutional neural network model based on neural network algorithm. This method has higher accuracy and smaller experimental error in mobile communication traffic prediction. The MAE value is optimized by 27.04%, 37.89% and 9.12%.

## 1. Introduction

With the rapid development of Internet technology and the increasing expansion of the network scale, the network traffic data in the base station also increases substantially, and it continues to grow. Network traffic is an important parameter to reflect the status of the local base station traffic network. The analysis and accurate prediction of the base station traffic can realize efficient network management and improve the utilization rate of the network. In terms of network security, the detection of intrusion can be completed by monitoring the abnormal traffic. In terms of network planning, accurate prediction of base station traffic can help operators to accurately and reasonably plan network resources, expand, adjust and optimize the network in advance, improve the service quality of local networks, and also provide effective data support for design engineers to design the network structure of local base stations. Therefore, the planning of network traffic is becoming more and more important.

Studies in the literature [1] demonstrated the predictability of network traffic. The predictability of the network also brings more technological innovation and considerable benefits to various sectors of the industry, such as network security, network planning, dynamic bandwidth allocation and congestion control. Therefore, a large number of researchers began to observe the trend of traffic and monitor the change of traffic from various angles. However, in the process, they found that the network traffic has the characteristics of timeliness, nonlinearity and randomness, which made it very difficult to accurately predict the base station network traffic. With the continuous maturity of machine learning technology in recent years, the development of base station traffic prediction

technology has also been promoted. Researchers have put forward many schemes for the prediction of base station network traffic data, which can be divided into linear time series model, nonlinear time series model and mixed model.

The linear time series prediction model has two popular submodels: Auto Regressive (AR) model and Moving Average (MA) model. They can be combined into an Auto Regressive Moving Average (ARMA) model. And it has many variants, and the linear time series is the traditional method of network traffic prediction. Literature [2] predicts base station traffic based on ARIMA model and combining AR and MA model; literature [3] proposed improved PCA algorithm to monitor communication traffic; literature [4] proposed prediction based on vector autoregressive VAR model and combines Lasso to improve the accuracy of prediction data. These linear time series prediction models are concise, which only need endogenous variables without other external variables, but the model can only capture linear relationships rather than nonlinear relationships; meanwhile, the data is stable, such as predicting stock data with the statistical model, because the data is non-stable and affected by other events such as policy and news. However, linear time series prediction is often accompanied by the calculation of huge data volume and the short board of long-term sequence prediction, so it is only applicable for short-term prediction.

Machine deep learning model belongs to the non-linear time series model. The popularity of deep learning has been continuously increased in recent years. The power of deep learning is that the input model can be transformed and extracted for many times, so that the model can finally capture the essential features in the data. Therefore, the machine deep learning model is also widely used in the base station traffic prediction. Base station traffic has both short-term local characteristics and long-term development trend. Deep learning can more accurately predict traffic data. Literature [5] proposed AdaptiveNeuro-Fuzzy Inference System (ANFIS) based on time series for modeling and predicting Internet traffic. Literature [6] uses back propagation wavelet neural network (BPWNN) technology to improve the defects of back propagation neural network (BPNN) technology in network traffic prediction, and achieve better results in multi-step prediction. Literature [7-8] predicts network traffic based on Elman neural network and adopts the method of wavelet transform to improve the performance of predicting network traffic based on long-and short-term memory model and verifies its main implementation scheme; Literature [9] further proposes urban short-time rail traffic prediction combined by CNN-ResNet-LSTM to improve the prediction accuracy in rail transit.

There has been made in base station traffic prediction. This paper proposes the prediction of base station traffic based on neural network optimization model-GRU model in machine deep learning. At the same time, the model and the basic time series prediction model AR model, ARIMA model MAE value comparison, using the method of machine learning prediction effect accurate than conventional AR model and ARIMA model value, and the GRU model and convolution neural network (CNN) parameters comparison, GRU model comprehensive parameters than the convolutional neural network GRU model comprehensive optimization effect compared with CNN optimization effect is more good and accurate. It provides a prediction method for setting reasonable base station switching carrier time period and alleviating base station load pressure and tidal phenomenon.

## 2. Correlation theory

### 2.1. CNN and GRU

Convolutional neural network network is widely used in the field of deep learning. It has the characteristics of local connection and weight sharing, which can efficiently realize the extraction of input features. Convolutional neural network is usually composed of convolutional layer, pooling layer and fully connected layer. The convolution layer is responsible for extracting the input features, the convolution data and the key-relu; the pooling layer summarizes the features obtained by the

convolution operation, reduces the data dimension through maximum value pooling and average pooling; the fully connected layer beds the bottom of the network in the form of BP neural network, merges the pooling features, and calculates the results of classification or regression. Its basic structure is shown below in Figure 1. However, its disadvantages are also obvious. It requires a large amount of data and ignores the overall and local correlation in the calculation, so it is easy to lead to the loss of some valuable information. Therefore, a better neural network model should be introduced to solve this problem.

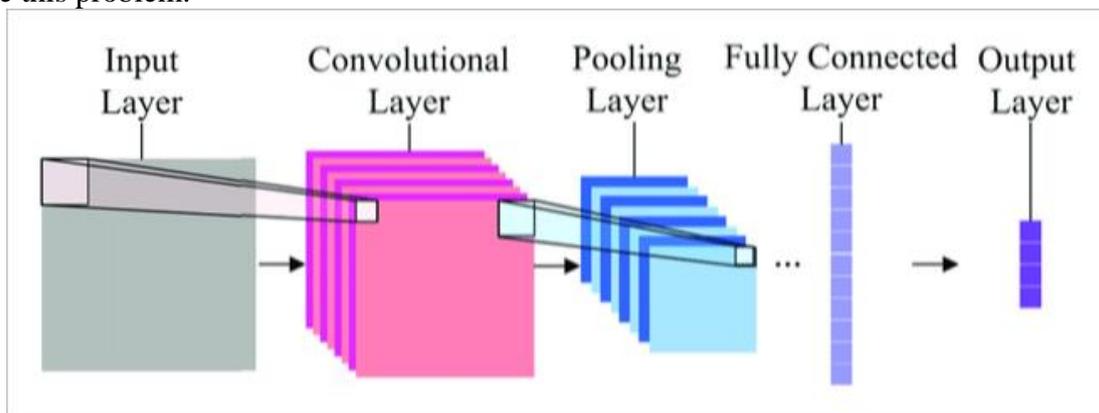


Figure 1: CNN Basic structure diagram

The gated recurrent unit neural network is simplified by the long and short-term memory neural network. The long and short-term memory network solves the problem of "gradient explosion" and "gradient dispersion" problem of the recurrent neural network through the dynamic control of the input gate, forgetting gate and output gate. The complementary combination of the input gate and the forgetting gate of the LSTM model can realize the forgetting of historical information and the acquisition of new information, but it still has some redundancy. The gated cycle unit neural network integrates the input gate and the forgetting gate into the update gate, and introduces the reset gate as an improved model of LSTM, which can reduce the network parameters while retaining the original function, with a high training rate and reduce the network complexity. The standard structure of the GRU is shown in Figure 2.

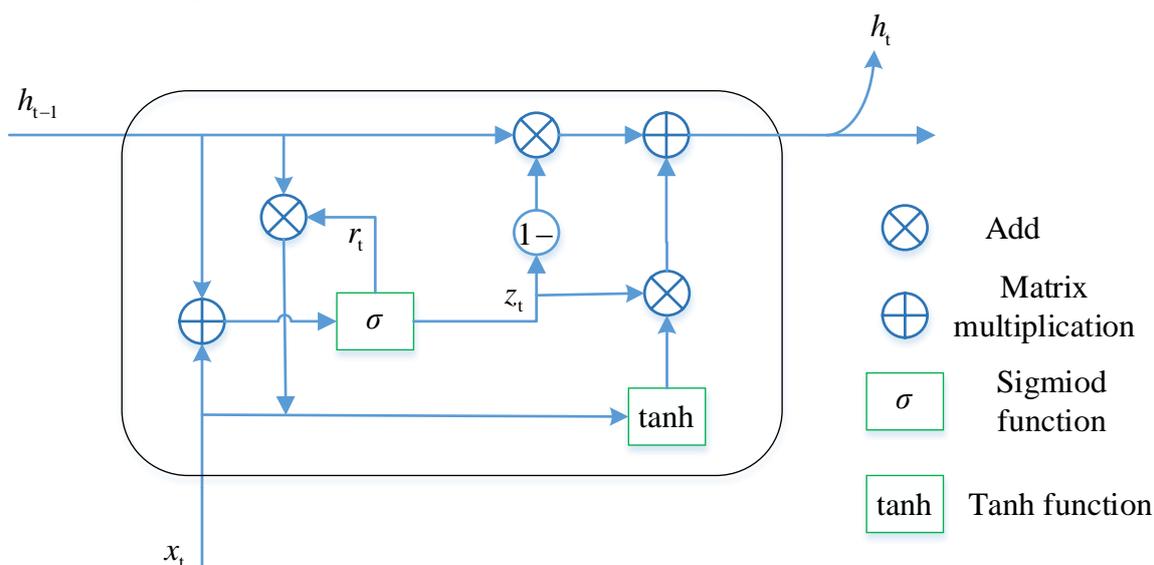


Figure 2: Basic structure diagram of the GRU

The update gate  $z_t$  in Fig is used to determine the importance of candidate hidden states  $h'_t$  and historical states  $h_{t-1}$  in the hidden states  $h_t$  of the final output.  $z_t$  values close to 0 leave the historical status  $h_{t-1}$ ,  $z_t$  value close to 1 abandons the historical state  $h_{t-1}$ . Reset gates  $r_t$  are used to determine historical states  $h_{t-1}$ , affecting the extent of candidate hidden states  $h'_t$ .  $r_t$  value close to 1 retains the historical state  $h_{t-1}$ ,  $r_t$  values close to 0 abandon the historical state  $h_{t-1}$ . The historical state  $h_{t-1}$  of the previous moment contains all the historical information from the previous moment. The candidate hidden states  $h'_t$  are the historical states  $h_{t-1}$  of the current input  $x_t$  with the reset gate control, mainly used in memory for short-term temporal correlations. The hidden state of the output  $h_t$  is the candidate hidden state  $h'_t$  controlled by the comprehensive update gate as well as the historical state  $h_{t-1}$ . Retaining valid information in long-term historical memories  $h_{t-1}$  while considering short-term memories  $h'_t$  related to recent input  $x_t$ . The  $z_t$ ,  $r_t$ ,  $h'_t$  and  $h_t$  specific calculation process of and is as follows:

$$z_t = \sigma(W_z \cdot [h_{t-1}, x_t] + b_z) \quad (1)$$

$$r_t = \sigma(W_r \cdot [h_{t-1}, x_t] + b_r) \quad (2)$$

$$h'_t = \tanh(W_c \cdot [r_t \odot h_{t-1}, x_t] + b_c) \quad (3)$$

$$h_t = (1 - z_t) \odot h_{t-1} + z_t \odot h'_t \quad (4)$$

In formula:  $W_z$ ,  $W_r$ ,  $W_c$  are the weight parameters.  $b_z, b_r, b_c$  are the offset values.  $\sigma(*)$ ,  $\tanh(*)$  are the activation functions.  $\odot$  represents the multiplication of the corresponding elements in the matrix, namely the Hadamard product. In the actual prediction process, first input the observed value of each historical moment into the corresponding GRU unit, and transmit the hidden state of the calculation to the GRU unit of the next moment; the GRU unit of the next moment takes the hidden state and the observed value of the previous moment as input, and cycle forward calculation according to the sequence length. Finally, the hidden state  $h_t$  of the most recent historical moment is linearly transformed to generate the time t prediction output  $\hat{y}_t$ :

$$\hat{y}_t = W_o h_t + b_o \quad (5)$$

In formula:  $W_o$  is the weight parameter.  $b_o$  is the bias value. The above is the process of information transmission operation by GRU neural network model, which effectively solves the problem of RNN gradient disappearance. At the same time, the structure is simpler and the operation efficiency is more efficient. Moreover, this design can solve the problem of data dependence in the timing problem, and effectively improve the accuracy of prediction.

### 3. Experimental Verification

#### 3.1. Data preprocessing

The mobile base station traffic data used in this paper from the actual data set in the game for simulation verification, collected a base station cell from August 28, 2021 to September 25, 2021 base station traffic data for experimental training test, data collection interval of 1 h, extracted a cell 11832 data, first data pretreatment, cleaning data screening 696 sets of effective data, using 522 data to complete the training of the model, 174 data is used for test performance. The raw network traffic

used in the experiment is shown in Figure 3.

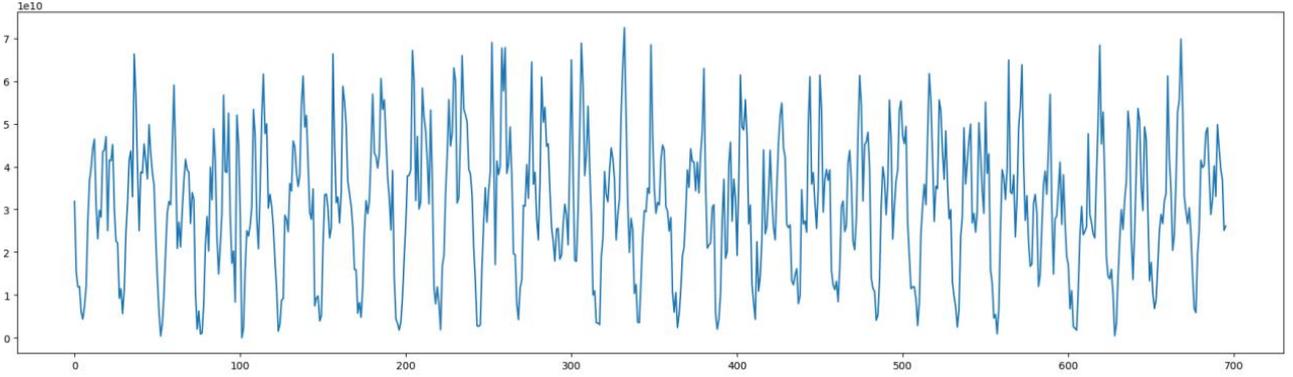


Figure 3: Raw flow data of the base station

Before the data enters the neural network, the data preprocessing should be carried out. Data standardization is one of the data preprocessing, and the purpose is to speed up the training speed of the neural network. The way is to subtract the mean value from the data, and then divide it by the variance:

$$z = (x - \mu) / \sigma \quad (6)$$

Where  $z$  represents the calculated values,  $x$  represents the raw data,  $\mu$  represents the mean value of the data,  $\sigma$  represents the variance of the data. Therefore, the data with mean 0 and standard deviation 1 are obtained. In data processing, the Z-score normalization (0-1 normalization) method is used to normalize the mean and standard deviation of the data of the original data.

### 3.2. Evaluating indicator

MAE evaluates the accuracy of the common error index, and the formula is:

$$MAE = \frac{1}{T_y} \sum_{i=1}^{T_y} |\hat{y}_i - y_i| \quad (7)$$

### 3.3. Experimental result

This paper using GRU neural network model to predict base station traffic, and added multi-step prediction AR model and ARIMA model, and convolutional neural network comparison table 1 gives the four methods of MAE parameters error evaluation index, from table 1, GRU model compared than AR model, ARIMA model, and the convolutional neural network the MAE value is smaller, which shows that the proposed GRU model in base station traffic prediction is closer to the true value, is better than the prediction performance of the other three models.

Table 1: Comparison of MAE values between GRU and the other three models

Model	AR	ARIMA	CNN	GRU
MAE	3.55	4.17	2.85	2.59

In this paper, the above two best effective models are selected to draw the images of MAE of the training test set. FIG. 4 and 5 are the images of MAE value of the base station traffic test set and MAE value of the validation set of convolutional neural network and GRU neural network.

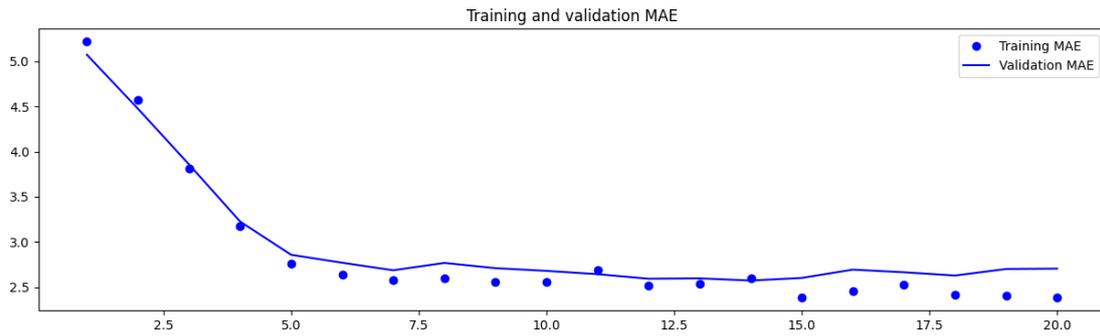


Figure 4: MAE values of convolutional neural networks

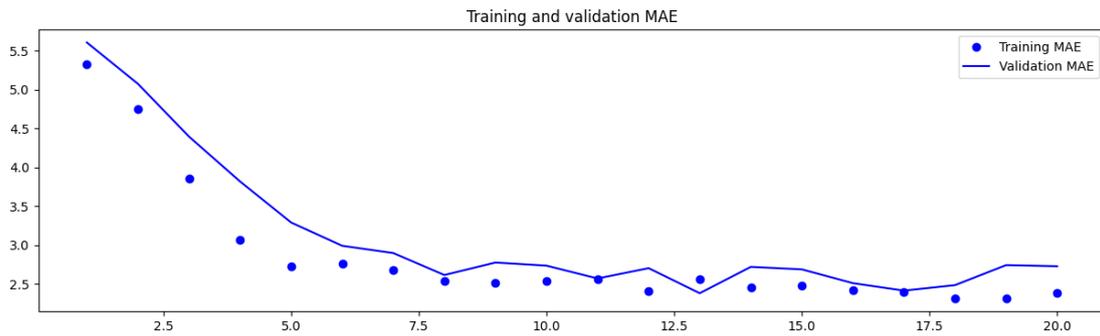


Figure 5: MAE values of the test set and validation set for the GRU model

It can be seen from the above two graphs that the convolutional neural network remains stable at around the 7.5th epoch, and the loss of the validation set no longer drops. The GRU model images converge at the 20th epoch. Moreover, the fitting of MAE value of GRU is closer to that of training set, and the loss is less than that of convolutional neural network. Therefore, it can be concluded that GRU neural network is better and more accurate than convolutional neural network.

#### 4. Conclusion

This paper for the problem of base station traffic prediction, put forward the GRU neural network prediction model method, the model is optimized version of LSTM model, further overcome the RNN itself has the gradient disappear and gradient explosion, can better the long-term trend of sequence data, at the same time compared to LSTM model has a simpler structure and more efficient operation rate. Its comparison with AR model, AR IMA model and convolutional neural network model has better prediction performance, which can improve the prediction accuracy of the periodic and fluctuating changes of the base station traffic, and provide a prediction method for solving the base station load and tidal phenomenon in the future. At the same time, it can better help operators to reasonably plan the allocation of network resources, so that users can feel more comfortable for the network experience, and at the same time provides an effective reference form for the future development of network technology.

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