The Research on Flow Prediction of Metropolitan Area Network Based on Recurrent Neural Network

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Abstract— **with the issuance of 5G operation license, the construction of communication network is like a raging fire. The prediction of city network flow is becoming more and more important in operators' communication engineering planning and design as well as equipment purchase. There exist some limitations of the traditional prediction of city network flow when used in the analysis of current flow prediction, so it is essential to explore a new predictive method of city network flow. Basing on flow prediction of metropolitan area network based on recurrent neural network, this paper discussed the modeling and prediction of metropolitan area network data flow, taking some area's data flow as research object. The prediction result shows that there's smaller error. And at the same time, it is proved that it is feasible to predict the peak flow of metropolitan area network through the recurrent neural network**

Key words: **Flow prediction , Metropolitan area network flow , Recurrent neural network**

I. Introduction

With the issuance of 5G licenses by the China Ministry of Industry and Information Technology on June 6, 2019, China's 5G construction officially kicked off and entered the first year of 5G commercial use. It means that China will become the fourth 5G-commercialized country. The 5G will build a mobile, secure and ubiquitous information infrastructure, accelerate the digital transformation of all kinds of occupations, and is applied to the expansion of the Internet of things, which will bring new opportunities, and strongly support the booming development of the digital economy. Meanwhile China's large-scale 5G communication infrastructure will also be launched. In 5G communication infrastructure, the prediction of city network flow plays a premising and key role in scientific rolling planning.

With the in-depth development of 5G communication infrastructure construction, the prediction of network flow is playing an increasingly important role in the rolling planning of major operators. Over the years, scholars and related practitioners at home and abroad have conducted extensive research on the prediction of communication network flow, and put forward many methods and models that will be applied to the prediction of communication network traffic. Traditional traffic models include regression model, non-parametric regression model and ARMA model and so on.

With the development of artificial intelligence, artificial intelligence has become a hotspot research direction nowadays. The neural network will get the abstract features in the existing samples through the feature changes layer by layer, and then establishes a digital space to obtain the implicit features of the samples, so as to achieve a better predictive result. Therefore, in this paper, recurrent neural network is adopted to establish the metropolitan area network flow predictive method which will improve the prediction accuracy of the metropolitan area network flow.

II. Recurrent Neural Network

Recurrent Neural Network (RNN) is a special neural network, which is arguably classified as deep network. When folded in time, it can be regarded as a deep neural network with infinite layers [1].For RNN, the basic function of each layer is to remember the data which cannot be processed by layers. Through each iteration, new information will be added to each layer, and RNN can pass the information down through an unlimited number of network updates, so that RNN can obtain infinite memory depth.

The layers of neural network are mainly divided into three kinds: input layer, hidden layer and output layer. The output layer is controlled by the activation function and the each layer is associated by weights. When activation function has been determined, the prominent feature of RNN is that the correlation between neuron layers is also established through weights. See figure 1 below:

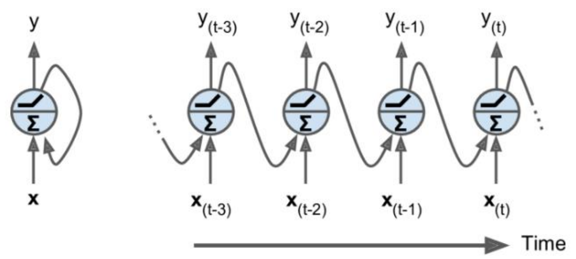

Figure1. Neur on association

In the above picture, every step is a transformation and every arrow is weighted.

Every neuron owns two sets of weights: one for the layer input x(t)x(t), and the other one for the upper layer output y(t−1)y(t−1).

The standard RNN propagation process is as the following: the given n-dimensional input sequence x1, x2...xn, m-dimensional network hidden layer state sequence h1, h2...hm, k-dimensional output sequence y1, y2..., yk, the iterative formulas are as the following[2]:

$$t_i=W_{hx}x_i+W_{hh}h_{i-1}+b_h \tag{1}$$

$$h_i=e(t_i) \tag{2}$$

$$s_i=W_{yh}h_i+b_y \tag{3}$$

$$y_i=g(s_i) \tag{4}$$

In the formula above, W_{hx}、W_{hh}、W_{yh} are weight matrices; bh 、 by are the base; ti is the input of the hidden layer; s_i is the input of the output unit, and both are k-dimensional variables. E and g are predefined nonlinear vector-valued functions.

One reason RNN is called Recurrent Neural Network is that the current output of a sequence is related to the previous output. To be specific, the network will remember the previous information that will be applied to the calculation of the current output, that is to say, the nodes between the hidden layers are connected and the input of hidden layers not only includes the output of the input layer but also the output of the hidden layer at the previous time. Its structure is shown in figure 2:

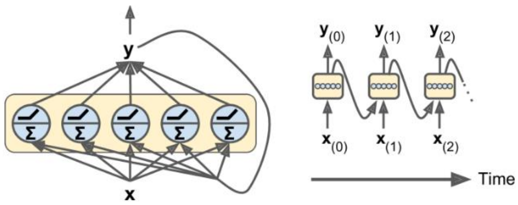

Figure2: Internal Structure Diagram Of Neural Network

X: the input sample; Y: the output sample weight. Using the output of current and previous time, it can predict the output of the next moment and obtain the predicted result.

III. Model Building And Application

3.1 Feature Data Selection

From the analysis of the Metropolitan Area Network flow based on the flow statistics and users of some province selected by operators in recent years, we can get a conclusion that only to meet the need of flow peak can be ensured the reliability of the communication network, because the peak flow matters plays a very decisive role in Operator's infrastructure construction.

3.2 Model Building

To process the Metropolitan Area Network flow trend in the way that data trend problem is handled, and build RNN Metropolitan Area Network flow predictive model. Its structure is shown in the figure 3:

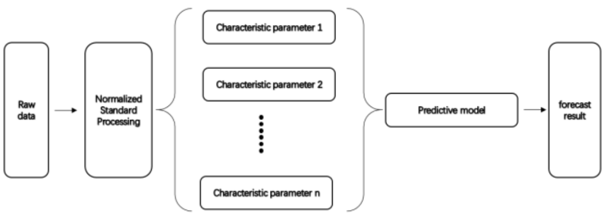

Figure 3: RNN Model Architecture Diagram

In this paper, the prediction of Metropolitan Area Network flow is conducted based on recurrent neural network. The model adopted contains three input neurons, a hidden layer and a output neuron. Its structure is shown in figure 4:

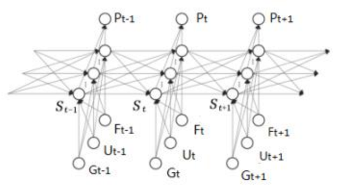

Fig 4: Predictive Model Diagram

The description of different layers in the metropolitan area network flow predictive model, which based on recurrent neural network, is as the following:

1) Input layer: take the GDP of the previous year (GT), users number (Ut) and metropolitan area flow (FT) as the input model, that is to say, the input node number is three, which means matrix 3×1

2)Hidden layer: $S_t=[S_{t,1},S_{t,2},\cdots,S_{t,n}]^T$, is the node of RNN in the hidden layer at the time T, in which N represents the node number of the hidden layer. The calculation of the hidden layer is shown in formula 5:

$$\begin{bmatrix} S_{t,1} \\ \cdots \\ S_{t,n} \end{bmatrix} = \tanh\left\{ \begin{bmatrix} u_{11} u_{12} u_{13} \\ \vdots \\ u_{n1} u_{n2} u_{n3} \end{bmatrix} \begin{bmatrix} G_t \\ U_t \\ F_t \end{bmatrix} + \begin{bmatrix} w_{11} w_{12} w_{13} \\ \vdots \\ w_{n1} w_{n2} w_{n3} \end{bmatrix} \begin{bmatrix} w_{t-1,1} \\ \vdots \\ w_{t-1,n} \end{bmatrix} \right\} \quad (5)$$

3)Output layer: this layer belongs to the full-connected layer. Take the output number of the hidden layer as the input and the flow at the time T as output. The node number of model output is 1. The calculation of this layer is shown in formula 6:

$$[P] = [v_{11} v_{12} \cdots v_{1n}] \begin{bmatrix} S_{t,1} \\ S_{t,1} \\ \vdots \\ S_{t,n} \end{bmatrix} \quad (6)$$

In the above formula, the letters" T" " A" " N" " H" are activation functions; N is the node number of the hidden layer; n×3 matrix、 n × n matrix and 1 × n matrix are weight parameter matrices U, W and V respectively.

Select the best loss function and optimizer through training test, the specific operation is as follows：

(1) Processing of the raw data. The raw data is collected from the flow data of each year, but due to the explosive development of the network, the influence of the data the in earlier years is greatly reduced. In order to achieve better modeling effect, it is essential to process the data in the earlier years. In this paper, only the quarterly data of the flow data of the earlier year are processed to ensure the consistency of influencing factors on the data.

(2) Normalized Standard Processing. Statistics from different regions often have different dimensions and dimension units, which will affect the data analysis. So data standardization and normalization processing are needed eliminate the dimensional impact among indicators and to reach the goal that data indicators are comparable. After the standardized procession of the raw data, all indexes are at the same order of magnitude which is suitable for comprehensive comparison. In this paper, all the flow data are converted into Gbps for unification. The maximum and minimum value normalization method is adopted to improve the speed of model training. Deviation is the normalized method (maximum-minimum method), and the formula is:

$$\bar{x} = \frac{x - \min(x)}{\max(x) - \min(x)} \quad (7)$$

(3) Processing of Featured Parameters. After the first two steps, the standard featured parameters were obtained, and the multi-parameters were sorted by time and became the featured parameters that be recognized by RNN. The featured parameters were made into data set and divided into training set and test set.

(4)Establishment of prediction model. According to the actual application data, the network model optimizer and loss function were determined through orthogonal experiment, and the optimal neural network prediction model was built to ensure the optimal prediction result.

3.3 Application

3.3.1 Data Analysis

According to the metropolitan area network flow of every city, choose the flow data of a certain operator in recent 5 years, the metropolitan area network flow data, the user number and the GDP at the end of last year, the metropolitan area network flow of each month. Take these parameters as characteristic parameters, which will change with time. We can predict through RNN network neurons. The following is the original data:

Table 1 Partial traffic raw data

Date	Type	City 1	…	City 11
1/1/2014	Broadband subscribers（household）	3803050	…	413950
	Outbound metro network traffic（Gbps）	1651	…	229
	Last year's GDP（100 million）	4863.6	…	1110
...	…	…	…	...
1/1/2018	Broadband subscribers（household）	6716	…	981
	Outbound metro network traffic（Gbps）	6246380	…	1240585
	Last year's GDP（100 million）	6003.5	…	1550.1

3.3.2 The Preparation of Data and Procession

The original data was normalized according to the two kinds of eigenvalue data, and then get training parameter set and test parameter set that needed in the model building.

Table 2 Partially normalized data table

Date	Type	City 1	…	City 11
1/1/2014	Broadband subscribers	0.000000000	…	0.000000000
	Outbound metro network traffic	0.015454474	…	0.048066109
	Last year's GDP	0.000000000	…	0.000000000
...	…	…	…	. . .
1/1/2018	Broadband subscribers	1.000000000	…	1.000000000
	Outbound metro network traffic	1.000000000	…	1.000000000
	Last year's GDP	1.000000000	…	1.000000000

According to the data in the above table, the normalized and standardized characteristic parameters are divided into training parameter set and test parameter set by a ratio of 3:1, of which eight sets are taken as training sample and three set as test sample set. Input the cyclic neural network according to the time series matrix.

3.3.3 Error Analysis

This paper can calculate the root mean square error (RMSE) that generated by same unit with the variable itself. That is to say, RMSE can be regarded as an important index in the valuation of model prediction result. Before RNN training, orthogonal experiment was conducted to compare the optimal combination of network model. The specific formula is as follows:

$$\text{RMSE}=\sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_t-\hat{x}_t)^2} \qquad (8)$$

The result is shown in table 3:

Table 3 Result Comparison

Training times	Loss function + Optimizer	Training time（S）	RMSE	Training loss
10	Mse+Adam	37	1.657	0.0041
10	Mae+Adam	40	0.843	0.0025
20	Mse+Sgd	70	1.243	0.0033
20	Mae+Sgd	75	0.614	0.0015
30	Mse+Adam	103	1.135	0.0039
30	Mae+Adam	110	0.530	0.0007
30	Mse+Sgd	120	1.662	0.0016
40	Mae+Sgd	140	2.651	0.0073
40	Mse+Adam	153	1.221	0.0043

From the table 3 we can know, the RMSE minimum is 0.530, and the training loss minimum is 0.0007 at the training round 30. If the training time is reduced, the model will be unsatisfied. If the training time is increased, the model will over fit. A good predictive model can be made out at the 30th rounds of training.

3.3.4 Model Training

RNN network model was built according to the above optimal parameter combination. And the training parameter set and test parameter set were input into the constructed RNN. The training loss is shown in the following picture:

Figure5 Change graph of training loss

3.3.5 Result Analysis

After the training and prediction of unified data through the RNN model, the RMSR of the training is 0.530, and the RMSR of the test process is 0.300, which achieved an ideal result. The predictive results of 11 regions on February 10, 2018 are shown in the following picture:

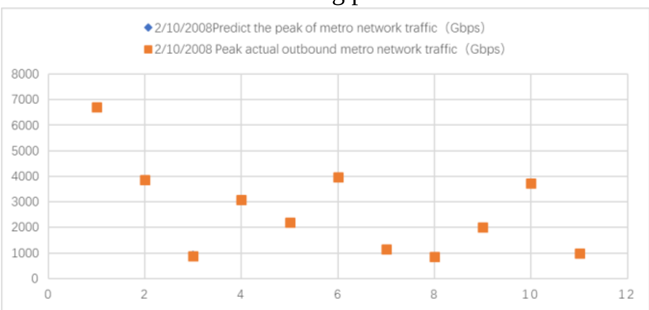

Figure6 Comparison chart of predicted and actual traffic

The abscissa is the city number of the test sample and the ordinate is the predicted peak of MAN flow in the current city at certain date, the unit is Gbps. The figure above shows that the predicted MAN flow and the real flow fit very well and the MAN traffic in each city at that date is successfully predicted. Through the set of data put into the cyclic neural network, the trained traffic prediction model can be used to obtain the specific MAN flow peak at certain date. The comparison of the real and predicted MAN peak flow of eleven cities at a certain date is shown in the following table.

Table 4 2018/2/10 Comparison table between peak traffic prediction and real traffic

Region	2/10/2008 Predict the peak of metro network traffic（Gbps）	2/10/2008 Peak actual outbound metro network traffic（Gbps）
City1	6718	6716
City2	3858	3855
City3	899	896
City4	3068	3077
City5	2199	2197
City6	3969	3967
City7	1139	1141
City8	869	867
City9	2019	2010
City10	3739	3733
City11	978	981

From the table above, the error between the real value and the predicted value is small, which achieves accurate prediction. It is proved that it is feasible to predict the MAN flow peak through recurrent neural network.

IV. SUMMARY

1) The new method was proposed in this paper that MAN flow is predicted through recurrent neural network. It is proved that this new method owns good convergence, good flow peak prediction ability and is a new prediction method.

2) Based on the research of RNN MAN flow prediction built on MAN data, universally applicable prediction model was established, which provided comparatively accurate parameter guidance in the communication enterprise network planning. It can ensure the stability of the network in engineering construction and good network experience.

3) Through the accurate prediction of MAN flow, the targeted network engineering expansion can ensure the network stability, cut the construction cost, reduce energy consumption and ease the operating burden of operators.

4) With network construction software-used and clouded, gradually realize the cooperation of cloud tube. The prediction method based on this paper can predict the metropolitan area network flow relatively accurate, so that operators have elastic network service ability, which can mobilize network resources flexibly, and avoid waste when the network is stable.

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