A Traffic Feature Analysis Approach for Converged Networks of LTE and Broadband Carrier Wireless Communications

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Abstract. With the emergence of new requirements for the application of network access network, network traffic presents new characteristics, and network management faces new challenges. The main contribution of this paper is to propose a new network traffic model and prediction method based on generalized linear regression model. Firstly, the network traffic is modeled and generalized linear regression model is used to model it. Then, using the generalized linear regression theory, we can calculate the modified parameters and determine the appropriate model, so that we can accurately predict the network traffic. The simulation results show that the method is feasible.

Keywords: Network traffic · Generalized linear regression · Traffic modeling · Parameter estimation · Traffic prediction

1 Introduction

With the rise of smart grid related research, due to its unique characteristics, power line communication plays an increasingly important role in the power network. In the communication from the user terminal to the service switching point, wireless communication technology occupies a place and occupies a dominant position. As a kind of connection communication mode [1, 2], wireless communication can save cost, provide voice, data, video and other comprehensive services, and can meet the bandwidth, speed, waiting time and other QoS requirements. However, with the combination of intelligent devices and the rapid development of new intelligent network applications, the traditional intelligent network technology has brought great pressure to the traditional intelligent network. How to solve this problem is an important research direction, and there is no feasible solution to solve this problem.

In the network of wireless communication LTE and broadband providers, the network traffic has the update and unknown characteristics compared with the traditional network structure [5, 6]. How to effectively analyze and evaluate the transmission characteristics

H. Song and D. Jiang (Eds.): SIMUtools 2020, LNICST 369, pp. 183–193, 2021.
https://doi.org/10.1007/978-3-030-72792-5_17

of the network is a difficult problem to be solved; many algorithms can be used for network feature modeling and analysis, which is a new method to extract network traffic characteristics [7, 8]. Principal component analysis (PCA), RBM model and decision tree based model can predict network traffic in aggregation network [9, 10].

Deep learning model can also be used for network traffic analysis. Specific transmission modes can be classified by monitoring machine learning [11, 12]. At the same time, time-frequency analysis can be combined with network feature analysis to analyze the characteristics of traffic flow [15, 16]; the combination of recurrent neural network (RNN) and convolutional neural network (CNN) can also be used to construct intelligent, network traffic classifier with high recognition rate [17, 18].

The above methods can be used for network traffic modeling and analysis, but in the converged network, the network feature types are more complex. Compared with the traditional methods, the advantage of this method is that the traditional transmission analysis method is difficult to apply to this situation.

Figure 1 shows the converged communication network architecture based on LTE mobile and broadband operators. LTE wireless base station can not only transmit IP signal through IP network, but also use broadband carrier as support carrier of data transmission, and use licensed frequency band as main carrier [19, 20]. At present, the free and unauthorized frequency resources are determined by the cognition of related professions [21, 22]. It is an accurate and effective method to model and predict network traffic based on AR model and Taylor series. Generally speaking, terminals and base stations can control wireless resources within the approved frequency band. Because of the high temporal variability of network traffic, it is difficult to describe it in mathematical terms, so it is difficult to establish a model to simulate network traffic. In this paper, we use AR model for static parts and Taylor model for inactive parts. This defines model parameters based on network data, and then. Then we propose a new prediction algorithm to accurately evaluate network traffic and the simulation results show the effectiveness and application prospect of this method.

The rest of this paper is structured as follows. In Sect. 2, we build a mathematical model and describe the method. In Sect. 3, the experimental simulation is carried out, and the analysis of the results is given. Finally, we summarize our work in Sect. 4.

2 Problem Statement

Network traffic divides into stable and unstable parts. The stable component is the most important Energy in the transmission. The unstable component changes greatly with the passage of time, and network traffic details will also change. We use $x_S(t)$ to represent stable components $x_{NS}(t)$, and show the Components prompt in it. To better simulate flow, two methods are used in [24].

Firstly, $x(t)$ can be divided into stable and unstable parts by STFT, and $x(t) \in L^2(R)$ (the STFT with the window function $g(t)$) is assumed to be the following STFT.

$$WX_g(\omega, b) = \int_{-\infty}^{\infty} x(t)g(t-b)e^{-j\omega t}dt \tag{1}$$

In the above equation, b is the time domain migration parameter, ω is the frequency domain migration parameter, and $WX_g(\omega, b)$ is the spectral characteristics near the $t = b$.

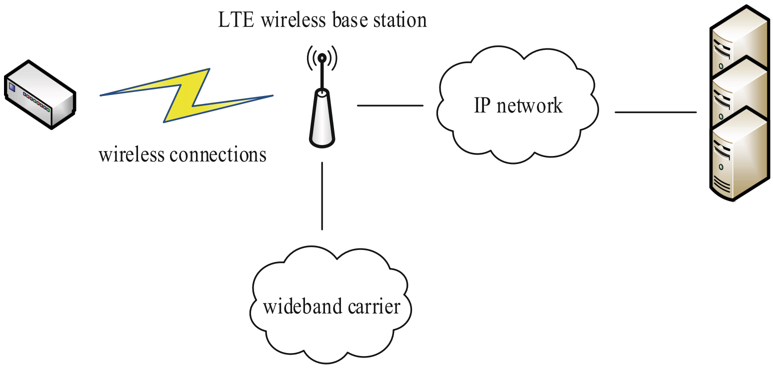

Fig. 1. The integrated network architecture of LTE wireless and broadband carrier communications.

Then, we can set $g(t)$ that meets this condition.

$$g_{\omega,b}(t) = g(t-b)e^{-j\omega t} \tag{2}$$

The Eq. (1) then is equal to:

$$WX_g(\omega, b) = \int_{-\infty}^{\infty} x(t)\overline{g}_{\omega,b}(t)dt = <x(t), g_{\omega,b}(t)> \tag{3}$$

When and only if the effective window width of $g(t)$ is D_t, $WX_g(\omega, b)$ can get the spectrum information of $x(t)$ in $[b - D_t/2, b + D_t/2]$ time interval.

Owing to the main Energy Sources of the Rivers are concentrated in the stable Components, the details are reflected in the unstable Components, it is only necessary to segment the Band signals in the frequency range.

Obviously, low pass filter and high pass filter are selected to filter the transformed time series $WX_g(\omega, b)$ [27, 28]. For low-pass filter, we can choose exponential low-pass filter, the formula is as follows.

$$H_L(u, v) = e^{-\left[\frac{\sqrt{u^2+v^2}}{D_0}\right]^{2n}} \tag{4}$$

Due to the filtering of low-pass filter, the stable part of the original signal can be obtained as follows:

$$WX_S(\omega, b) = WX_g(\omega, b) \circ H_L(\omega, b) \tag{5}$$

For high pass filter, since Butterworth high pass filter is selected, its formula will be as follows:

$$H_H(u, v) = 1 \Big/ (1 + (D_0 \Big/ \sqrt{u^2 + v^2})^{2n}) \tag{6}$$

The unstable components of $WX_g(\omega, b)$ can be obtained by high pass filter [29, 30].

$$WX_{NS}(\omega, b) = WX_g(\omega, b) \circ H_H(\omega, b) \tag{7}$$

What we have to do next is to make different transformations for different distributions, and get the unstable component and the stable time-domain component as follows

$$\begin{aligned} x_S(t) &= STFIT[WX_S(\omega, b)] \\ &= \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} WX_S(\omega, b)g(t-b)e^{j\omega t}d\omega db \end{aligned} \tag{8}$$

$$\begin{aligned} x_{NS}(t) &= STFIT[WX_{NS}(\omega, b)] \\ &= \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} WX_{NS}(\omega, b)g(t-b)e^{j\omega t}d\omega db \end{aligned} \tag{9}$$

The stable component $x_S = \{x_S(t), t = 1, 2, 3, ...\}$ changes slowly and become a strong short correlation term. The author's AR model is widely used in linear forecasting, which can extract data from the model. The AR model is better than the interpolation method [31, 32], which is the representation of historical data Random. The process of this model may be as follows.

$$\begin{cases} x_S(t) = \varphi_1 x_S(t-1) + \cdots + \varphi_p x_S(t-p) + \theta(t) \\ E(\theta(t)) = 0 \\ E(\theta(s)\theta(t)) = \begin{cases} \sigma^2, s = t \\ 0, s \neq t \end{cases} \\ E(\theta(s)X_L(t)) = 0, s \neq t \end{cases} \tag{10}$$

where φ_i is the auto-regressive coefficient that affects the other parameters, $\theta(t)$ is the disturbance term at the time t, p is the order of the AR model.

Then, we establish a queue model to describe the disturbance term of the network traffic, so as to obtain a model which obeys Poisson distribution and probability distribution [33, 34]. Finally, we express the mathematical description of the stable component as follows.

$$\theta(t) = \alpha\theta_p(t) + \beta\theta_e(t) \tag{11}$$

In the above formula, the parameters $\theta_p(t) \sim P(\lambda_1)$ and $\theta_e(t) \sim e(\lambda_2)$, λ_1 and λ_2 are the relevant parameters of the model distribution respectively. In addition, α and β are traffic interference coefficients. The probability function of our model can be written as

$$P\big(\theta_p(t)\big) = \lambda_1^k \exp\big(-\lambda_1/\theta_p(t)!\big) \tag{12}$$

$$P(X < \theta_e(t)) = \begin{cases} 1 - \exp(-\theta_e(t)/\lambda_2), \theta_e(t) > 0 \\ 0, \qquad \theta_e(t) \leq 0 \end{cases} \tag{13}$$

Since we need to estimate the AR model parameters, there are three methods that can be considered. Moment. According to the characteristics of the model, we choose the moment estimation method [35, 36]. In this way, the coefficients of the model can be described by mathematical formulas, as shown below.

$$\begin{bmatrix} \varphi_1 \\ \varphi_2 \\ \cdots \\ \varphi_p \end{bmatrix} = \begin{bmatrix} \rho_0 & \rho_1 & \cdots & \rho_{p-1} \\ \rho_1 & \rho_0 & \cdots & \rho_{p-2} \\ \vdots & \vdots & \ddots & \vdots \\ \rho_{p-1} & \rho_{p-2} & \cdots & \rho_0 \end{bmatrix}^{-1} \begin{bmatrix} \rho_1 \\ \rho_2 \\ \cdots \\ \rho_p \end{bmatrix} \tag{14}$$

In the above formula, $\hat{\rho}_k = \gamma_k/\gamma_0 = \sum_{t=k+1}^{N} X_t X_{t-k} \Big/ \sum_{t=1}^{N} X_t^2$ is the autocorrelation function of the model. Furthermore, we can get the stable component of network traffic according to the above conclusions and expressions.

$$\hat{x}_S(t) = \begin{cases} \sum_{i=1}^{p} \varphi_i x_S(t-i), t = 1 \\ \sum_{t=1}^{s-1} \varphi_i \hat{x}_S(t-i) + \sum_{t=1}^{p} \varphi_i x_S(t-i), \ 1 < t \le p \\ \sum_{i=1}^{p} \varphi_t \hat{x}_S(t-i), t > p \end{cases} \tag{15}$$

Naturally, the stable part $x_S(t)$ can be predicted by known conditions.

The unstable part includes more detailed information on network traffic and fluctuations. A general function can be approximated to a finite number of dates in the Taylor series. Theoretical Taylor gives a quantitative estimate of the error produced using this approach. It is the polynomial that records several initial conditions of Taylor's sequence. It's Taylor polynomial. This model extracts two concepts from the Taylor series of unstable components.

Therefore, we use the classical theory of Taylor series to express the unstable component.

$$x_{NS}(t) = \sum_{n=0}^{\infty} \frac{x_{NS}^{(n)}(t_0)}{n!}(t-t_0)^n \tag{16}$$

In the allowable range of error, the redundant terms of Taylor series of unstable components are removed.

$$\hat{x}_{NS}(t) = \frac{x'_{NS}(t_0)}{n!}(t-t_0) + \frac{x''_{NS}(t_0)}{n!}(t-t_0)^2 \tag{17}$$

The final expression of the flow is as follows.

$$\hat{x}(t) = \hat{x}_S(t) + \hat{x}_{NS}(t) \tag{18}$$

Combined with the above mathematical derivation, we can design such an algorithm.

Step 1: According to formula (8), (9), the network is classified into two categories: steady state and unsteady state;

Step 2: According to formula (10), for Part 1, the method in (10) can be used for parameter setting;
Step 3: The selected probability method be used for parameter estimation;
Step 4: According to formula (17), the mathematical description of Part 2 is carried out and the approximate expression is established;
Step 5: Combine part one and part two to get the whole estimation model and calculate the result;

The final algorithm flow chart is shown in Fig. 2.

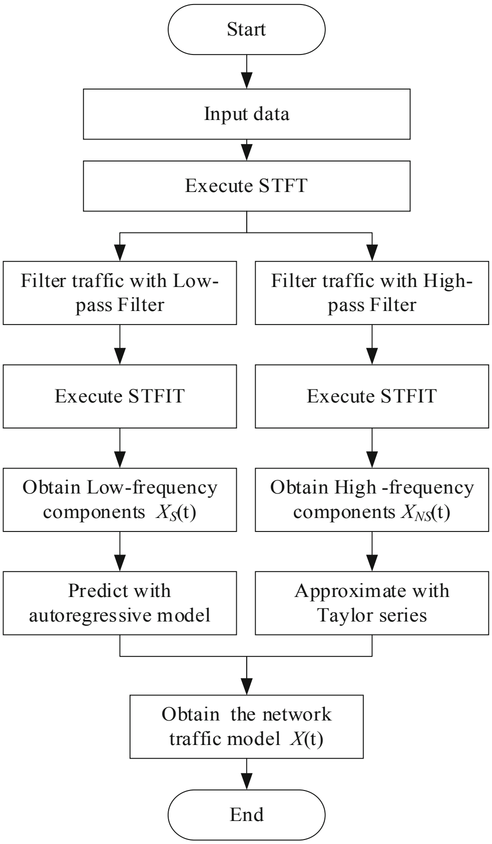

Fig. 2. The flow chart of the flow traffic model.

3 Simulation Results and Analysis

In this part, we conducted many tests to demonstrate our algorithm GLMTMA. We verify GLMTMA using real data from the U.S. real Abilene backbone. In order to highlight the performance of our algorithm, we compare our method with the best method today. All the experimental data are true and reliable. First of all, we carried out several groups of experiments on different methods. After the experiment, we analyze the network traffic prediction results of GLMTMA algorithm, and compare GLMTMA with other methods, and give the average relative error of network traffic of four algorithms. Moreover, in order to better highlight the performance ratio of the algorithm, we discuss the performance improvement of GLMTMA on PCA, WABR and HMPA. In our simulation, the data of the first 500 slots are used to train the models, while the other data are used to verify the performance of all algorithms.

Figure 3 shows the prediction results of network traffic 53 and 96, in which network traffic 53 and 96 are randomly selected from 144 end-to-end service pairs (or flows) in the Abilene backbone network. In our experiments, the results are basically in a stable range. The experiment only selected the most classic network traffic 53 and 96. Network traffic is also known as an origin destination (OD) pair. Figure 1(a) shows that GLMTMA can detect the dynamic changes of network flow 53 very quickly. For different time slots, the network traffic in the experiment also has a significant change law with time.

Obviously, we can draw the following conclusion from Fig. 3(a). Our algorithm can well detect the change trend of network traffic. In addition, as shown in Fig. 3(b), the change trend of network flow 96 is in winter. Although our method has a large prediction error for network traffic 96 under experimental conditions, it can still capture its changing trend. We also show a method that can effectively predict the change in network traffic over time.

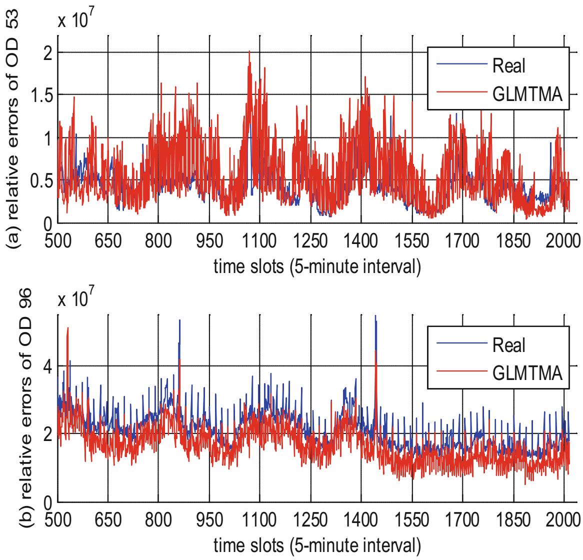

Fig. 3. Prediction results of network traffic flows 53 and 96.

From the above we can see that our method has good performance. In view of the limitation that traditional methods are difficult to detect the dynamic trend of network traffic, we can effectively solve this limitation. In order to further verify our method, we conducted a number of grouping experiments, each of which had more than 500 repetitions. The average relative prediction error is calculated.

The expression of average relative prediction error is as follow:

$$d(t) = \frac{1}{N}\sum\nolimits_{i=1}^{N} \frac{||\hat{y}_i(t) - y_i(t)||_2}{||y_i(t)||_2} \tag{19}$$

In the above formula, $i = 1, 2, \ldots, N$ and N are the running times of the experimental algorithm, $||.||_2$ is the norm of L_2, and $\hat{y}_i(t)$ is the traffic prediction value of i running in time slot t.

Figure 4 shows the average relative prediction error of four algorithms for network level traffic 53 and 96. It can be seen from the figure that the relative errors of three methods (WABR, HMPA and GLMTMA) are relatively small for the two classic traffic 53 and 96, while the prediction error of PCA is relatively large. In addition, we can also see that the relative error of GLMTMA is the smallest. Based on this, we can conclude that GLMTMA has better network traffic prediction ability than the other three methods. More importantly, considering the comparison of repeated experiments, we can see the stability of the algorithm from the fluctuation of the average value of the experiment. Compared with the other three algorithms, GLMTMA has better stability, especially in detecting the dynamic trend of network traffic, which makes it more suitable for network traffic prediction and network analysis modeling. Based on the above conclusion, GLMTMA can predict network traffic more effectively than previous methods.

Finally, the performance of the algorithm is also an important part. Through many experiments, we have obtained the performance improvement rate of network traffic

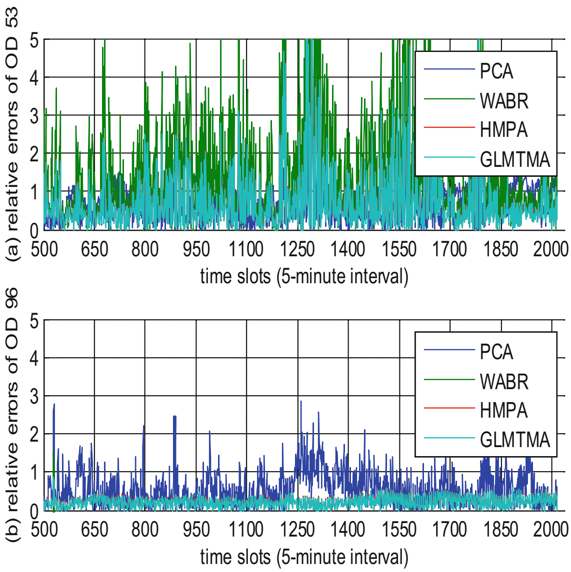

Fig. 4. Average relative errors for network traffic flows 53 and 96.

53 and 96, as shown in Fig. 5. For network traffic 53, GLMTMA is 23.1%, 20.3% and 1.33% higher than PCA, WABR and HMPA, respectively. In addition to the first time, for another network traffic, our method improves by 13.6%, 26.2% and 4.77% respectively compared with PCA, WABR and HMPA. The performance improvement of our method for other methods is at least 1.33%, and the maximum performance improvement is 23.1%. Moreover, this is the performance improvement under the condition of ensuring the prediction effect. This shows that our method has a comprehensive improvement over other methods in terms of performance. This is of great significance for the implementation of the algorithm. Because the efficiency and performance of the algorithm are closely related, the less the performance consumption and the faster the speed, the better the overall energy efficiency ratio. Based on this, we can see that our method has relative advantages in specific implementation, and can be better used as a tool for network traffic prediction.

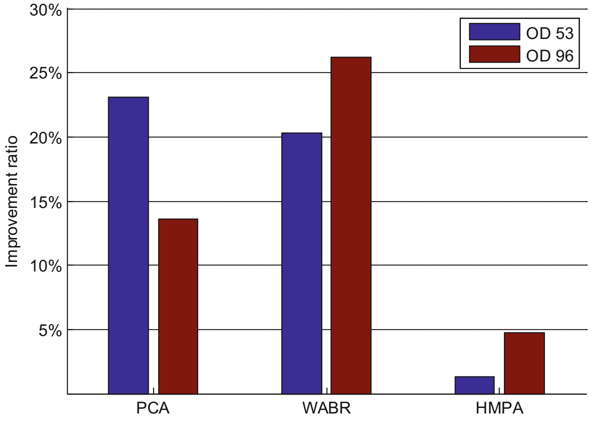

Fig. 5. Improvement ratio of network traffic flows 53 and 96.

4 Conclusions

A network traffic modeling and prediction method proposed in this paper, which is based on generalized linear regression theory. Different from the traditional methods, the generalized linear regression model with good robustness is selected to forecast the network flow. Firstly, we model the model in the way of probability, and express the parameters of the model with probability formula. Secondly, according to the regression characteristics of the model, the parameters of the model are iterated by the algorithm. Finally, through repeated iterations and calculations, we get the appropriate model parameters, so as to get a model that can effectively describe the network traffic. The simulation results show that the method is effective.

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