A Traffic Prediction Algorithm Based on Converged Networks of LTE and Low Power Wide Area Networks

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Abstract. Network traffic plays an important role in network management and network activities. It has an important impact on traffic engineering and network performance. However, we have larger difficulties in capturing and estimating them. This paper proposes a new estimating algorithm to forecast and model network traffic in time-frequency synchronization applications. Our approach is based on the normal regression theory. Firstly, normal regression theory is used to characterize and model network traffic. Secondly, the corresponding normal regression model is created to describe network traffic by finding the model parameters using the samples about network traffic. Finally, the estimation algorithm is proposed to predict network traffic in time-frequency synchronization applications. Simulation results indicate that our approach is effective.

Keywords: Network traffic · Traffic estimation · Traffic modeling · Normal regression model · Dynamic changes

1 Introduction

Within the transmission network, network services have a significant impact on network management, transmission technology and optimization of improvements, reception of network messages, and transmission of activities, in particular with regard to deadlines [1, 2]; network services are one of the specific communications energy terminal services Form. The article describes the behavior, characteristics, and working methods and procedures of network users; The Network (OD) between source and destination shall be provided as a network service [3, 4]. Network transfer assessment is always a burning issue in the area of network research, which has attracted the attention of others. Okay, They are difficult to estimate and predict, different. Actually, To improve the expected accuracy of intelligent network traffic, a two-dimensional method of forecasting is based on analysis: Li Wei and other characteristics are recommended [5, 6]. The phone suggested a new traffic forecast to predict the Bay space network. Unlike existing methods, this method integrates all available waste information into the transport network in order to predict the current flow of local traffic [7, 8].

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Zhi, et al. analyzed the characteristics of network traffic data of power grid industrial control system, built a global security monitoring and early warning platform for power grid industrial control system and proposed a suitable platform architecture and detection method of network traffic anomaly detection security monitoring and early warning of power grid industrial control system [9–11]. W. Chen proposed a dynamic baseline Traffic detection Method which is based on the historical traffic data for the Power data network [12–14]. Zhao, et al. expounded the electric power communication network traffic prediction research present situation, summarized the characteristics of the forecast and the influencing factors, put forward to the return of the electric power communication network traffic based on libsvm prediction method and the PSO (Particle Swarm Optimization) algorithm is adopted to model parameters optimization [15–18]. Tang, et al. presented an analytical study of the traffic in power distribution communication network and proposed a new feature matching model. Simulation results show that the proposed model can not only capture the distribution probability faithfully but also depict the self-similarity and multi-fractal characteristics of the traffic [19, 20]. Li, et al. analyzed business traffic according to business characteristics of electric power communication network and proposed an algorithm for uniform business optimization based on entropy [21–23]. Others are very sensitive about this. Summer, yeah. Since the accuracy and accuracy of the network traffic forecasting model are low, they should be further described.

Figure 1 shows the integrated network architecture of LTE wireless and low power wide area network. The network mainly includes User Equipment (UE), Evolved UMTS Terrestrial Radio Access Network (E-UTRAN), Evolved Node B (eNB), Packet Core Evolution (EPC), and Low Power Wide Area Network (LPWAN). Evolved packets the core network communicates with packet data networks such as the Internet, private enterprise networks, or IP multimedia subsystems. Different from these algorithms, this paper proposes a new method for LTE low power wide area fusion communication network traffic estimation based on Principal Component Analysis (PCA) and linear regression model. First, the principal component analysis method is used to decompose the network traffic into a principal component and a non-principal component. Second, the main components were analyzed using a linear regression model and the third noise model was used to perform unnecessary component analysis, which included: closure. network traffic samples shall be used to determine model parameters and calculate the next network traffic. The samples are given below. At this point, our model can effectively and accurately reflect the dynamic characteristics of network traffic. Fergus. NGN. The algorithm can effectively stop low-voltage bush regular traffic. The simulations show that the TEMUNE method offers good prospects for implementation. This algorithm can effectively estimate the network traffic in the LTE low-power wide-area converged communication network. Simulation results show that this method has a good application prospect.

The rest of this article is organized as follows. The second part is the problem statement and prediction method. The third part is the simulation results and analysis. The fourth part summarizes the work of this paper.

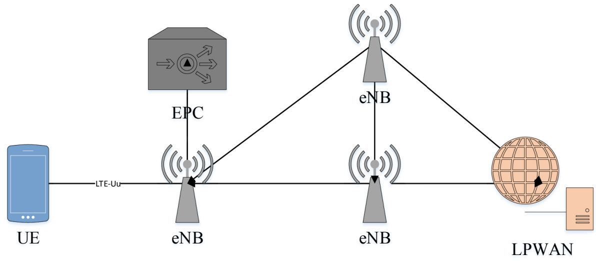

Fig. 1. The integrated network architecture of LTE wireless and low power wide area network.

2 Problem Statement

The principal component analysis is used to divide the network traffic $x(t)$ into the main component and a non-principal component. In order to systematically analyze the problem, the forecast network traffic analysis must take into account several factors [24, 25]. Due to the auto-correlation of network traffic, each piece of traffic data reflects to some extent certain information about network traffic at the next moment, and the traffic data has a certain correlation with each other. According to the characteristics of the automatic correction of network traffic, it must be possible to follow up direct traffic data to some extent association data. Therefore, because the variables in the quantitative analysis are small, the information is large so that the main method of analysis DOS components are used for separate network traffic. First, the raw data is standardized as follows:

$$x_{ij} = \frac{x_{ij} - x_{\bar{i}}}{s_i}(i = 1, 2, \ldots, n; j = 1, 2, \ldots, p) \tag{1}$$

where x_{ij} is the original data, and $x_{\bar{i}}$ s_i are the sample mean and standard deviation of the *i–th* and *j–th* flow vectors, respectively. Then we can get the normalization matrix X [26–29].

Find the correlation coefficient matrix for the normalization matrix X:

$$R = \left[r_{ij}\right]_p xp = \frac{X^T X}{n-1} \tag{2}$$

where $r_{ij} = \frac{\sum z_{kj} z_{kj}}{n-1}$, $i, j = 1, 2, \ldots, p$. Solve the characteristic equation of Eq. 2:

$$\left|R - \lambda I_p\right| = 0 \tag{3}$$

Get p characteristic roots, and Then identify the key elements.

Determine the value of m according to

$$\frac{\sum_{j=1}^{m} \lambda_j}{\sum_{j=1}^{p} \lambda_j} \geq 0.85 \tag{4}$$

so that the utilization rate of the data reaches more than 85%. For each $\lambda_j, j = 1, 2, \ldots, m$, solve the system of equations $Rb = \lambda_j b$ to obtain the unit eigenvector b_j^O.

Convert the standardized indicator variable into a main component:

$$U_{ij} = z_i^T b_j^O, j = 1, 2, \ldots, m \tag{5}$$

For the obtained m principal component components,

$$U = (U_1, U_2, \cdots, U_M) \tag{6}$$

The main elements shall be modelled and analysed using the linear regression equation. We perform linear regression modeling:

$$f(u_i) = \omega^T u_i(t) + \varepsilon_i \tag{7}$$

Parameters ω and ε_i are determined using the least square method. It is assumed that the error ε_i follows a Gaussian distribution [30–33].

$$p(\varepsilon_i) = \frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{\varepsilon_i^2}{2\sigma^2}\right) \tag{8}$$

The objective function of less squared method is as follows:

$$\begin{aligned} J(\omega) =& \frac{1}{2}\sum_{i=1}^{m}(y_i - \omega^T u_i)^2 = \frac{1}{2}\left\| y - \omega^T X \right\|^2 \\ =& \frac{1}{2}(y - \omega^T x)^T (y - \omega^T x) \end{aligned} \tag{9}$$

The objective function finds the main derivative of inflated surface, finds position 0 and finds the best solution. The solution process is as follows:

$$\begin{aligned} \frac{\partial J(\omega)}{\partial \omega} =& \frac{1}{2}\frac{\partial}{\partial \omega}\left((y - \omega^T x)^T (y - \omega^T x)\right) \\ =& X^T X\omega - Xy \end{aligned} \tag{10}$$

$$\frac{\partial J(\omega)}{\partial \omega} = 0 \tag{11}$$

$$\omega^* = X^T X^{-1} X^T y \tag{12}$$

Using a linear regression model, you can see the speed of movement below at the moment. However, the value is closer to the actual value [34–36], we model the noise of the sub-components 3 times as follows:

$$g(t) = a_3(x(t))^3 + a_2(x(t))^2 + a_1 x(t) + a_0 + \delta(t) \tag{13}$$

By building a model, the final network traffic can be expressed as:

$$\begin{aligned} y(t) =& u(t) + g(t) \\ =& \omega u(t) + b_0 + a_3(x(t))^3 + a_2(x(t))^2 + a_1 x(t) + a_0 + \delta(t) \end{aligned} \tag{14}$$

The modeling algorithm proposed in this paper is as follows:

Step 1: Use principal component analysis to divide network traffic into principal and non-principal components.

Step 2: For the principal component, according to Eq. (7), use a linear regression model to model it.

Step 3: According to Eq. (9), use the least squares method to find the parameters of the linear regression model.

Step 4: For the non-principal component, according to Eq. (13), use the third-order noise model to model and analyze it.

Step 5: According to Eq. (14), use the established network traffic prediction model to perform network traffic prediction.

The algorithm flowchart is shown in Fig. 2.

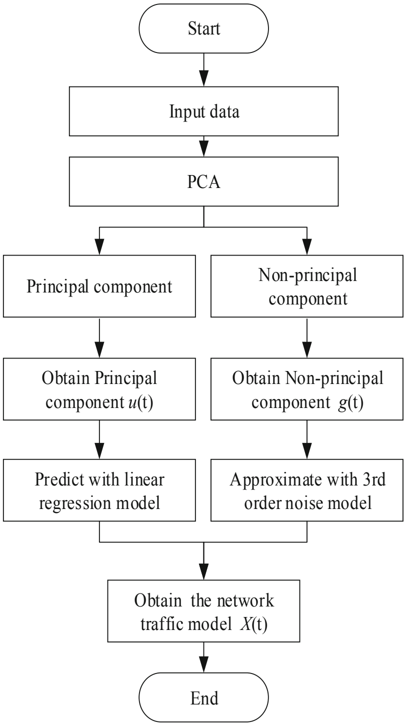

Fig. 2. The flow chart of the flow traffic model.

3 Simulation Results and Analysis

Now we perform many experiments to validate our algorithm NRTA. Using the acronym to simulate the mainframe's current Keyboard. STKCS [7], WABR [12], PCA [15], and TomoG [19] are reported as good estimation approaches for network traffic. Here, we use real traffic data to compare NRTA with them [37, 38]. Accordingly, their estimation performance is analyzed in detail.

Figures 3 and 4 illustrate the estimation results of four algorithms for ODs 23, 68, 83, and 123, respectively, where Real denotes the real network traffic in the real network. From Fig. 3, These four algorithms show that you get better results for pets. Compared with the other three algorithms, NRTA has exhibited the best estimation value of network traffic for ODs 23 and 68. In contrast, TomoG indicates larger estimation errors than the other two algorithms. Figure 4 illustrates that four algorithms can also better estimate the traffic of ODs 83 and 123. Although network traffic changes significantly over time, these four algorithms can change which way to go. This will also enable the Committee to assess more accurately the EM network movements. TomoG holds better estimation ability, while STKCS and WABR indicate the larger estimation errors for network traffic. WABR products the larger under-estimation for OD 123. This shows that NRTA holds a better prediction performance for network traffic.

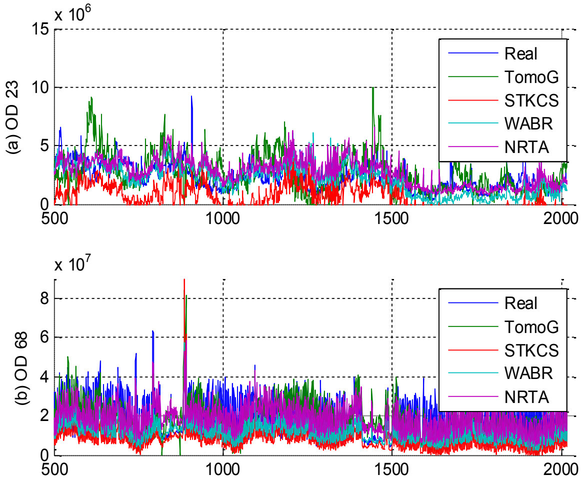

Fig. 3. Prediction results of four algorithms for ODs 23 and 68.

Figures 5 and 6 describe the relative estimation errors of four algorithms for ODs 23, 68, 83, and 123, relative to the real network traffic. Figure 5 demonstrates that NRTA shows the lowest relative prediction errors in four algorithms for network traffic of ODs 23 and 68. TomoG has the largest estimation errors, but STKCS and WABR illustrate the lower estimation errors. WABR shows much lower estimation errors than STKCS. This demonstrates that NRTA holds the best estimation ability for network traffic. Figure 6 shows that for OD 83, STKCS and WABR hold similar errors, and they are the largest. TomoG and NRTA hold lower errors and NRTA is much lower than TomoG. For OD 123, we can see that NRTA has the lowest error. This further indicates that NRTA exhibits a better estimation ability for network traffic.

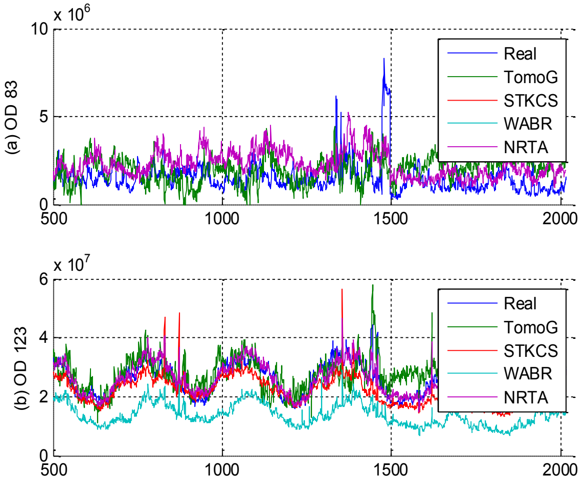

Fig. 4. Prediction results of four algorithms for ODs 83 and 123.

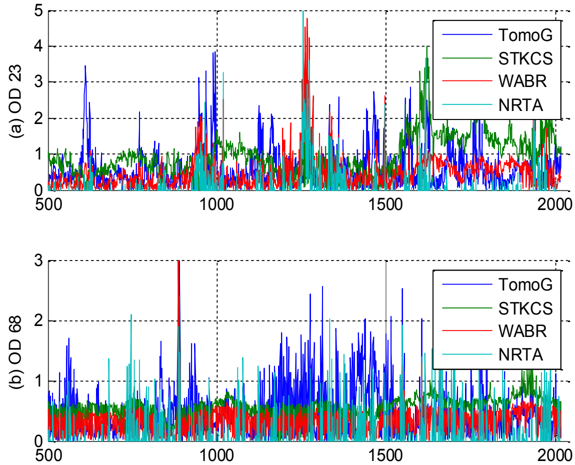

Fig. 5. Relative prediction errors of four algorithms for ODs 23 and 68.

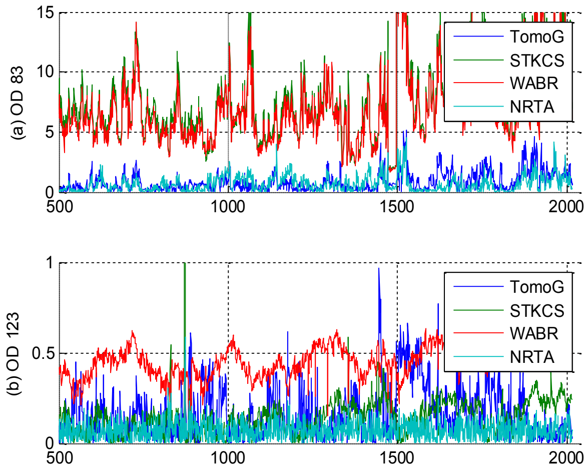

Fig. 6. Relative prediction errors of four algorithms for ODs 83 and 123.

4 Conclusions

This paper uses the normal regression theory to model network traffic in time-frequency synchronization applications in power communications. Using the theory of normal regression, the dynamic properties over time can be accurately measured. Network traffic is converted into the normal regression process to capture dynamic features of network traffic. Then the normal regression theory-based estimation model is created to estimate network traffic. Finally, we propose the corresponding estimation algorithm to estimate network traffic accurately. Simulation results shows that the proposed approach in this paper is feasible.

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