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An Integrated Prediction Model for Network Traffic based on Wavelet Transformation

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***Abstract*—To deal with the characters with the changing trend of the steady state and dynamic state of network traffic, an integrated prediction model for network traffic based on wavelet transformation is presented in this paper. First, the network traffic is decomposed using wavelet transformation and is reconstructed using a single branch algorithm. Next, the low frequency components of the network traffic are predicted using an improved gray theory. They are used to depict the changing trend of the steady state. Then, the high frequency components of the network traffic are predicted using a BP neural network algorithm. They are used to reveal the dynamic effect. Finally, all those results are synthesized to predict the network traffic. Simulation results show that the presented integrated model increased the prediction accuracy and decreased the negative effect brought by the burstiness and uncertainty.**

***Index Terms*—Wavelet transforms, prediction methods, communication system traffic, neural networks.**

I. INTRODUCTION

Much attention has been paid to the network traffic prediction in recent years. At present, there are many prediction models for the network traffic, such as Poisson model, Markov model and autoregression. With the development of the self-similar theory about the network traffic, ARMA model, ARIMA model, FARIMA model, and SFARIMA model have been presented [1]–[4]. At present, the artificial intelligence has been successfully applied to deal with the network traffic, such as the prediction models based on neural network [5], [6], the prediction model based on gray theory [7], the prediction model based on wavelet transformation and analysis [8], and the combined prediction model based on wavelet analysis and neural network [9], etc.

A non-linear preprocessing network traffic prediction method is presented in [10], which indicates the least square rule is no longer suitable to the time sequence model build with the estimated model parameters using given data, for there is too much burstiness in distributed data set and the serious deviation of network traffic from Gaussian distribution. Ming Jiang and Chunming Wu analyzed the prediction precision of the time sequence model using different time scale in detail, and demonstrated the prediction model using big time scale (minute) had a higher precision than the prediction model using small time scale (second, millisecond). The paper indicates the essence of the time sequence model is to find the special law through the research of history data, and predict the trend in the future. In addition, the paper indicates the network traffic of small time scale has the strong burstiness, uncertainty and complexity, and it is hard to grasp the statistical law [11]. The network traffic prediction based on wavelet transformation and FARIMA is presented in [12]. First, the original network traffic was decomposed using wavelet transformation and was reconstructed using a single branch algorithm. Next, FARIMA model was applied on each branch to predict. Finally, all those results were synthesized to predict the network traffic. The gray theory was applied to predict the network traffic of different time scale [13], the results shows the precision is related to the main period of the original network traffic of different time scale, and the prediction model based on gray theory has a higher precision than the prediction model based on FARIMA under the condition of small time scale.

The conclusion can be drawn from the research mentioned above, which shows network traffic has the features of variations of steady state and dynamic state, and the precision is closely related to the used prediction model. This paper applies the improved gray theory to predict the changing trend of the steady state of the network traffic, and applies the BP neural network to predict the changing trend of the dynamic state of the network traffic. At last, all those results are synthesized to predict the network traffic.

II. DESIGN IDEA OF INTEGRATED PREDICTION MODEL

First, the original network traffic is decomposed using wavelet transformation and is reconstructed using a single branch algorithm. Next, the low frequency components of the network traffic are predicted using an improved gray theory. Then, the high frequency components of the network traffic are predicted using a BP neural network algorithm. Finally, all those results are synthesized to predict the network traffic.

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A. Decomposing and reconstructing based on Wavelet transformation

The Mallat's fast Wavelet transform is always used to decompose the signal. The decomposition of the Mallat algorithm can be described as:

$$\begin{cases} a_{j+1} = Ha_j, \\ d_{j+1} = Ga_j, \end{cases} \quad j = 0,1,2,\cdots, \tag{1}$$

where H can be considered as a low-pass filter, and G can be considered as a high-pass filter. The low-frequency part reveals the profile feature and the changing trend of the original network traffic, and the high-frequency part reveals the effect brought by the dynamic factors such as random disturbance, etc.

The reconstruction of Mallat algorithm can be described as

$$a_{j-1} = a_j\bar{H} + d_j\bar{G}, \quad j = 1,2,\cdots,n, \tag{2}$$

where $\bar{H}$ and $\bar{G}$ are the dual operators of H and G respectively. The reconstruction is the reverse process of the decomposition.

B. Prediction model based on improved gray theory

The equal time interval sequence, $\boldsymbol{g}(0)$ is given by

$$\boldsymbol{g}^{(0)} = \{g^{(0)}(1), g^{(0)}(2), \ldots, g^{(0)}(n)\}, \tag{3}$$

where n indicates the dimensions of the model. Carrying out the accumulation operation for k=1,2, …,n

$$g^{(1)}(k) = \sum_{i=1}^{k} g^{(0)}(i) \quad (k = 1,\cdots,n), \tag{4}$$

we obtain the accumulated sequence

$$\boldsymbol{g}^{(1)} = \left\{g^{(1)}(1), g^{(1)}(2), \cdots, g^{(1)}(n)\right\}. \tag{5}$$

To reveal the changing trend, the first-order differential equation is given by

$$\frac{dg^{(1)}(t)}{dt} + r \cdot g^{(1)}(t) = u, \tag{6}$$

where r is a development coefficient and u is the gray input. They are determined by the least-squares method

$$\hat{\boldsymbol{a}} = \begin{bmatrix} r \\ u \end{bmatrix} = \left(\boldsymbol{X}^{\mathrm{T}}\boldsymbol{X}\right)^{-1} \boldsymbol{X}^{\mathrm{T}}\boldsymbol{Y}, \tag{7}$$

where $\boldsymbol{X}$ and $\boldsymbol{Y}$ are

$$\boldsymbol{X} = \begin{bmatrix} -0.5\left(g^{(1)}(1) + g^{(1)}(2)\right) & 1 \\ -0.5\left(g^{(1)}(2) + g^{(1)}(3)\right) & 1 \\ -0.5\left(g^{(1)}(3) + g^{(1)}(4)\right) & 1 \\ \vdots & \vdots \\ -0.5\left(g^{(1)}(n-1) + g^{(1)}(n)\right) & 1 \end{bmatrix} \tag{8}$$

and

$$\boldsymbol{Y} = \left[g^{(0)}(2), g^{(0)}(3), g^{(0)}(4), \ldots, g^{(0)}(n)\right]^{\mathrm{T}}. \tag{9}$$

Then GM(1,1) is obtained by

$$\hat{g}^{(1)}(k+1) = \left[g^{(0)}(1) - \frac{u}{r}\right] \cdot e^{-rk} + \frac{u}{r}, k = 0,1,\cdots,n. \tag{10}$$

The real value is obtained by the following subtraction rule:

$$\begin{cases} \hat{g}^{(0)}(1) = g^{(0)}(1), \\ \hat{g}^{(0)}(k+1) = \hat{g}^{(1)}(k+1) - \hat{g}^{(1)}(k) \; (k = 1,\ldots,n). \end{cases} \tag{11}$$

Then the prediction model of the network traffic is

$$f(k+1) = [g^{(0)}(1) - \frac{u}{r}] \cdot [e^{-r \cdot k} - e^{-r \cdot (k-1)}]. \qquad 12)$$

The traditional gray theory has no the capability of modification on line, and it can't obtain the changes timely when the monotonic changes happen in the data sequence [14]. To improve the precision, the corresponding formulas are proposed according to the monotonic changes of the data sequence and the data numbers after these changes. When the monotonic changes of the data sequence are from monotone increasing to monotone decreasing, the modification is given by

$$f' = f(1 - \frac{0.1 \cdot \lg\beta}{j}), \tag{13}$$

where f means the prediction value of the traditional gray theory, j means the data numbers after the monotonic changes, and β means the sampling interval of the network traffic. When the monotonic changes of the data sequence is from monotone decreasing to monotone increasing, the modification is given by

$$f' = f(1 + \frac{0.1 \cdot \lg\beta}{j}). \tag{14}$$

The realizing process is as follows:

Step 1. The dimensions of the model are set to 4, and the traditional gray theory is applied to predict the network traffic;

Step 2. The monotonic changes are used to judge whether the prediction value of the traditional gray theory should be modified. When the monotonic changes of the data sequence are from monotone increasing to monotone decreasing, the modification is given by the formula (13), or else the formula (14). When the monotonic changes of the data sequence happen more than one time, we just consider the first one.

C. Prediction model based on neural network

BP neural network is widely applied to deal with nonlinear problem, and can timely reflect the changing trend of the dynamic state of the network traffic. So the BP neural network is applied to predict the high-frequency part of the network traffic, then we have

$$f=\sum_{j=1}^{7} w_j^{\mathbf{O}}\,\mathrm{tansig}\Big(\sum_{i=1}^{4} w_{i,j}^{\mathbf{H}} x_i + b_j^{\mathbf{H}}\Big) + b^{\mathbf{O}}, \tag{15}$$

where $\mathrm{tansig}(x) = 2/(1+\exp(-x))-1$, x_{i} (i=1,2,3,4) means the network traffic data at the first i sampling time. In this equation, for i=1, …, 4, and j=1,…,7, $b_j^{\mathbf{H}}$ is the bias of the j-th hidden neuron, $w_{i,j}^{\mathbf{H}}$ is the weight of the signal from the i-th input neuron to the j-th hidden neuron, b^{O} is the bias of the output neuron, w_j^{O} is the weight of the j-th hidden neuron to the output neuron.

D. Realizing process of the integrated prediction algorithm

The realizing process is as follows:

Step 1. The db3 wavelet is applied to perform the 3-level Mallat wavelet decomposition for the obtained original network traffic sequence, then, we get the low-frequency part a, and the high-frequency part d1, d2, d3. When the low-frequency part a and the high-frequency part d1, d2, d3 are respectively reconstructed by single branch algorithm, the corresponding part A, D1, D2, and D3 will be obtained;

Step 2. The improved gray theory is applied to deal with A, and the corresponding prediction value A' will be obtained. The BP neural network algorithm is applied to deal with D1, D2, and D3, and the corresponding prediction value D_1', D_2', D_3' will be obtained;

Step 3. All the above prediction value is synthesize to predict the network traffic, and the synthesized value is $A'+D_1'+D_2'+D_3'$.

III. EXPERIMENT RESULTS

The original network traffic sequence obtained from campus area network is used to make experiment. Considering the network traffic in the period from 22:00 to 9:00 is nearly 0 and no sense to predict, we use the network traffic in the period from 9:00 to 22:00 to verify the integrated prediction model proposed in this paper. The precision of the prediction model is given by the average relative error, thus we have

$$s=\frac{1}{n}\sum_{i=1}^{n}\frac{|y_i-\hat{y}_i|}{y_i}, \tag{16}$$

where $\hat{y}_i$ and y are respectively the predicted and the original value of the i-th sample, n is total sample number. Now we use 600 samples obtained by sampling period of 5 minutes to make experiment, 500 samples among of them are used to train BP neural network, and the rest 100 samples are used to predict. The precision of the gray theory model is 12.6%, and the precision of the BP neural network model is 9.4%. The testing result is shown in Fig. 1. We can find that the BP neural network (BPNN) model has a higher precision than the gray theory when the intense variation happens in the original network traffic sequence, but the gray theory model has a higher precision than the BP neural network model when the original network traffic sequence changes gently.

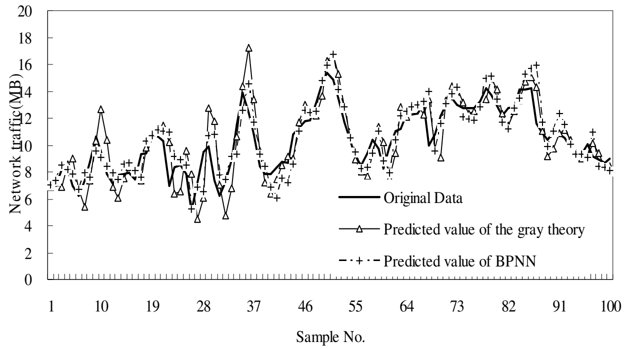

Fig. 1. Results of runs of the gray theory and BPNN model.

The precision of this integrated prediction model is 6.5%, the testing result is shown in Fig. 2.

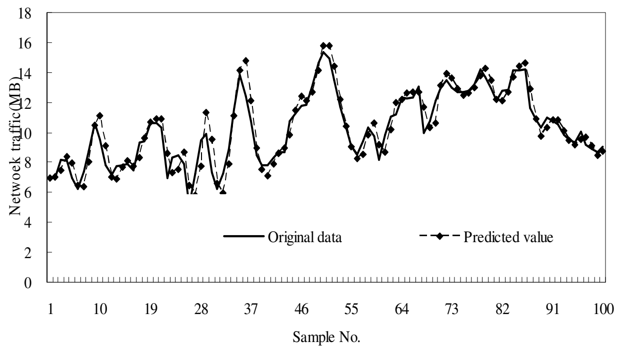

Fig. 2. Results of runs of the integrated prediction model.

Table I shows that two different series of samples obtained by sampling period of 5s and 5min are applied to predict respectively. The results demonstrate that compared with the integrated prediction model (IPFM) presented in [12], the proposed prediction in this paper (IPGB) can increase the precision, and is more suitable to deal with the network traffic at small time scale.

TABLE I.. RESULTS OF THE EXPERIMENT.

Algorithm	**Average relative error (%)**	
	5 s	**5 min**
IPFM	13.3%	7.1%
IPGB	9.7%	6.5%

IV. CONCLUSIONS

An integrated prediction model based on wavelet transformation is proposed in this paper. The improved gray theory prediction is applied to predict the low-frequency part of the network traffic, and the BP neural network is applied to predict the high-frequency parts, at last all the results is synthesized the whole network traffic. At last the simulation experiment shows that compared with the IPFM, the IPGB proposed in this paper is more suitable to deal with the uncertainty, complexity, and burstiness of the network traffic at the small time scale.

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