A NOVEL COMBINED NETWORK TRAFFIC PREDICTION MODEL IN COGNITIVE NETWORKS

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Abstract: With the development of the network technology, the concept of Cognitive Network has been proposed and studied, and various kinds of algorithms and models in Cognitive Networks thus have become an hot topic of research. This paper proposes a novel model, which includes three stages. The proposed model may achieve a high-precision traffic prediction in cognitive networks. The model solves some problems in cognitive networks, such as low adaptive capability and an easy trap in local optimum when coming up with a fluctuated network flow.

1 INTRODUCTION

The structure of Next Generation Network (NGN) is becoming complicated and heterogeneous, while Cognitive Network (CN) (Thomas R W, 2005) is justly adaptive to the NGN because it has the ability of autonomous learning and reconfiguration. A CN can provide, over an extended period of time, better end-to-end performance than a non cognitive network. Cognition could be used to improve resource management, Quality of Service (QoS), security, access control, or many other network goals.

In the research area of CN, the design of a multi-time scale network traffic predication model with “congnition” will play a key role in the cognitive performance of the entire network and in the load-balancing and traffic scheduling algorithm of the congnitive network. According to the result of traffic prediction, the CN can allocate the network resource in advance, make data flow distributes reasonably in the net, cope with load fluctuation, reduce network congestion.

In the research of network traffic prediction model, there are two difficulties (Kasabov N, 2002):

(1) A large scale network contains many complex nonlinear systems, meanwhile it works under some periodic fluctuations and trends of nonlinear rising and falling.

(2) Computer network is subjected to interferences of many random factors, but traditional single models have poor adaptive capacity. So we need combination models to realize traffic prediction.

We analyze the present situation of network traffic prediction, improve the wavelet pretreatment method and BPNN(BP Neural Network) method, design a network prediction model using combined NN(Neural Network), and we simulate our model in the environment of MATLAB to verify and analyze the model. The conclusion proves the new model work more precisely than traditional model.

The remainder of this paper is organized as follows. Section 2 introduces the present research of network traffic prediction. Section 3 accordingly describes the related theories of this new model. Section 4 presents the combination schemes and the three-stage prediction model. The simulate results of this new model are presented and analyzed in section 5. Finally, section 6 makes an overall conclusion.

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2 A BRIEF REVIEW OF NETWORK TRAFFIC PREDICTION

The conception of CN is developed on the basis of cognitive radios, and current researches mainly focus on link layer, so research in network traffic prediction of CN is not enough. However, fundamentally the algorism of traffic prediction in CN is to show “cognition”, provide necessary data to other elements of CN. Thus, from the aspect of time and data, it demands higher efficiency and precision than traditional model.

The present technologies of network traffic prediction can be divided into linear prediction and nonlinear prediction. ARIMA model (Feng Huifang, 2005) and Kalman Filter model are the examples of linear prediction model, such as self-adaptive linear model proposed by Lv Jun (2004). As the linear model can hardly describe the true features of real network traffic, nonlinear prediction models are proposed by scholars. Of course, nonlinear models sometimes may include linear elements, such as multi-scale combination predication model proposed by Khotanzad A (2003). In these kind models, as nonlinear elements play a more important role than linear elements, we still call them nonlinear model. The typical model of nonlinear model is NN model.

The predication model based on NN can be divided into two kinds. One is to put some algorithm inside NN, form the scheme as Figure 1 shows.

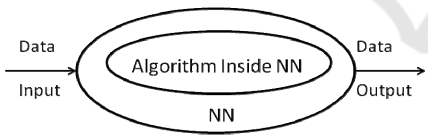

Figure1: The forcasting model of algorithm inside NN.

WNN (Wavelet Neural Network) proposed by Wang Peng (2008) just put wavelet decomposition algorithm into hidden layer of NN. We call this Prediction Model of NN with Build-in Algorithm.
The other is to separate the data processing and onefold NN’s prediction as figure 2.

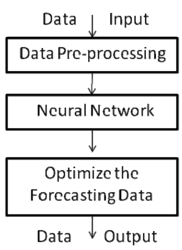

Figure 2: The forecasting model of algorithm outside NN.

The data pre-processing provides data more suitable to the input of NN, we call this Prediction Model of NN with Outside Algorithm. One such combined NN model is presented by (Feng Hailiang, 2006). This is the main form nowadays. The model we designed is just based on this.

Considering the character of nonlinear and multi-scale in network traffic, Lei Ting (2006) gives the resolution. They demonstrate the traffic and then forecast the irregular part with ENN. Combine with linear NN and nonlinear NN, a model that optimize the forecasting result 4 times is proposed by Feng Hailiang (2006), the precision is improved, but the time it needs is not short enough. As for the traditional problem in prediction model proposed by Kasabov N (2002), some scholars, such as Wang Peng (2008) and Cheng Guang (2004) have formed all kinds of improved models based on NN,. Also, traditional NN models have the problem of lagging in learning and are easy to trap in local optimum, owning limited ability in coping with sudden load in the net. In order to solve this problem, the main resolution is put wavelet decomposition algorithm inside the 3rd layer of BPNN, Han Zhijie (2008) properly deals with the local suboptimal, but still spends much time getting a satisfying result. Combine wavelet decomposition with NN as prediction model is also a main resolution (Feng Hailiang, 2006), but after the wavelet decomposition, only a single kind of NN still have the problem of rap into local optimum and cannot develop the advance of multi-scale analysis of wavelet.

3 RELATED THEORIES

3.1 Wavelet Transform

If square integrable function ψ(t) ε L2(R) meet the following condition: $\int_{-\infty}^{+\infty} |\hat{\psi}(\omega)|^2 |\omega|^{-1} d\omega < +\infty$, or $\int_{-\infty}^{+\infty} \psi(t)dt = 0$ Where Ψ^(ω) is the Fourier transform of Ψ(ω), than call it mother wavelet. Through stretching and translation transformation, the mother wavelet can be changed into wavelet function:

$$\psi a,b(t)= \psi(at-b),b \ \varepsilon \ R\text{-}\{0\} \qquad (1)$$

In our model, we use the form of discrete wavelet transformation as follows:

$$D_j(k) \le f, \psi_{j,k} \ge 2^{-\frac{j}{2}} \int_{-\infty}^{+\infty} f(\psi(2^{-j}x - k))dx \tag{2}$$

Where j is frequency domain resolution and k is time shifting amount. Then we do expansion on time series.

$\{f(t),\ t=1,2,\cdots\}$ is traffic time series, wavelet function and scaling function can be described as:

$$f(t) = \sum_{k=-\infty}^{+\infty} A_j(k)\phi_{j-1,k}(t) + \sum_{-\infty}^{+\infty} D_{j-1}(k)\psi_{j-1,k}(t) \tag{3}$$

Where $\phi_{j,k}(t) = 2^{-\frac{j}{2}}\phi(2^{-j}t-k)$ and $\phi_{j,k}(t) = 2^{-\frac{j}{2}}\psi(2^{-j}t-k)$ are scale space orthogonal basis and wavelet space orthogonal basis separately, Aj(k) and Dj(k) are scale coefficient and wavelet coefficient separately. $\sum_{k=-\infty}^{+\infty} A_j(k)\phi_{j-1,k}(t)$ is the part of high frequency in signal which shows detail signal and usually contains noisy. And $\sum_{-\infty}^{+\infty} D_{j-1}(k)\psi_{j-1,k}(t)$ is the part of low frequency in signal, it reflects the nature character of signal, such as the trend of a signal or the signal period.

As for this thesis, we demonstrate the traffic with Mallat Algorithm, the algorithm can realize the demonstrate simply and rapidly, and we have no need to know the concrete structure of wavelet function, wavelet decomposition or reconstruction can be done with just a set of filter coefficients.

$$\begin{aligned} &A_0(k) = f(k) \\ &A_j(k) = 2^{-\frac{1}{2}}[A_{j+1}(2k) + A_{j+1}(2k+1)],\ j = 1,2,\ldots,L \\ &D_j(k) = 2^{-\frac{1}{2}}[D_{j+1}(2k) + D_{j+1}(2k+1)] \end{aligned} \tag{4}$$

L is the number of layer, $Aj(k)$ is approximation signal, and $Dj(k)$ is the detailed signal.

3.2 Auto-regression Model

Auto-regression (AR) model is a time series model. Let $\{X_t\}$ denote time series, it is the linear function of prophase expectation and stochastic component:

$$X_t = \phi_1 X_{t-1} + \phi_2 X_{t-2} + L + \phi_p X_{t-p} + \varepsilon_t \tag{5}$$

Where ϕ_1, ϕ_2, L, ϕ_p are autoregressive coefficients, we use Levinson-Durbin recursive algorithm (Burg J P, 1975) to get their specific value. Stochastic component ε_t, is a white noise series, and it obeys standard normal distribution.

As for this thesis, we use AR model to forecast the low frequency data that meet the stationary condition, this may improve the forecasting speed and promote forecasting efficiency.

3.3 Neural Network Model

Nowadays, BPNN, ENN, HNN, and KNN, etc. are the popular NN models in use. We just introduce KNN and BPNN that we used in the novel model.

KNN's main idea is to self organize the information outside into a conception in brain. As for a system, it is just to organize a corresponding presentation format in system automatically when affected by information outside the system. This includes adjustment of the NN's weight coefficient.

KNN is a typical self organizing neural network which is also called SOM. Its input layer is monolayer and single-dimensional neurons, while the output layer is two-dimensional neurons. The format of lateral interaction between neurons in output layer is Mexican Cap. So in the output layer, KNN has the feedback character that the neurons are closer, the effect is stronger. Thus, KNN can be the detector of mode characteristics and an effective method to enhance the ability of self adaptivity. In this view, KNN can be a prompt model in the use of network traffic prediction.

Based on the original NN, through self-organized learning to simulate the biological nerve reflex is the typical character of KNN. In a complex nonlinear system that changes greatly, KNN can improve the forecasting precision by the change of the content and amount of study.

The learning process of KNN is as follows:

(1) Initialize the link weights, each weight can be initialized from the training data arbitrarily;

(2) $X^k = (x_1, x_2, \ldots, x_n)$ is input vector, for each input vector, calculate the Euclidean distance W_{ij} which between X_i^k and all of the output node N_j;

(3) N_{j*}, which has the minimum distance in output node, is the winner in competition: $d_{j*} = \min_{j \in \{1,2,\ldots,m\}} \{d_j\}$;

(4) Adjust the link weights between output node N_{j*} and every input node X_i^k in geometric neighborhood: $w_{ij} = w_{ij} + \eta(t)\ (x_i^k - w_{ij})$, $i \in \{1, 2, \ldots, n\}$, where $\eta(t)$ is learning rate: $0<\eta(t)<1$;

(5) As for different t: t=1,2,…, come back to step (3).

BPNN is a multilayer feed forward network based on error back-propagation algorithm, which is one of the broadly used ANN models. BPNN can learn and restore many input-output mapping relations without mathematical equations that reveal the relation between them. The learning rule of BPNN is to make use of the steepest descent method, continuously adjust the net weights value and net threshould value by back propagation in order to get a minimum square sum of error. The learning course of BPNN is as figure 3.

As the one of the basic ANN model, BPNN works on the principle of continuous error feedback: The error is transmitted through output layer, then to the hidden layer and input layer, and weight in every layer can be corrected in the method of gradient descent algorithm. In cycles of information forward propagation and error back propagation, weights in every layer can be modified, and this is the process of NN's learning. This process will last until the output error can be accepted or the set learning times are met.

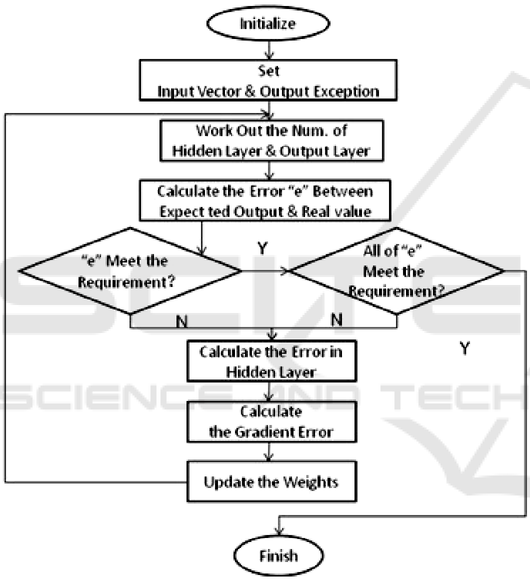

Figure 3: The learning course of BPNN.

4 A NOVEL THREE-STAGE COMBINED NETWORK TRAFFIC PREDICTION MODEL

4.1 Basic Thinking of the New Model

The network traffic is generally a kind of non-stationary time series signal. The non-stationary of traffic increased the difficulty of prediction, thus we shall consider the preprocessing of the traffic signal, so as to achieve relative stationary in-put signals in the prediction of our model. The technology of wavelet decomposition (Ardagna C A, 2008) is the best solution. Wavelet decomposition can decompose non-stationary time series into several detailed signals and a more stationary signal via low-pass filter. After decomposition, the traffic is more unitary in frequency, and thus help improve the prediction of the model.

AR model has a good performance in the prediction of relative stationary traffic, and it can reduce the prediction time and improve the efficiency of the whole forecasting model.

KNN model can keep the character of wavelet's multi-scale analysis, avoid poor adaptive ability of wavelet coefficient in processing, achieve the aim of dynamic learning while reduce the NN's learning period, avoid being trapped in local optimum, thus improve the performance of prediction model.

According to Kolmogorov Theory, if the number of input unit is N, then the unit number of hidden layer is always $2N+1$. In this model, we use the superposition of traffics which predicted by AR and KNN model as the input of BPNN. For BPNN's excellent ability of function approximation, we can get a more accurate forecasting result with small error.

4.2 Describe in Detail of the Novel Model

Based on the analysis above, we form the structure of the new model as Figure 4.

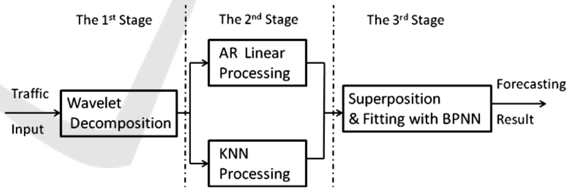

Figure 4: Three-stage combined NN model in CN.

In the first stage of the model, decompose the nonlinear traffic signal with Mallat algorithm according to formula (4).

In the second stage, in line with formula (5), forecast the relatively stationary signal by AR model; as for the nonlinear and non-stationary high frequency signal, we use KNN model to make the forecasting. In the last stage, BPNN fit the superposition of former forecasting results, output a high precision final result.

Compared with the traditional single NN model, this model avoid the problem of trapping in local optimum. And compared with ENN model proposed by Wang Peng (2008) and put wavelet decomposition inside the hidden layer of BPNN, the new model resolve the problem of long learning period and poor self-adaptivity under a sudden load.

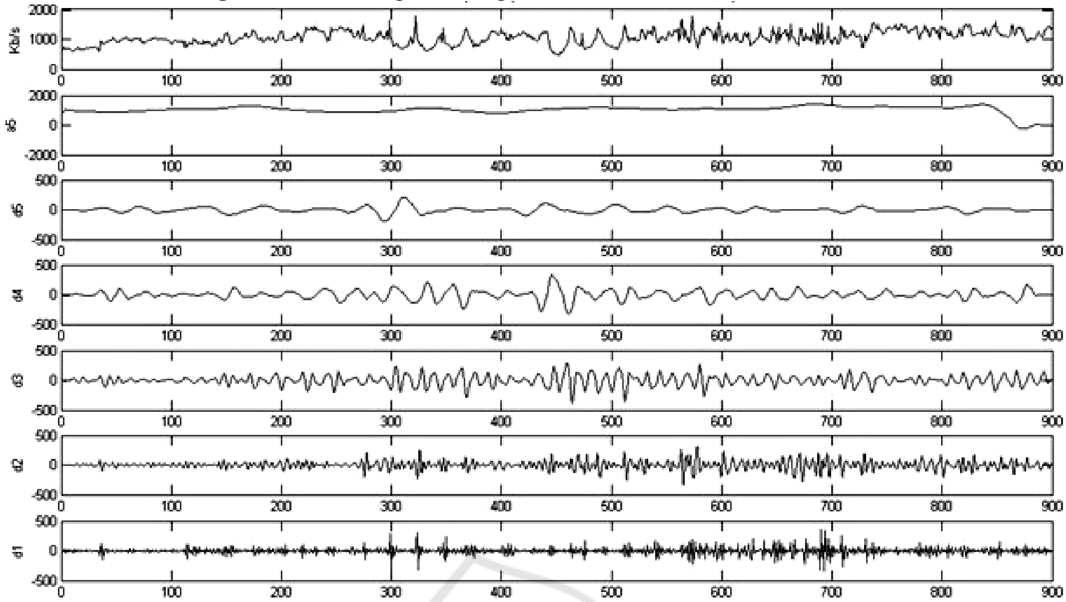

Figure 7: Wavelet decomposition of network traffic.

The speed of wavelet decomposition and linear forecasting can make up the delay of NN's learning, improve the efficiency of the whole model. In reality application, regular learning cycle can be written into protocol and save the net resource in CN. As a NN with good output performance, BPNN makes the forecasting result more accurate. Also, its ability in learning can make up the defect of long time learning and poor self-regulation mentioned above.

Meanwhile, as a non-stationary model, BPNN is suitable to depict the non-stationary traffic.

Because this novel model can reduce the forecasting time, improve the forecasting precision, and receive a result with high precision under wide traffic fluctuation. So in the aspect of time and precision, this new model shows the meaning of cognition. It can work in the net under the condition of multi-background traffic or multi-scale time variation, provide a timely, accurate, steady cognitive platform to the high level algorithms in CN.

5 SIMULATION AND ANALYSIS

We simulate in the environment of MATLAB (Liu Linhui, 2008). MATLAB is an advanced computing language and interactive environment which is widely used in algorithm development, data visualization, data analysis and data computing.

As figure 5 shows, we collect the network traffic from a core router in the backbone network. The sampling interval is an hour, we gathered 900 samples, each sample is the average traffic value in an hour, and the last 100 samples have been used to test the forecasting result. Figure 6 is the curve line of traffic.

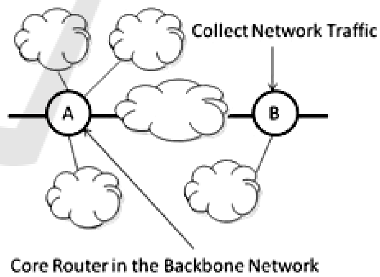

Figure 5: Collection of network traffic data.

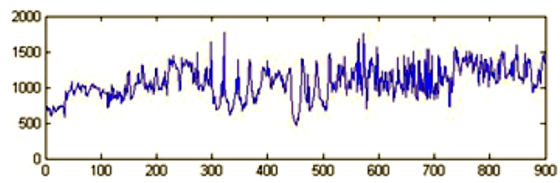

Figure 6: Curve line of network traffic.

For the traffic above, according formula (4), use Mallat algorithm to decompose it. In order to improve the precision without loss of generality, we set scale coefficient L=5. Thus we can get series{ D1(k), D2(k), D3(k), D4(k), D5(k), A5(k)} after wavelet decomposition, the original signal $S=d1+d2+d3+d4+d5+a5$. The result of wavelet decomposition is as figure 7.

Then we input the low frequency a5 into AR model to forecast. At the same time, normalize the high frequency d1, d2, d3, d4, d5, and input them into KNN to forecast. The weight values and threshold values of KNN are determined by self-learning. We set the start learning rate on 0.95, the minimum learning rate on 0.001, the maximum step of training on 5000. At last, composite the AR model's forecasting result and KNN model's forecasting result, make it as the input of BPNN. According the Kolmogorov algorithm mentioned above, there are 3 hidden layers in BPNN.

Figure 8 is one-step forecasting result of the 100 data samples, and we compare the real traffic with the prediction result in one Figure.

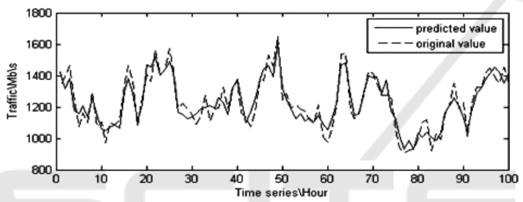

Figure 8: One-step forecasting result compared with real traffic.

Figure 9 is the comparison of two-step forecasting result and the real traffic. And figure 10 is the forecasting result of WNN model which has put wavelet decomposition into BPNN as described earlier in the thesis.

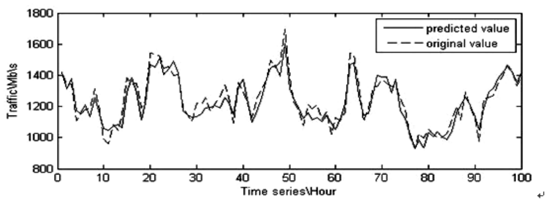

Figure 9: Two-step forecasting result compared with real traffic.

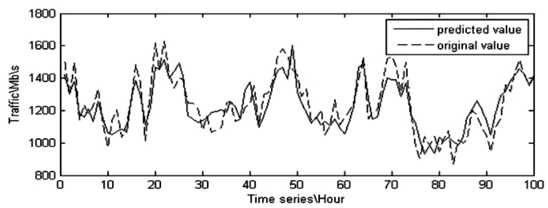

Figure 10: WNN forecasting result compared with real traffic.

By the contrast of forecasting result and real traffic, and the contrast of new model and WNN model, the simulation proves the high precision of the novel model. And we have expatiated earlier the advantage of efficiency and time cost of this model.

Some data of the model's performance are listed in Table 1. We make a contrast between statistic data of one-step, two-step forecasting result and the statistic data of WNN model. In table 1, SSE means Squared Sum Error, MSE means Mean Squared Error, MAE means Mean Absolute Error and MRE means Mean Relative Error.

Table 1: Comparison of forecasting performance.

Method	SSE %	MSE %	MAE %	MRE %
WNN	10.79	1.84	7.60	21.17
One-step	5.12	0.98	4.50	16.02
Two-step	7.01	1.38	5.04	18.98

6 CONCLUSIONS

Taking into account the multi-scale and non-linear characters of the network traffic, combined with the wavelet decomposition, AR model and NN models, the thesis proposes a novel network forecasting model that suitable in CN. The main idea of the model are as follows: In stage one, the traffic signal is decomposed into low-frequency part and high-frequency part. In stage two, two kinds of the signals are predicted with AR model and KNN model respectively. To enhance the prediction accuracy and merge the traffic characters captured by individual models, the output of the previous models are combined using BPNN. At the end of the thesis, the simulation and comparison suggest that the proposed model has better performance than WNN model, and may achieve a high-precision traffic prediction result, thus can work satisfactorily in the use of CN.

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