Application of Neural Network for Network Rout Planning

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ABSTRACT

This paper proposes a new forecasting approach for telephone network routing plan by applying Neural Network concept. For experimental results, traffic data from Khonkhaen1 and Khonkhaen3 exchanges are collected and then compared with the values forecasted by using back propagation neural network method and using the Conventional Method. This paper shows that the forecasting method which applying neural network are convenient and suitable for network routing plan. This method can effectively forecast the traffic flowed between the exchanges, and dimensioning for each future network routing plan can be done appropriately.

Keywords: traffic forecast, neural network, routing plan, and back propagation.

1. INTRODUCTION

Now a day the telecommunication traffic have increase quite a lot (such as x2) just the one or two month period in order to provide the facility to the users. So that the forecasting of the users requirement and the traffic, which proportional to the telecommunication service is quite difficult or impossible to measured the actually requirement value. In general, the measurement result is a carried traffic. Since, the forecaster should be transfer the data that receive for adjust with the suitable value for each area or country.

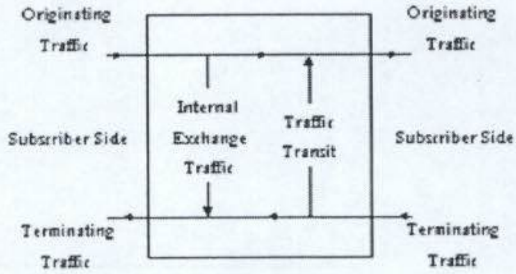

Fig. 1 Point to Point Traffic

Forecasting can be separate the type of traffic in to outgoing traffic, incoming traffic, terminating traffic, originating traffic and transit traffic as shown in fig. 1 [1-5]. Normally the traffic value of user is in Erlang per subscriber.

In this paper forecasting the traffic by suing back propagation neural network method. This method can be forecast the traffic, which has huge data correctly and quickly. In the experiment had study and choose neural network parameter that suitable for the most correctly forecasting.

2. FORECASTING METHOD FOR NETWORK PLANNING

2.1 Kruithof's double factor method

Kruithof's method can be use for approximated the traffic A(i,j) in traffic matrix table [6,7], by

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take the present value as the assumption of the sum of horizontal and vertical valued in the future. This method done by adjust each traffic A(i,j) adaptive with the new value as expression (1).

$$A_{i,j(new)} = A_{i,j(old)} \frac{S_1}{S_0} \tag{1}$$

Where S_0 is the sum of the present value, S_1 is the sum of new value, both horizontal and vertical, i stand for originating and j stand for terminating. Start from adjust the traffic A(i,j) along the horizontal, which the sum of each traffic is equal to the forecasting value S(j). But the forecasting value at the vertical may be not equal to the sum of vertical, then adjust the vertical value for the equal value S(i). The result may be cause the horizontal not equal, so the next step is alternate adjust the vertical and horizontal value until the result is equal to the future value of both, that is the correct result of each traffic.

Table 1 The assumption traffic (before forecasting)

i \ j	KKN1	KKN3	SO
KKN1	200.50	5.10	205.60
KKN3	10.50	50.00	60.50
ST	211.00	55.10	266.10

Table 2 the sum of future traffic (which require to forecast)

Called between exchange	The sum of vertical (SO)	The sum of horizontal (ST)
KKN1-KKN1, KKN1-KKN3	326.60	340.00
KKN3-KKN1, KKN3-KKN3	86.50	73.10

2.2 Back propagation neural network method

This paper using back propagation neural network algorithm, which learning the human brain. The basic structure consist of node or unit, input layer, output layer and weight value. Neural network model divide into 3 group. There are Perceptron, Associative memory and Biological model [10].

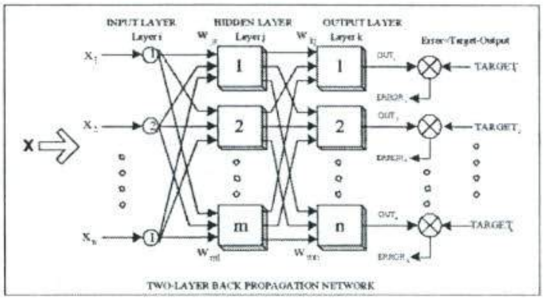

Fig. 2 The structure of Back propagation Neural Network

By using the neural network application, the procedure separate into 2 steps as training or learning and testing or the actual using.

The training step of back propagation neural network is create the neural network, which have the input and output layer equal to input and output bits number of the problem. For the hidden layer can be define independently but should be start with the greater value first. Then define the initial value for weight value of every path, which is random between -1 to 1 for each neural j of hidden layer as following [10].

$$\sum_{i=1}^{i=n} X_i W_{ij} = U_j \tag{2}$$

Where X_i is input bit i in total n bits.

Y_i is Activation of bit j of hidden layer in total m bits

Z_k is output bit k in total P bits

α is training rate (0,1)

and activation value for each neural j can be calculate from output of hidden layer as expression (3).

$$Y_j = f(U_i) \tag{3}$$

since, the logistic function is;

$$f(X) = \frac{1}{1+e^{-x}} \tag{4}$$

for each neural k of output layer is;

$$\sum_{i=1}^{i=m} Y_i W_{ij} = V_j \tag{5}$$

and activation value for each neural k of output layer is;

$$Z_k = f(V_i) \tag{6}$$

Compared Z_k with actual output value, which should be and calculate the error. If the error is less than the training setting level then the training finish. Else adjust the each weight value as following.

Calculate the weight value for the connection between hidden and output layer.

$$\Delta W_{jk} = \alpha \delta_k Y_j \tag{7}$$

By $$\delta_k = (t_k - Z_k) f'(V_k) \tag{8}$$

And calculated the weight value for the connection between hidden and input layer.

$$\Delta W_{ij} = \alpha \delta_j X_i \tag{9}$$

$$\delta_k = \sum_{k=1}^{o} \delta_k W_{jk} f'(U_j) \tag{10}$$

Adjust the weight value of connection path from neural r to neural s with expression (11).

$$W_{rs}(new) = W_{rs}(old) + \Delta W_{rs} \tag{11}$$

2.3 ERROR VALUE CHECK

There are many method for check the forecasting correction but the suitable method is mean square error [9] as expression (12).

$$MSE = \frac{1}{n} \sum_{i=1}^{n} (x_i - \bar{x}_i)^2 \tag{12}$$

Where X_i is mean value of real data, $\bar{X}_i$ is the forecast value in ideal. Coefficient value MSE should be 0 if the coefficient value reach 0, that mean the forecast value closed to real data. By define η as learning rate and μ is momentum value.

3. EXPERIMENT AND RESULT

This experiment has measured the traffic between exchange KKN1 and exchange KKN3, which arrange the rout as fig. 3. Then using program simulated the neural network structure and comparison as fig. 4.

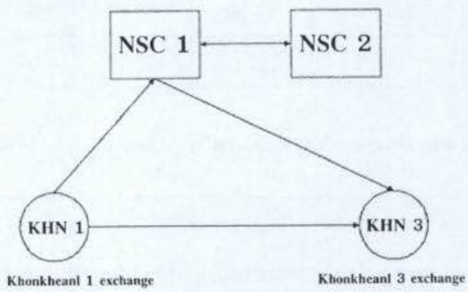

Fig. 3 Routing between KKN1 and KKN3

Comparing the forecast result from back propagation neural network method with conventional method. The comparison show the back propagation neural network method give the result closer to the real traffic than the other (the real traffic take from the measurement of the network then assume as the future traffic) as show in fig. 4.

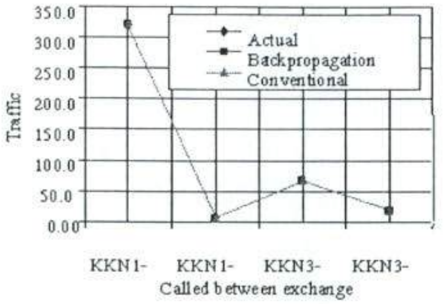

Fig. 4 comparison between the back propagation neural network method with conventional method

3.1 Consideration of the result

The experiment network was a small network consists of two exchanges for the forecasting. So the result very similar together. The experiment had increased the network into 7 exchanges as shown in fig. 5.

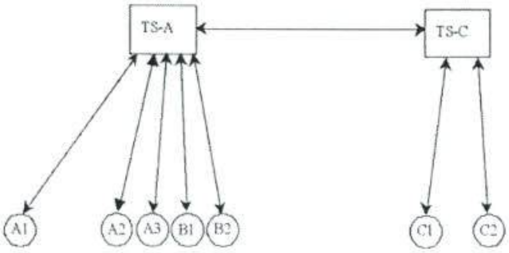

Fig. 5 the network model for 7 exchanges

In fig. 5 show the network model under test for indicate the difference between the back propagation neural network method and the conventional method. The network was increase into 7 exchanges, then using the traffic before forecast in 2000 and the forecast traffic in 2005 as the result shown in fig. 6, which show the back propagation neural network method give the result closer to the real traffic than the conventional method.

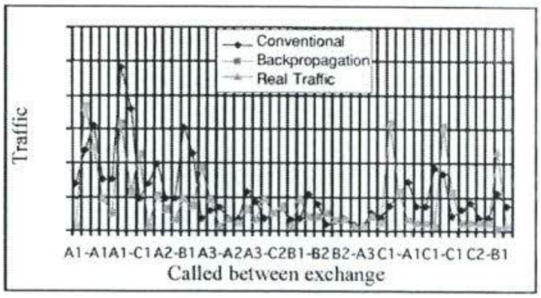

Fig. 6 Comparison the back propagation neural network method with the conventional method when the network larger

4. CONCLUSIONS

By using the neural network method for forecasting the telephone traffic. The result show, that the neural network, which had adjust the data good enough, construct with the suitable model and parameter, learning rate and momentum equal to 0.1 can be give the correct forecast (for the experiment the MSE lower than 0.1). In other hand this model also can be use for improved the traffic forecast for the other network. Just change the learning model follow the network under forecast. The correct forecasting help to improve the telephone circuits as the increase traffic in the future on each exchange and show the circuits on each rout, which should be increase or decrease relate to the real traffic for unblocking network. Furthermore, the method can be use for network rout planning in order to increase the routing between exchange, which give the forecast and the real traffic closest as ITU-T,E.506 [6].

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