Transactions of Tianjin University
Vol. 6 No. 1 May 2000

APPLICATION OF INTELLIGENCE FORECASTING METHOD IN TRAFFIC ANALYSIS OF EGCS*

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Abstract: Traffic flow forecasting is an important part of elevator group control system (EGCS). This paper applies time series prediction theories based on neural networks(NN) to EGCS's traffic analysis, and establishes a time series NN traffic flow forecasting model. Simulation results show its validity.

Keywords: traffic flow; time series; forecast; elevator group control system; neural networks

The elevator group control system (EGCS) is a control system that manages three or more elevators in a building in order to optimize elevator assignment to transport passengers efficiently and improve service. For the purpose of improving EGCS's performance and efficiency of operation, many experts devote themselves to group control method research, looking for group control methods that can realize the real-time optimization of elevator assignment. Obviously, it is an effective method to optimize elevator assignment to apply suitable control strategy with the change of traffic flow. So the application of prediction theories in EGCS to forecast traffic flow is the foundation of realizing optimal assignment. A traffic flow forecasting method based on neural networks(NN) is introduced in this paper.

1 Traffic Flow Forecasting Model

Traffic flow is the status variable on the interval of passengers appearing and the distribution of passengers in a building. For an EGCS, traffic flow can be described by many kinds of data, but only part of them can be used to indicate the feature of traffic flow, such as the number of passengers coming in lobby, the number of passengers leaving lobby, total number of passengers, the max proportion of interfloor passenger traffic flow, the second proportion of interfloor passenger traffic flow in a time interval (5 min), etc. The time interval is decided by an important parameter of up-peak traffic-RTT (the round trip time)[1], and the time interval in this paper is 5 min.

While the system collects traffic flow data from every time interval of every working day according to a statistical method, these data form time series. So we can apply time series prediction theories in the field of traffic flow forecasting, that is, according to historical observation data $x(t), x(t-1), x(t-2), \cdots, x(t-m)$, we can establish a forecasting model by the time series forecasting method to forecast the traffic flow $x(t+k)$.

Over the last decades researchers proposed many forecasting methods, such as the Exponential Smoothing, Box-Jenkins, Grey Model GM(1, 1), etc. In recent years, the NN theory has been applied in the field of forecasting. Applying NN in the field of time series forecasting is to establish a forecasting model based on internal relation of data. It overcomes inherent limitations of traditional time series forecasting methods. It has many advantages: Firstly, it has been proved that the three-layer feedforward NN with sigmoid activation function can approximate whatever function. Secondly, NN have strong learning capacity and adaptability[2]. Thirdly, time series often contain a great deal of strong noise, but NN have stronger capacity to overcome noise than other traditional forecasting methods[3]. So neural networks are capable of approximating time series with whatever features.

Received date: 1999-08-23; revised date: 1999-10-26.

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* Supported by the Tianjin Natural Science Foundation(Major Item, No. 993801211).

The NN used in forecasting are feedforward networks, which are made up of input layer, hidden layer and output layer[4]. The meanings are: 1) Input layer (N_0), the number of input layer nodes denotes the number of input variables of the forecasting model. The input layer is composed of two parts. The first part has L input nodes $\{x(t-i), 0\leqslant i\leqslant L-1\}$, it denotes the traffic flow of the past L time intervals. The second part has N input nodes $\{x((t+1)-144i), 1\leqslant i\leqslant N\}$, it denotes the traffic flow of the same time of the past N working days, the coefficient 144 denotes the number of time intervals of one working day (the time range of collecting traffic data is 7: 00~ 19: 00). This part of input nodes reveals the periodicity and the long-term trend of the traffic flow data. 2) Output layer (N_2), the output layer has one node, and its output denotes the forecasting value of the next time interval. 3) Hidden layer (N_1), according to requirements, NN can have one or several hidden layers. The decision of the hidden layer node depends on the requirement of the problem. In this paper, we select one hidden layer, the number of hidden layer nodes is $N_1 = N_0$. Fig. 1 is the architecture of neural networks, where the input layer's function is data transmission. Thus we have

$$I_{0i} = u_{0i} \qquad O_{0i} = I_{0i} \qquad i = 0, 1, \cdots, N_0 - 1$$

The hidden layer nodes and output layer nodes are revealed as

$$I_{ns} = \sum_{j=0}^{N_{n-1}-1} w_{(n-1)js} \times O_{(n-1)j}$$

$$O_{ns} = \frac{1}{1+e^{-(I_{ns}-\theta_{ns})}} \qquad s = 0, 1, \cdots, N_n - 1$$

$$n = 1, 2 \qquad j = 0, 1, \cdots, N_{n-1} - 1$$

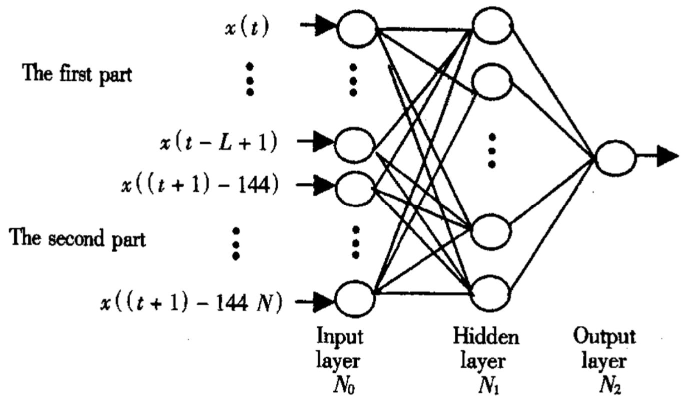

Fig. 1 Structure of NN

In above formulations, u is the input of the network, I is the input of the node, O is the output of the node, w is the connection weight between neurons, θ_{ns} is the bias of the node. Thus we have an NN-based time series forecasting model used for forecasting the traffic flow of the next time interval

$$\hat{x}(t+1) = g(x(t), x(t-1), \cdots, x(t-L+1), x((t+1)-144), \cdots, x((t+1)-144N))$$

Function g is the transformation function of NN, it is realized by training the NN.

2 Periodical Learning of NN

After the structure is decided, the NN need to be trained periodically to adapt themselves to the trend of traffic flow variation. The periodical learning is performed once a working day. The samples are selected by synthesizing the latest data and historical data from previous days through using the Clustering method, and samples should be unified for the training of networks. So the affection of both historical data and the latest data are considered in forecasting NN, and the NN model can follow not only the long-term trend but also new traffic flow variation, the forecasting result is more reliable.

The learning algorithm is an advanced BP algorithm. We defined the sum of square errors of the system as

$$E = \frac{1}{2}\sum_{i=1}^{T}[T^i - O^i]^2$$

In order to minimize the function E, the weight updates are

$$\Delta w_{(n-1)js}(t+1) = -\eta_{(n-1)js}(t+1) \times \frac{\partial E}{\partial w_{(n-1)js}} + \alpha \times \Delta w_{(n-1)js}(t)$$

($0< \alpha< 1$; $n = 1, 2$; t is adjustment time)

For $0< \eta_{(n-1)js}< 1$, $\eta_{(n-1)js}$ is adjusted as:

If $\eta_{(n-1)js} > 0.1$, and

$$\operatorname{sgn}\left|\frac{\partial E}{\partial w_{(n-1)js}(t)} \times \frac{\partial E}{\partial w_{(n-1)js}(t-1)}\right| < 0$$

then $\eta_{(n-1)js}(t+1) = \eta_{(n-1)js}(t) - 0.1$.

If $\eta_{(n-1)js} < 0.9$, and

$$\operatorname{sgn}\left|\frac{\partial E}{\partial w_{(n-1)js}(t)} \times \frac{\partial E}{\partial w_{(n-1)js}(t-1)}\right| > 0$$

then $\eta_{(n-1)js}(t+1) = \eta_{(n-1)js}(t) + 0.1$.

The above method is used to train the network until the error of all samples is in an allowable range.

3 Simulation Results

We respectively establish the forecasting NN of the number of passengers coming in the lobby, the number of passengers leaving the lobby, total number of passengers, the max proportion of interfloor passenger traffic flow, and the second proportion of interfloor passenger traffic flow. The architecture of networks is: 12 input layer nodes (The first part has 6 nodes, it denotes the new trend of traffic flow. The second part has 6 nodes, it denotes historical information of traffic flow), 12 hidden layer nodes and 1 output node. The initial weights $w(0)$ are stochastic data between -0.5 and 0.5, and $\alpha = 0.7$. We train these networks respectively and apply them to forecast traffic flow. The output of the network is the traffic forecasting value of the next time interval. In order to show the advantages of the NN forecasting model, we compare it with the Exponential Smoothing used in traditional EGCS[6].

In order to assess the prediction result, we use the mean square root error. It is defined as

$$e=\sqrt{\frac{\sum_{i=1}^{N}(y_{fi}-y_{ri})^2}{N}}$$

Fig. 2 to Fig. 6 are forecasting results of NN (—), forecasting results of the Exponential Smoothing (—·—) and real traffic data (——). e_n denotes the forecast error of NN, e_p denotes the forecast error of the Exponential Smoothing.

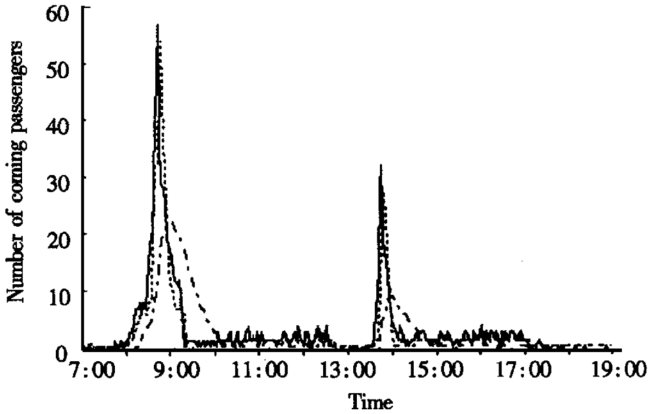

Fig. 2 Number of passengers coming in lobby on a working day
($e_n = 3.2758$, $e_p = 5.6686$)

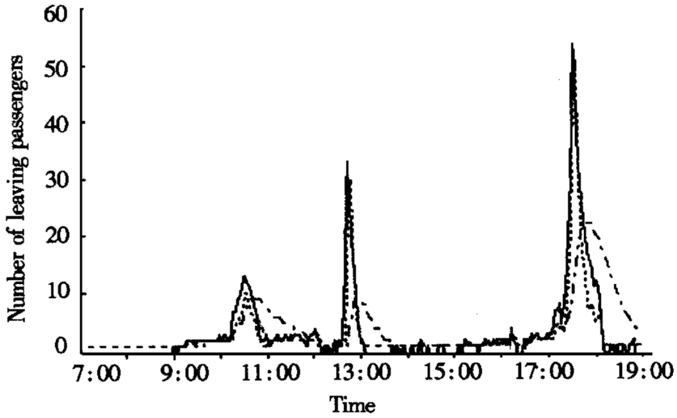

Fig. 3 Number of passengers leaving lobby on a working day
($e_n = 2.6845$, $e_p = 5.9252$)

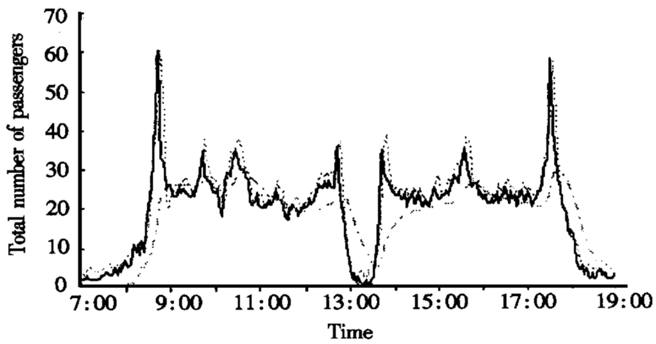

Fig. 4 Total number of passengers on a working day
($e_n = 4.1950$, $e_p = 7.6786$)

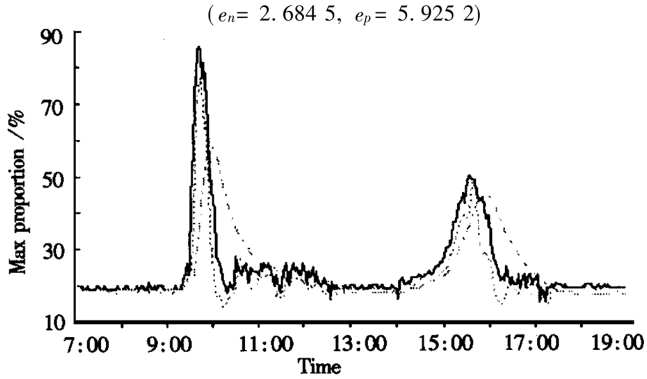

Fig. 5 The max proportion of interfloor passenger traffic flow
($e_n = 0.047765$, $e_p = 0.093652$)

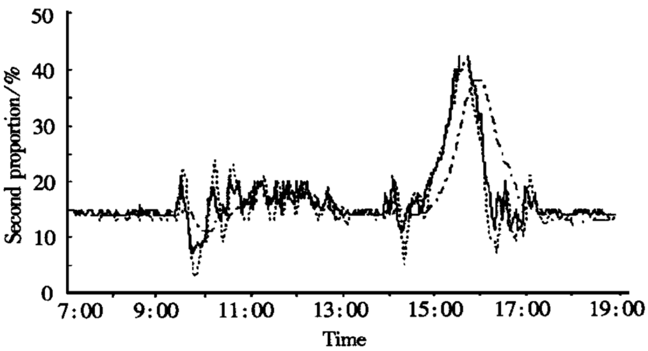

Fig. 6 The second proportion of interfloor passenger traffic flow

4 Conclusion

From the above five figures, we can see that the forecasting model based on NN is significantly better than the Exponential Smoothing. The main factors affecting the precision of the forecasting model is the structure of NN and samples. While applying NN to time series forecasting, we must adjust the structure of the NN input layer according to the traffic environment in different buildings, and the samples reflecting the feature of traffic flow must be selected. Compared with the Exponential Smoothing, the input of NN includes both historical data and new traffic data, the forecasting model can acquire both the new variation trend of traffic flow and historical information of traffic flow. And NN have strong learning capacity and adaptability, and it can acquire new knowledge continuously by learning new samples. Besides, it is not necessary to establish complex explicit relation expressions while NN are applied to time series forecasting. So using NN to establish a time series forecasting model of traffic flow is highly effective.

References

[1] Barney G C, Dos Santos S M. Elevator Traffic Analysis, Design and Control[M]. IEE, Peter Peregrinus, London, 1985.

[2] Wei Gang, He Qianhua. On the function approximation ability of multi-layer perceptron[J]. Information and Control, 1996, 25(4): 321~330.

[3] Panlo Cortez, Miguel Rocha. A neural network based time series forecasting system[C]. IEEE International Conference on Neural Networks. 1995, Vol. 5: 2689~2693.

[4] Tim Hill, Marcus O' cormor, Willam Remus. Neural network model for time series forecasts[J]. Management Science, 1996, 42(7): 1082~1092.

[5] Li Shiyong. Fuzzy Control, Neural Networks, Intelligence Control Theory[M]. Publishing House of Harbin Institute of Technology, 1996.

[6] Nader Kameli, New Britian Conn. Elevator Traffic Prediction Using Historical Data Checked for Certainty[P]. United States Patent, US005272288A, Dec. 21, 1993.

一种智能预测方法在电梯群控系统交通分析中的应用

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摘　要: 交通流预测是电梯群控系统的重要组成部分. 将基于神经网络的时间序列预测理论应用到电梯群控系统的交通分析中, 构造了一种神经网络时间序列交通流预测模型. 仿真实验表明, 这种交通流智能预测方法是有效的.

关键词: 交通流; 时间序列; 预测; 电梯群控系统; 神经网络
中图分类号: TP183　　**文献标识码**: A　　**文章编号**: 1006-4982(2000)01-0018-04