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RESEARCH PAPER

Urban Road Short-term Traffic Flow Forecasting Based on the Delay and Nonlinear Grey Model

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Abstract: Concerning the delay and nonlinear properties of traffic flow in urban road systems, this paper forecasts the short-term traffic flow based on the grey $\mathrm{GM}(1,1|\tau,r)$ model. Firstly, the delay factor τ is determined by the speed-flow relationship when volume is greater than it capacity. Then, the nonlinear parameter r is determined by a particle swarm optimization algorithm, where the prediction effect is unsurpassed. Finally, verification of this model is done by collecting traffic flow data on one section of Youyi Avenue and comparing the prediction value of $\mathrm{GM}(1,1|\tau,r)$ with GM(1,1) and SVM. The results show that the prediction effect of $\mathrm{GM}(1,1|\tau,r)$ model for short-term traffic flow is significantly improved, which plays an important role in intelligent traffic systems.

Key Words: urban traffic; $\mathrm{GM}(1,1|\tau,r)$ model; short-term traffic flow forecasting; speed-flow model; delay time; nonlinear

1 Introduction

With the development of China's reformation and urbanization, the traffic accidents increase while the transportation is developing rapidly. The traffic problem exists due to a bottleneck restricting the development of urban areas. It is necessary to develop urban intelligent transportation systems (ITS), which is an effective method to alleviate the urban traffic problems. ITS is commonly constituted with many subsystems [1]. However, a common prerequisite of these subsystems require future traffic flow forecasting using historical data. Additionally, short-term traffic flow forecasting is a vital component to ITS in implementing traffic information services, traffic control and induction. The prediction result is directly related to the quality of traffic information service and the effect of traffic control and induction. Therefore, it is urgent and practically significant for the development of ITS to investigate the theory and methodology for forecasting short-term traffic flow effectively and distinguish traffic conditions accurately from accumulated information.

Recently, many scholars have studied this issue. Queen and Albers developed a multivariate Bayesian dynamic model to predict traffic flow[2]. Ghosh *et al*. applied the Bayesian method to estimate the parameters of the SARIMA model and predict the traffic flow[3]. Xie and Zhao proposed a Gaussian processes (GPs) model, which has received attention for its outstanding generalization capabilities and superior nonlinear approximation[4]. Chaos in traffic flow was demonstrated by Xue and Shi, who sampled traffic flow every five minutes, and overall provided better prediction than traditional statistical methods[5]. Yang *et al.* predicted traffic flow using a radial basis SVM neural network model[6]. However the method requires a large number of training samples. Huang and Sadek developed a novel forecasting approach inspired by human memory for short-term traffic volume forecasting[7].

The uncertainty of traffic flow is caused by environmental factors (visibility, wind direction and temperature, etc.) and man-made factors (traffic accidents and incidents, and the driver's psychological state, etc.). These factors all determine the nonlinear characteristic of traffic flow. Lag effects on the traffic system commonly exist. They signify that the system's input at time t impacts the system's output and rate of change at time t and later time periods. Commonly, traffic jams at one intersection create congestion at the upstream intersection, demonstrating delayed effects of the traffic system. However, the current short-term traffic flow forecasting method rarely considers the nonlinear and delaying parameters simultaneously. Therefore, it cannot make adjustment

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according to actual traffic conditions, nor can it acquire effective traffic information. This may result in negative effects on ITS.

Grey systems theory was formally introduced by Deng to study the uncertainty system in 1980's, where grey models became important prediction methods [8,9]. However, the initial grey models did not account for the delay and nonlinear. Additionally, the development coefficients were limited within a specified range. In 2002, Deng proposed a new nonlinear grey model $\mathrm{GM}(1,1|\tau,r)$, whose grey index is out of the interval constraint (-2, 2), in which τ represents the delay time and r is the non-linear parameters[10-12]. Xin proposed a moving object segmentation algorithm based on $\mathrm{GM}(1,1|\tau,r)$ model[13]. Huang used $\mathrm{GM}(1,1|\tau,r)$ model to forecast and analyze how to use the limited resources to improve competition ability[14]. Since the traffic flow has obvious characteristics of grey system, traffic flow is forecasted by the $\mathrm{GM}(1,1|\tau,r)$ model which is considers delay and nonlinear parameters[15]. The delay factor τ is determined by the three parameters relationship of traffic systems and the nonlinear factor r is developed via particle swarm optimization.

2 Urban road short-term traffic flow forecasting based on $\mathrm{GM}(1,1|\tau,r)$ model

2.1 $\mathrm{GM}(1,1|\tau,r)$ model and its related characters

Define 1 Let $X^{(0)}=(x^{(0)}(k)), k=1,2,\cdots,n$ is the raw series, $X^{(1)}=(x^{(1)}(k))$ is the accumulated generation sequence of $X^{(0)}$, $Z^{(1)}=(z^{(1)}(k))$ is the back ground value of $X^{(1)}$, the grey model $\mathrm{GM}(1,1|\tau,r)$ is as Eq.(1).

$$x^{(0)}(k)+az^{(1)}(k-\tau)=bk^{r} \tag{1}$$

where, τ is the delay factor; r is the nonlinear factor.

Note

$$B=\begin{bmatrix} -z^{(1)}(2) & (\tau+2)^{r} \\ -z^{(1)}(3) & (\tau+3)^{r} \\ \vdots & \vdots \\ -z^{(1)}(n-\tau) & n^{r} \end{bmatrix},\quad Y=\begin{bmatrix} x^{(0)}(\tau+2) \\ x^{(0)}(\tau+3) \\ \vdots \\ x^{(0)}(n) \end{bmatrix}$$

Then parameters a,b can be obtained by the least square method as Eq. (2).

$$[a\ \ b]^{T}=(B^{T}B)^{-1}B^{T}Y \tag{2}$$

Further, let

$$C=\sum_{i=2}^{n-\tau}z^{(1)}(i)(i+\tau)^{r};\quad E=\sum_{i=2}^{n-\tau}[z^{(1)}(i)]^{2};\quad F=\sum_{i=2}^{n-\tau}(i+\tau)^{2r};$$

$$G=\sum_{i=2}^{n-\tau}z^{(1)}(i)x^{(0)}(i+\tau);\quad H=\sum_{i=2}^{n-\tau}x^{(0)}(i+\tau)(i+\tau)^{r}$$

We have

$$a=\frac{CH-GF}{EF-C^{2}},\quad b=\frac{EH-CG}{EF-C^{2}} \tag{3}$$

Generally the numerical value of traffic flow is very lager, even for a five minute time interval. It is likely to result in a singular matrix and account for error during the computing process of modeling prediction. To avoid this occurrence, it is necessary to transform the original series [16]. Whether or not multiple transformations will change the prediction precision of the $\mathrm{GM}(1,1|\tau,r)$ model, additional studies must be conducted.

If $x^{(0)}(k), k=1,2,\cdots,n$ is the original series, then $x'^{(0)}(k)=\rho x^{(0)}(k), k=1,2,\cdots,n$, which is the multiple transformation, where ρ is a constant and $\rho\neq 0$ .Via multiple transformations, the parameters of the model note as a',b', the following conclusions are obtained.

Theorem 1: Suppose $[a\ b]^{T}$, $[a'\ b']^{T}$ are parameter vectors of the $\mathrm{GM}(1,1|\tau,r)$ separately constructed by original series $x^{(0)}(k)$ and multiple transformation series $x'^{(0)}(k)$, and $x'^{(0)}(k)=\rho x^{(0)}(k)$, then $a'=a, b'=\rho b$.

Proof: If $x'^{(0)}(k)=\rho x^{(0)}(k), k=1,2,\cdots,n$, then

$$x'^{(1)}(k)=\sum_{i=1}^{k}\rho x^{(0)}(i)=\rho\sum_{i=1}^{k}x^{(0)}(i)=\rho x^{(1)}(k) \tag{4}$$

And C,E,F,G,H be changed respectively as following

$$C'=\sum_{i=2}^{n-\tau}z'^{(1)}(i)(i+\tau)^{r}=\sum_{i=2}^{n-\tau}\rho z^{(1)}(i)(i+\tau)^{r}=\rho C$$

$$E'=\sum_{i=2}^{n-\tau}[z'^{(1)}(i)]^{2}=\sum_{i=2}^{n-\tau}[\rho z^{(1)}(i)]^{2}=\rho^{2}E$$

$$F'=\sum_{i=2}^{n-\tau}(i+\tau)^{2r}=F$$

$$G'=\sum_{i=2}^{n-\tau}z'^{(1)}(i)x'^{(0)}(i+\tau)=\sum_{i=2}^{n-\tau}\rho^{2}z^{(1)}(i)x^{(0)}(i+\tau)=\rho^{2}G$$

$$H'=\sum_{i=2}^{n-\tau}x'^{(0)}(i+\tau)(i+\tau)^{r}=\sum_{i=2}^{n-\tau}\rho x^{(0)}(i+\tau)(i+\tau)^{r}=\rho H$$

where, C',E',F',G',H' are respectively on behalf of the model parameters by original series transformation, that the result is

$$a'=\frac{C'H'-G'F'}{E'F'-C'^{2}}=\frac{\rho^{2}CH-\rho^{2}GF}{\rho^{2}EF-\rho^{2}C^{2}}=a$$

$$b'=\frac{E'H'-C'G'}{E'F'-C'^{2}}=\frac{\rho^{3}EH-\rho^{3}CG}{\rho^{2}EF-\rho^{2}C^{2}}=\rho b$$

The above outcome shows that the development coefficient is unchanged after the original series transformation. That is to say, multiple transformations do not change the trend of the model prediction value.

2.2 Traffic system delay time determinations

When road traffic flow is beyond the traffic capacity in a certain period, according to the classical speed-flow model (the Green-shields parabola model, see Fig. 1), the speed of the flow will reduce. The traffic flow of capacity needed to cross with the speed of V_m and $V_m=0.5V_o$, the remaining vehicles need to enter the queue and pass when the queue dissipates[17].