Short-time traffic flow prediction based on seasonal gray Fourier model

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Short-time traffic flow prediction based on seasonal gray Fourier model

Zhou Shen*

Abstract

To handle the periodic, nonlinear, and stochastic aspects of short-time traffic flow data, a seasonal gray Fourier model based on the complex Simpson formula is proposed. The seasonal GM (1, 1) model is used to optimize the background values first, and then the prediction results are adjusted using the Fourier series method. The new model was applied to the prediction of traffic flow on Whitemud Drive in Canada, and the numerical results indicated that the new model's mean absolute percentage error was 1.54 percent and its fit was 0.996, which were significantly better than those of the traditional GM (1, 1) model, the seasonal GM (1, 1) model, and the Fourier optimized seasonal GM (1, 1) model.

1 Introduction

Intelligent transportation systems may maximize the potential of current transportation infrastructure, which is a significant step toward increasing transportation efficiency, ensuring traffic safety, and reducing congestion. Short-term traffic flow prediction, as the foundation for traffic guidance and management, is at the heart of intelligent transportation systems and the focus of traffic flow theory research.

Numerous experts and researchers have undertaken study on short-term traffic flow prediction using the various features of short-term traffic flow, such as delay, nonlinearity, volatility, periodicity, and geographical and temporal dependence. For example, Kang Jun proposed a method for predicting short-term traffic flow based on Gaussian process regression, Li Song proposed a method for predicting short-term traffic flow based on an improved particle swarm algorithm optimized BP neural network, Liu Zhao proposed a combined prediction model, and KUMAR proposed a SARIMA model based on the characteristics of short-term traffic flow periodic fluctuations.

Gray prediction has been widely utilized in short-term traffic flow forecasting because to its advantages of requiring less modeling data, achieving a greater prediction accuracy, and having a broad application range. However, due to the complexity of the volatility and nonlinearity of short-term traffic flow, as

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well as its seasonal characteristics, the standard GM (1, 1) prediction is not very accurate. Numerous scholars have improved the model from a variety of angles, including Guo Huan et al. introduction of the GM (1, 1) model, LIU et al. establishment of a rolling GM (1, 1) prediction model, Tan Champion et al. improvement of the GM (1, 1) model's prediction accuracy through reconstruction of the background values, and HSU et al. improvement of the prediction residuals through the use of Fourier series. Recently, Xiao et al. exploited the seasonal characteristics of short-time traffic flow by first employing a circular truncated cumulative generation operator to reduce the volatility of the data and then proposing a seasonal GM (1, 1) (SGM (1, 1)) model based on the original GM (1, 1) concept.

To further increase the prediction accuracy of the SGM (1, 1) model, this research proposes a new seasonal gray Fourier model based on the complex Simpson formula. The new model optimizes the background values using the complex Simpson formula and corrects the anticipated residuals using the Fourier series method. The anticipated numerical findings indicate that the new model has a lower mean absolute percentage error (MAPE) and a higher goodness of fit (FD) than the conventional GM (1, 1) model, the SGM (1, 1) model, and the Fourier-optimized SGM (1, 1) model.

2 GM (1,1) Model and SGM (1,1) Model

2.1 GM (1,1) Model

A set of non-negative primitive series is known as

$$x^{(0)} = (x^{(0)}(1), x^{(0)}(2), \dots, x^{(0)}(n))$$

whose once-accumulated (1-AGO) sequence is defined as

$$x^{(1)} = (x^{(1)}(1), x^{(1)}(2), \dots, x^{(1)}(n))$$

where,

$$x^{(1)}(k) = \sum_{i=1}^k x^{(0)}(i)$$

and $k=1, 2, \dots, n$. The basic form of the GM (1, 1) model is

$$x^{(0)}(k) + az^{(1)}(k) = b$$

where the background values $z^{(1)}(k)$, $k=2, \dots, n$ can be represented by a mean generating sequence, $z^{(1)}(k) = 0.5x^{(0)}(k) + 0.5x^{(0)}(k-1)$. Let

$$p = \begin{bmatrix} a \\ b \end{bmatrix}, Y = \begin{bmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ \vdots \\ x^{(0)}(n) \end{bmatrix}, B = \begin{bmatrix} -z^{(1)}(2) & 1 \\ -z^{(1)}(3) & 1 \\ \vdots & \vdots \\ -z^{(1)}(n) & 1 \end{bmatrix},$$

The parameters a, b are obtained by the least squares method,

$$\mathbf{p} = \left(\mathbf{B}^T \mathbf{B} \right)^{-1} \mathbf{B}^T \mathbf{Y}.$$

The corresponding whitening differential equation for the GM (1, 1) model is defined as

$$\frac{dx^{(1)}(k)}{dt} + ax^{(1)}(k) = b$$

Taking $x^{(0)}(1)$ as the initial condition, the time response series is obtained by solving the above whitening differential equation

$$\begin{aligned} \hat{x}^{(1)}(k+1) &= \left(x^{(0)}(1) - b/a \right) e^{-ak} + b/a \\ k &= 1, 2, \dots, n. \end{aligned}$$

The predicted values of the original series are obtained by first order cumulative reduction

$$\hat{x}^{(0)}(k+1) = \hat{x}^{(1)}(k+1) - \hat{x}^{(1)}(k).$$

2.2 SGM (1,1) Model

For the original non-negative sequence

$$x^{(0)} = \left(x^{(0)}(1), x^{(0)}(2), \dots, x^{(0)}(n) \right)$$

Take q as a cycle, and use the cycle truncation accumulation generation operator (CTAGO) to obtain the new sequence

$$\begin{aligned} y^{(0)} &= \left(y^{(0)}(1), y^{(0)}(2), \dots, y^{(0)}(r) \right) \\ r &= 1, 2, \dots, n - q + 1 \end{aligned}$$

where

$$\begin{aligned} y^{(0)}(k) &= \text{CTAGO} \left(x^{(0)}(k) \right) = \\ &\sum_{j=1}^q x^{(0)}(k+j-1), \forall k = 1, 2, \dots, n - q + 1. \end{aligned}$$

The 1-AGO sequence of y (0) is

$$y^{(1)} = \left(y^{(1)}(1), y^{(1)}(2), \dots, y^{(1)}(r) \right)$$

The calculation gives

$$y^{(1)}(k) = \sum_{i=1}^k y^{(0)}(i) = \sum_{i=1}^k \sum_{j=1}^q x^{(0)}(i+j-1).$$

Substituting the obtained $y^{(0)}$ sequence into the conventional GM (1, 1) model, the basic form of SGM (1, 1) model can be defined as

$$y^{(0)}(k) + az^{(1)}(k) = b$$

Let

$$\mathbf{Y} = \begin{bmatrix} y^{(0)}(2) \\ y^{(0)}(3) \\ \vdots \\ y^{(0)}(r) \end{bmatrix}, \mathbf{B} = \begin{bmatrix} -z^{(1)}(2) & 1 \\ -z^{(1)}(3) & 1 \\ \vdots & \vdots \\ -z^{(1)}(r) & 1 \end{bmatrix},$$

Similarly, the least squares solution gives

$$\mathbf{p} = (a, b)^T = \left(\mathbf{B}^T \mathbf{B} \right)^{-1} \mathbf{B}^T \mathbf{Y}.$$

The time response sequence of SGM (1, 1) model is obtained by solving the whitening differential equation with reference to the GM (1, 1) model

$$\hat{y}^{(1)}(k+1) = \left(y^{(0)}(1) - \frac{b}{a} \right) e^{-ak} + \frac{b}{a},$$

$$k = 1, 2, \dots, r,$$

A single cumulative reduction is performed to obtain

$$\hat{y}^{(0)}(k+1) = \hat{y}^{(1)}(k+1) - \hat{y}^{(1)}(k),$$

$$k = 1, 2, \dots, r,$$

The reduced value is

$$\hat{x}^{(0)}(k+1) =$$

$$\hat{y}^{(0)}(k-q+2) - \hat{y}^{(0)}(k-q+1) + x^{(0)}(k-q+1) =$$

$$\left(\hat{y}^{(1)}(k-q+2) - \hat{y}^{(1)}(k-q+1) \right) -$$

$$\hat{y}^{(0)}(k-q+1) + x^{(0)}(k-q+1),$$

$$k = q, q+1, \dots, n.$$

3 Seasonal gray Fourier model based on the complex Simpson formula

The SGM (1, 1) model firstly accumulates the original data periodically to weaken the volatility of the data, but the new series generated after accumulation is still using the traditional gray forecasting method with limited improvement in accuracy. In this paper, we introduce a new seasonal gray Fourier model based on the complex Simpson formula based on the SGM (1, 1) model to further improve the forecasting accuracy.

3.1 Improved background values by compounding Simpson's formula

The error of the traditional GM (1, 1) model is mainly due to the use of the trapezoidal formula

$$\frac{1}{2} \left[x^{(1)}(k) + x^{(1)}(k-1) \right]$$

instead of the integral value in the calculation of the background value

$$\int_{k-1}^k x^{(0)}(t) dt$$

In order to reduce the error of calculating the background value, this paper uses the complexified Simpson formula to calculate the background value $z^{(1)}(k)$.

Definition 1: Let $[k-1, k] = [a, b]$, and divides the interval $[a, b]$ into n equal parts, each equal part being

$$x_{i+\frac{1}{2}} = x_i + 0.5h$$

$h = (b-a) / n$, then, $i=0, 1, \dots, n$, and uses Simpson's formula on each small interval $[x_i, x_{i+1}]$, thus obtaining the complexified Simpson's formula

$$\begin{aligned} S_n &= \int_a^b f(x) dx = \\ &= \frac{h}{6} \sum_{i=0}^{n-1} \left[f(x_i) + 4f\left(x_{i+\frac{1}{2}}\right) + f(x_{i+1}) \right] = \\ &= \frac{h}{6} \left[f(a) + 4 \sum_{i=0}^{n-1} f\left(x_{i+\frac{1}{2}}\right) + 2 \sum_{i=0}^{n-1} f(x_i) + f(b) \right]. \end{aligned}$$

Since 1-AGO is a discrete sequence, it is impossible to find the function value corresponding to x_i in the complex Simpson formula, so this paper proposes to use the Lagrangian interpolation to fit the function to obtain

$$\begin{aligned} &f\left(x_{i+\frac{1}{2}}\right) \\ &f(x_i) \end{aligned}$$

Definition 2: Denote three points $k-1, k, k+1$ as interpolation nodes, and the quadratic interpolation polynomial $f(t)$ of $x^{(1)}(t)$ is obtained as

$$\begin{aligned} f(t) &= \frac{(t-x_1)(t-x_2)}{(x_0-x_1)(x_0-x_2)} \cdot x^{(1)}(k-1) + \\ &\quad \frac{(t-x_0)(t-x_2)}{(x_1-x_0)(x_1-x_2)} \cdot x^{(1)}(k) + \\ &\quad \frac{(t-x_0)(t-x_1)}{(x_2-x_0)(x_2-x_1)} \cdot x^{(1)}(k+1), \end{aligned}$$

where $x_0=k-1$, $x_1=k$, $x_2=k+1$.

The background value is obtained by substituting the complexified Simpson formula

$$z^{(1)}(k) = \int_{k-1}^k x^{(1)}(t)dt = \frac{h}{6} \left[f(a) + 4 \sum_{i=0}^{n-1} f\left(x_{i+\frac{1}{2}}\right) + 2 \sum_{i=0}^{n-1} f(x_i) + f(b) \right].$$

3.2 Fourier series improved residuals

Due to the limitation of the traditional gray prediction model that generates a single exponential rate of change cumulatively, its residuals have both positive and negative and are highly volatile. In order to further improve the prediction accuracy of the model, this paper introduces Fourier series to correct the residuals. First, based on the results obtained from the above prediction, the residual series can be obtained

$$\varepsilon^{(0)} = \left(\varepsilon^{(0)}(2), \varepsilon^{(0)}(3), \dots, \varepsilon^{(0)}(n) \right)$$

where

$$\varepsilon^{(0)}(k) = x^{(0)}(k) - \hat{x}^{(0)}(k), k = 2, 3, \dots, n$$

Let the residuals after the Fourier series correction be

$$\varepsilon'^{(0)}(k) = \frac{1}{2}a_0 + \sum_{i=1}^m \left[a_i \cos\left(\frac{2\pi i}{T}k\right) + b_i \sin\left(\frac{2\pi i}{T}k\right) \right],$$

$$k = 2, 3, \dots, n,$$

where $T=n-1$, $m = \left[\frac{n-1}{2}\right] - 1$, $a_0, a_i, b_i, i=1, 2, \dots, m$ are the Fourier parameters to be found. Let $\varepsilon(0) = \text{DC}$, expand as

$$\begin{bmatrix} \varepsilon^{(0)}(2) \\ \varepsilon^{(0)}(3) \\ \vdots \\ \varepsilon^{(0)}(n) \end{bmatrix} = \begin{bmatrix} \frac{1}{2} & \cos\left(2\frac{2\pi}{T}\right) & \sin\left(2\frac{2\pi}{T}\right) & \cdots & \cos\left(2\frac{2\pi m}{T}\right) & \sin\left(2\frac{2\pi m}{T}\right) \\ \frac{1}{2} & \cos\left(3\frac{2\pi}{T}\right) & \sin\left(3\frac{2\pi}{T}\right) & \cdots & \cos\left(3\frac{2\pi m}{T}\right) & \sin\left(3\frac{2\pi m}{T}\right) \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ \frac{1}{2} & \cos\left(n\frac{2\pi}{T}\right) & \sin\left(n\frac{2\pi}{T}\right) & \cdots & \cos\left(n\frac{2\pi m}{T}\right) & \sin\left(n\frac{2\pi m}{T}\right) \end{bmatrix}$$

Using the least squares method to find the parameters

$$C = \left(D^T D\right)^{-1} D^T \varepsilon^{(0)}$$

The initial prediction value is corrected by Fourier series to obtain the final prediction value

$$\begin{cases} x^{(0)}(1) = \hat{x}^{(0)}(1) \\ \hat{x}^{(0)}(k) = \hat{x}^{(0)}(k) + \varepsilon^{(0)}(k), k = 2, 3, \dots, n \end{cases}$$

3.3 Model steps

In summary, the steps of the seasonal gray Fourier model based on the complex Simpson formula are as follows:

Step 1 Determine the original series $x^{(0)} = (x^{(0)}(1), x^{(0)}(2), \dots, x^{(0)}(n))$, and seasonally accumulate the original series with q as the period to obtain the CTAGO series $y^{(0)}(r)$, $r=1, 2, \dots, n-q+1$;

Step 2 Perform first-order accumulation on the series $y^{(0)}(r)$, construct the background values using the complex Simpson formula, and solve for the parameters a, b ;

Step 3 Substitute the parameters into the SGM (1, 1) model to obtain the time response series, and calculate the initial prediction value;

Step 4 Calculate the residual $\epsilon^{(0)}(k)$ of the initial prediction and correct it by Fourier series to obtain the final prediction.

4 Case studies

4.1 Data sources

The traffic flow data used in this paper were obtained from the OpenITS data platform, which provides traffic flow data for the Whitemud Drive highway in Edmonton, Alberta, Canada, from August 8 to 28, 2015, from 7:00 to 8:00 with a time interval of 15 min, and the data were organized to obtain The raw data are shown in Figure 1.

4.2 Prediction error index

In order to verify the prediction accuracy and validity of the model, we define the indexes of prediction error - mean absolute percentage error (MAPE) and goodness of fit (FD) The smaller the value of MAPE, the higher the prediction accuracy, i.e., MAPE values below 10% indicate high accuracy, 11%-20% indicate high accuracy, 21%-50% indicate fair accuracy, and greater than or equal to 51% indicate poor accuracy. $FD > 0.95$ is considered as a satisfactory prediction.

4.3 Forecast results

In this paper, Matlab simulations were performed with the traditional GM (1, 1) model, SGM (1, 1) model, Fourier-optimized SGM (1, 1) model and the new model for the section measured by the VDS1030 ground sensor coil in the west direction of the highway. In the complex Simpson formula, theoretically, the larger the value of n , the more accurate the numerical integration, the higher the fitting and prediction accuracy, but the improvement will be smaller and smaller. In this paper, we take $n=500$ and select the data set of 7:30-7:45 as the object of analysis, and calculate the fitting results as shown in Table 1.

Date	Ground Truth	GM (1,1)		SGM (1,1)		SGM (1,1) + Fourier		Proposed	
		Predicted	MAPE	Predicted	MAPE	Predicted	MAPE	Predicted	MAPE
20150808	356	356.0000	0	356.0000	0	356.0000	0	356.0000	0
20150809	179	912.8140	4.0995	179.0000	0	179.0000	0	179.0000	0
20150810	1326	925.7596	0.3018	1326.0000	0	1326.0000	0	1326.0000	0
20150811	1327	938.8889	0.2925	1327.0000	0	1327.0000	0	1327.0000	0
20150812	1364	952.2043	0.3019	1364.0000	0	1364.0000	0	1364.0000	0
20150813	1381	965.7086	0.3007	1381.0000	0	1381.0000	0	1381.0000	0
20150814	1242	979.4044	0.2114	1242.0000	0	1242.0000	0	1242.0000	0
20150815	285	993.2945	2.4852	187.3438	0.3427	290.8710	0.0206	280.4784	0.0159
20150816	155	1007.3815	5.4992	179.8588	0.1604	145.2585	0.0628	164.0432	0.0583
20150817	1313	1021.6683	0.2219	1326.8589	0.0106	1317.9740	0.0038	1303.9568	0.0069
20150818	1287	1036.1577	0.1949	1327.8590	0.0317	1287.7787	0.0006	1296.0432	0.0070
20150819	1304	1050.8527	0.1941	1364.8591	0.0467	1297.6228	0.0049	1294.9568	0.0069
20150820	1337	1065.7560	0.2029	1381.8592	0.0336	1347.7125	0.0080	1346.0432	0.0068
20150821	1237	1080.8707	0.1262	1242.8593	0.0047	1224.0739	0.0104	1227.9568	0.0073

From Table 1, we can see that the mean values of the conventional GM (1, 1) model, SGM (1, 1) model, Fourier-optimized SGM (1, 1) model, Simpson-optimized SGM (1, 1) model and the new model MAPE are 109.25%, 11.50%, 11.18%, 5.76% and 1.54%, respectively, and the FD values are The results show that the new model outperforms the traditional GM (1, 1) model, SGM (1, 1) model, Fourier-optimized SGM (1, 1) model and Simpson-optimized SGM (1, 1) model in terms of prediction accuracy, and can be effectively applied to short-time traffic flow prediction.

5 Conclusion

Accurate traffic flow prediction is a prerequisite for implementing traffic signal control, traffic assignment, path guidance, and accident detection in intelligent transportation systems, and the results of traffic flow prediction will directly affect the effectiveness of traffic control and management. In this paper, we propose a seasonal gray Fourier model based on the seasonal gray prediction model, which makes full use of the periodic, nonlinear and stochastic characteristics of short-time traffic flow data. Compared with the traditional GM (1, 1) model and SGM (1, 1) model, the new model has obvious accuracy advantage and better fit, which is worth to be applied in practice.

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