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Measurement and Prediction of Regional Traffic Volume in Holidays

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Abstract— **Accurate regional traffic volume projection is important for department of transportation to plan investments, and also helps forecast oil or electric energy demand and CO_2 emissions. Based on a 4.5 years' daily traffic volume measurement data of the highway network of Guizhou province of China, this paper conducts a comprehensive measurement analysis of the network's traffic volume growth pattern and proposes a new time series model, which improves the projection accuracy of non-holiday and holiday traffic considerably. We first find that the holiday traffic volume is considerably higher than that on the neighboring non-holidays (e.g., 1.88 times), which could bring tremendous pressure on the road network. We then find that the traffic of network increases exponentially, in particular, the increase rates in holidays are higher than those in non-holidays. Thus, we propose an Exponential-Growth (EG) holiday component model, which models the holiday component with exponential growth. Experimental results show that our model considerably improves the holiday traffic's prediction accuracy compared with the existing models. For instance, for the first day of National Day holiday, which is usually the heaviest day in a whole year (from Jan. 1 to Dec. 31), the model decreases the prediction relative error from 18.7% to 7%.**

I. INTRODUCTION

The department of transportation (DoT) and other agencies need long-term traffic volume growth projection for highway administration. First, the traffic demand growth pattern and its impact on the road network are the primary focus of transportation agencies. The geographic planning and financing decisions for highway network capacity investments are also mainly driven by them. In USA, the Federal Highway Administration (FHWA) requires DoT to forecast long-term traffic volume growth [1]. Second, long-term traffic volume growth projections can also help forecast oil demand, CO_2 emission, and electric energy consumption [2], [3].

Holiday traffic projection is important for long-term traffic volume growth projection, because holiday traffic is usually heavier than non-holiday traffic, meaning bigger impact on the network. However, the existing long-term traffic volume growth projection model does not consider holiday traffic specially. For instance, Liu *et al.* [4] measured and analyzed the uncertainty of traffic growth of the highway network in Shanxi and Anhui Province, China. But they deliberately chose to analyze traffic volume in the months without main holidays (i.e., March, July, September and December) to represent traffic conditions in the four seasons.

Based on long-term and large-scale toll station measurement results (which last for 4.5 years and include more than 390M trips) of a large highway network (whose mileage is more than 5.1K kilometers) in Guizhou province of China, we characterize the long-term daily traffic volume growth pattern in the network. Our contributions are two folds:

- We find that traffic volume in holidays is considerably higher than that in neighboring non-holidays, e.g., 1.88 times. The peak traffic of a year occurs on one holiday. Moreover, the traffic volume increases exponentially in both non-holidays and holidays, but the growth rate in holidays is higher than that in non-holidays.
- We propose a new holiday traffic growth model to accurately predict holiday traffic. The model models the holiday component with exponential growth. Experimental results show that our model considerably improves the accuracy of traffic prediction in holidays compared with the existing models. For instance, to predict the traffic on the first day of National Day holiday, which is usually the heaviest day in a whole year, the model decreases the prediction relative error from 18.7% to 7%, which means (18.7-7)/18.7 = 62.6% performance gain. For the day before the Spring Festival, which usually has the lowest traffic volume in a whole year, our model reduces the prediction relative error from 18.7% to 3.27%, which means (18.7-3)/18.7 = 83.96% performance gain.

The remaining parts of this paper are organized as follows: Sec. II introduces the related work. Sec. III introduces the dataset. Sec. IV characterizes the traffic growth pattern. Sec. V introduces our holiday traffic model. Sec. VI presents the evaluation results. Sec. VII concludes this paper.

II. RELATED WORK

Measurement of long-term trend of region traffic volume: [5] characterized the long-term trend of daily peak time in Seoul's traffic in south Korean for 15 years. However, they did not predict the traffic during the peak time.

Long-term regional traffic volume model and prediction: Elastic model [3], [6] is used to obtain the relationship between traffic increase and related factors, e.g., economic growth. As elastic model is based on coarse-grained data statistic (i.e., per year), it cannot be used to accurately predict daily traffic. For comparison, this paper establishes a fine-grained time series model to predict long-term daily traffic, especially the holiday traffic.

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Short-term road traffic volume prediction: There are a lot of work in short-term road traffic prediction, e.g., traffic forecast within 5 minutes. Recently, deep learning based methods have achieved impressive results [7]. For comparison, this paper studies long-term traffic in a few years. It also studies regional traffic, which is the whole traffic of a regional road network, rather than a single road.

Prediction of Long-term road traffic volume: In comparison to short-term prediction, long-term road traffic prediction is thought to be very difficult, because the lack of historical traffic data [8]. Existing practices first estimate the annual average daily traffic (AADT) of a road, and then predicts it as the road for the coming one year by applying annual adjustment factors, i.e., annual growth rates, to accommodate annual traffic growth. Such a prediction method is simple, coarse-grained, and may be inaccurate. For comparison, this paper builds a fine-grained time series model to predict long-term daily traffic. The model is also applicable for long-term road traffic prediction,too.

III. BACKGROUND

This section introduces the highway network we measured and the dataset. The measurement was conducted in Guizhou province in China. The mileage of the province's highway network is 5.1K kilometers (i.e., 3.2K miles). Similar to [4], we use highway toll station data to characterize the long-term traffic volume growth trend of the network. There are more than 280 toll stations in the network. We use the daily total exit vehicle volume of all toll stations as traffic volume of the network.

Our measurement lasted for 4.5 years, from Jan. 2010 to Jul. 2014. The average daily traffic volume (number of vehicles) is 378,766. In our data, vehicles are categorized into two types: passenger cars and trucks. The passenger cars take up more than 79% of all traffic. Such a result is consistent with the reported measurement results [4] of Shanxi and Anhui, which are another two provinces in China.

IV. TRAFFIC GROWTH PATTERN

We now observe the traffic growth pattern during the 4.5 years' measurement period. Fig. 1 plots the daily traffic in the 4.5 years. We have the following observations.

A. Exponential Growth of Long Term Trend

As shown in Fig. 1a, the increasing trends of both the non-holiday and holiday traffic are not linear. Therefore, we plot the same data in Fig. 1b with y-axis on logarithmic scale, to observe whether they are increase exponentially. As shown in Fig. 1b, it seems that they increase exponentially. To prove this observation, we fit all non-holiday data (from 2010 to 2014) with an exponential growth model and plot the result in Fig. 1b. The exponent of the growth pattern is 6.95e-04, and R^2 is 0.946, which means that the non-holiday traffic indeed grows exponentially. Such a result is consistent with the measurement result in USA in the 20th century, when the number of vehicles using highway grew year by year and the growth was exponential in certain regions [1]. We further fit the traffic of each holiday in the 4.5 years with an exponential growth model. Their average R^2 is 0.97. We also tried to fit the data with linear and polynomial model, but the results are not as good as that of exponential growth model.

We further compare the increasing rates in holidays and non-holiday days. As an example, we plot the fitting result of one day in National Day holidays in Fig. 1b. As shown in Fig. 1b, the slope of the holiday is larger than that in non-holidays, which means that the increase rate of holidays is higher than that in non-holidays.

B. Burst Traffic in Holidays

As shown in Fig. 1a, there are a few days when traffic is considerably higher than that in their adjacent days. For instance, the heaviest daily traffic during the 4.5 years occurs on May 1st, 2014. The traffic volume is more than 700k vehicles. In order to observe the detail of traffic growth in the last year, we plot the traffic of from July 2013 to June 2014 in the sub-figure in Fig. 1a. As shown in the sub-figure, there are four traffic bursts in the year (see the red points). For each burst, the traffic quickly increases and reaches a very high value, and then returns to the normal value in just several days. For instance, on about 1580th day, the traffic quickly increases from about 400k to about 750k, meaning 750k/400k=1.88 times' increasing, and then returns to about 400k in just several days. Such a significant increasing means huge pressure in the highway network during the holiday, and should be taken into consideration for the management and planning of the road network and other support services, e.g., refueling service.

The four traffic burst periods correspond to four main holidays in China, i.e., Spring Festival, Ching Ming Festival, Labor Day, and the National Day. The four legal holidays last 7 days, 3 days, 3 days and 7 days, respectively. Fig. 2 plots the daily traffic volume during these four holiday periods. To observe the traffic in adjacent non-holiday days, we plot traffic in three non-holiday days immediately before and after the holiday, respectively. Thus, the holiday begins from the day 1 in the figures. Similar to Fig. 1b, the y-axis adopts logarithmic scale. We have the following observations from Fig. 2:

1) The traffic growth pattern of Spring Festival is different from the other three groups of holidays. Specifically, before the Spring Festival holidays, the traffic first significantly decreases. This is because on the day before the holiday, many people stay at home to spend the Spring Festival Eve with families, like what western people do on Christmas Eve. Thus, there are fewer people driving on the highway and the traffic is relatively low. After the Spring Festival Eve, the traffic gradually increases. On the end day of the holiday period, the traffic reaches its peak, as a large number of people leave home and go back to work.
2) For Ching Ming Festival, Labor Day, and National Day holidays, the traffic abruptly increases on the first day of the holiday period, meaning that a large number of

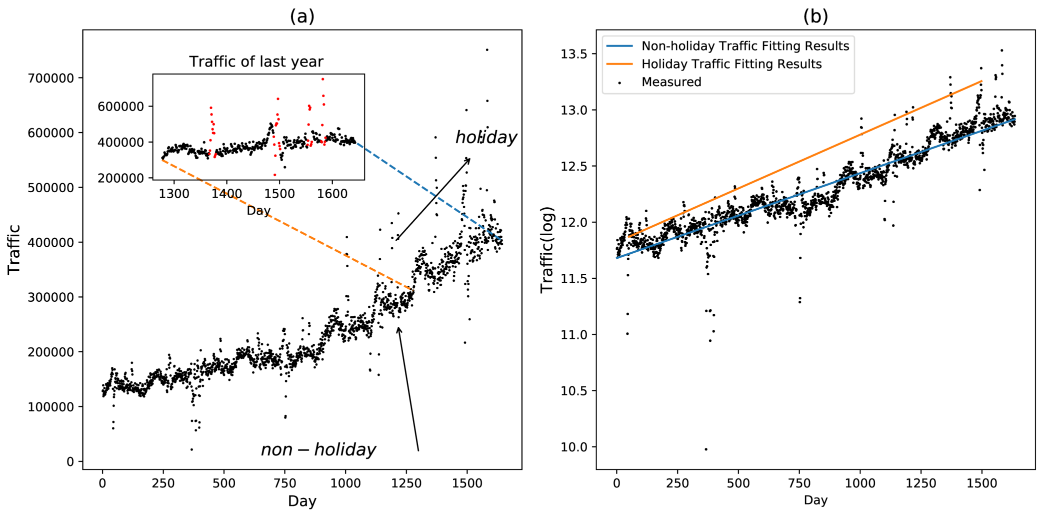

Fig. 1. Daily traffic volume of Guizhou highway network in the 4.5-years measurement periods. The two subgraphs plot the same data, but the scale of y-axis is linear in (a) but logarithmic in (b).

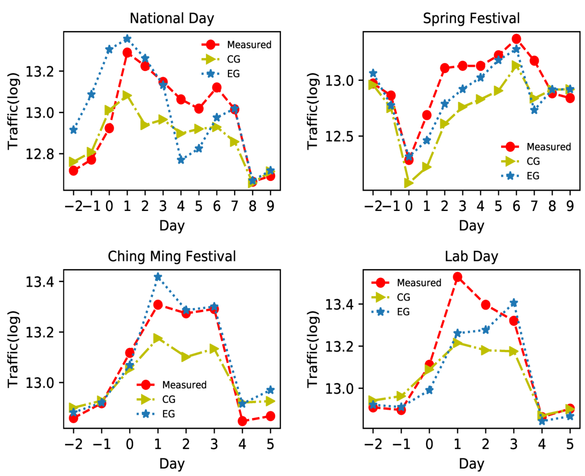

Fig. 2. Measured and predicted traffic of four holiday periods in the last year of the measurement period. The EG curve is the prediction result of our model, and the CG curve is the prediction result of the best existing model

people leave at the beginning of the holidays. During the holidays, the traffic keeps relatively high, means a lot of people are on the road, until the end of the holidays. The peak day of traffic usually occurs on the first day of the holiday period.

V. LONG-TERM TRAFFIC MODEL

Similar to the existing works [9], we model the traffic with three components which are trend, seasonal and holidays. The model is as below:

$$\begin{cases} f(t) = g(t)s(t)h(t) \\ g(t) = e^{a_g + b_g t} \\ s(t) = e^{y(t)} \end{cases} \tag{1}$$

, where

- $f(t)$ is the time series of the traffic volume.
- $g(t)$ is the trend component. Inspired by the measurement results presented in Sec. IV-A, i.e., the non-holiday traffic grow exponentially, we model the growth trend of the non-holiday traffic as $g(t) = e^{a_g + b_g t}$, i.e., the non-holiday traffic increases exponentially over time.
- $s(t)$ is the seasonality component. It models the periodic changes of the time-series. We model the seasonality component as $s(t) = e^{y(t)}$, where $y(t)$ is a yearly periodical function, and we model it as $y(t) = \sum_{n=1}^{N} \left(a_n \cos\left(\frac{2\pi n t}{P}\right) + b_n \sin\left(\frac{2\pi n t}{P}\right)\right)$. Where a_n and b_n are solved by fitting seasonality, $P = 365.25$ and $N = 10$ for yearly data.
- $h(t)$ is the holiday component. It models the traffic growth which occurs only in holidays. We specify its model details in Sec. V-A.

A. Exponentially Increasing Holiday Component Model

Inspired by the measurement results presented in Sec. IV-A, we model the holiday component as

$$h(t) = \begin{cases} e^{a_h^{i,j} + b_h^{i,j} t} & \textit{if } t \textit{ is a holiday} \\ 1 & \textit{if } t \textit{ is not a holiday,} \end{cases} \tag{2}$$

where $a_h^{i,j}$ and $b_h^{i,j}$ are constants. i is a holiday's *holiday ID*, and j is its *group ID*. As there are four groups of holidays, we have $j \in [1, 2, 3, 4]$. As there are 7 days' vacations for Spring Festival and National Day, and 3 days' vacations for Ching Ming Festival and Labor Day, we have $i \in [1, \dots, 7]$ for Spring Festival and National Day, and $i \in [1, 2, 3]$ for Ching Ming Festival and Labor Day.

Thus, Eq. (2) means that if a day is a holiday, its holiday component $h(t)$ increases exponentially over time. Accordingly, we call our model *exponential growth* (EG) holiday component model. For comparison, if a day is not a holiday, then $h(t) = 1$, meaning that the holiday component does not exist and the traffic only includes non-holiday traffic. For comparison, existing long-term time-series model, like

Prophet [9], which is a probabilistic graphical model, models the holiday component $h(t)$ as a constant. Thus, we name the model *constant growth* (CG) holiday component model. We will use CG as a baseline model to evaluate the performance of EG model. Besides the linear exponent $a + bt$, we also tried higher-order exponent model, e.g., $a+bt+ct^2$, and find they cannot obtain better results than the EG model. Thus, we only report the result of EG model in the paper. We fit the Prophet's Stan model with our data to get the results of CG model. We then modified Prophet's Stan model code [9] to implement EG model. The modified model code is shown in Appendix A.

VI. PERFORMANCE EVALUATION

This section presents the performance evaluation results of EG model. In our 4.5-years measurement data, we use the data of the starting 3.5 years to train the model, and then predict the daily traffic of the highway network in the last year.

A. Baseline Models

We compare the performance of EG model against the following time series models:

- STL-ARIMA and STL-EST, i.e., the data is firstly decomposed into seasonal and trend by Seasonal Decomposition of Time Series by Loess (STL) [10]. Then, Exponential Smoothing State Space Model (ETS) [11] and ARIMA [12] are used to model the trend and predict the future, respectively. Finally, the seasonal component from the last year of data is added to obtain the forecasts. Accordingly, we name these two models as STL-ARIMA and STL-EST, respectively.
- Holt–Winters [13].
- Constant Growth (CG) model [9].

We evaluate the performance of STL-ARIMA, STL-EST, and Hot-Winters using R language forecast package [9] and evaluate CG model with Prophet [9].

B. Evaluation Metrics

To evaluate performance of models, we use the following three metrics:

- MRE (Mean Relative Error): It is the average relative error of the modeling and predicting results, i.e., $\frac{1}{n}\sum_{i=1}^{n}|\frac{Y_i-\hat{Y}_i}{Y_i}|$, where n is the number of days in the evaluation period, i is the ID of a specific day, Y_i is the measured traffic of day i, and $\hat{Y}_i$ is the modeling or predicted traffic of day i.
- REPV (Relative Error of Peak Volume): It is the relative error of the predicted peak traffic volume in a holiday period, i.e., $|\frac{max(Y_i)-max(\hat{Y}_i)}{max(Y_i)}|$, where i represents a specific day in the holiday period, Y_i and $\hat{Y}_i$ represent the measured and predicted traffic of day i, respectively. Note that the predicted peak volume and the measured peak volume may not occur at the same day. Thus, this metric measures the capacity of the model to predict the heaviest traffic volume during the holiday period. Such prediction is useful for road management and planning, which only cares the predicted peak traffic volume, no matter when it occurs.
- REPD (Relative Error of Peak Day): It is the relative error of the modeling and predicting result at the measured peak traffic day. For instance, the real peak traffic day of National Day holiday is Oct. 1st. Thus, the metric is the relative error of the modeling result on Oct. 1. Such prediction is important for the timely road traffic management. We report the REPD for each holiday period and the whole year.

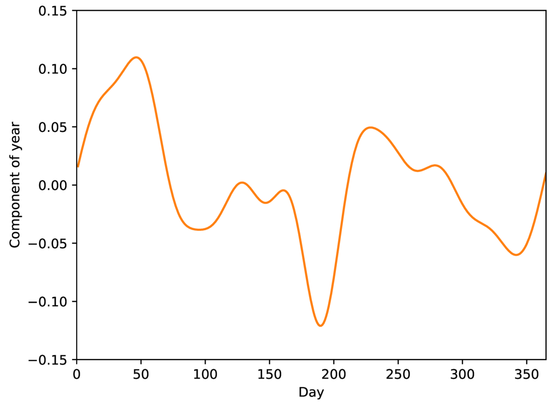

Fig. 3. Seasonal components: yearly component

C. Components of EG models

In this subsection, we present the resulting traffic components of EG models.

1) Trend component: We first observe the trend component, i.e., $a_g + b_g t$ in Eq. (3). We reuse Prophet's trend component module, which supports splitting the whole measurement period into multiple segments and fitting a trend component for each segment. The number of segments is a hyperparameter and we set it 49. As a result, the obtained trend curve is a 49-segment fold line. As shown in Fig. 4a, the basic trend of the traffic growth is linear. We use a linear model to fit the trend fold line and have $g(t) = e^{11.75+6.7\times10^{-4}t}$, where t is the sequence ID of the day. Such a model means that the traffic increases $e^{6.7\times10^{-4}\times365} = 1.28$ times every year.

2) Seasonal component: We first observe the seasonal component, i.e., $y(t)$ in Eq. (3). Fig. 3 plots the seasonal component obtained by EG models. For the task of predicting holiday traffic, we only consider the yearly seasonal component and do not consider the weekly seasonal component, as we believe that the traffic in holidays should not be affected by the traffic's weekly regularity. For the yearly seasonality component $y(t)$, as shown in Fig. 3, the traffic varies considerably in a year: the highest point 0.104 appears in August, meaning $e^{0.104} - 1 = 11\%$ increasing. The lowest point -0.116 appears in January, meaning $1 - e^{-0.116} = 11\%$ decreasing.

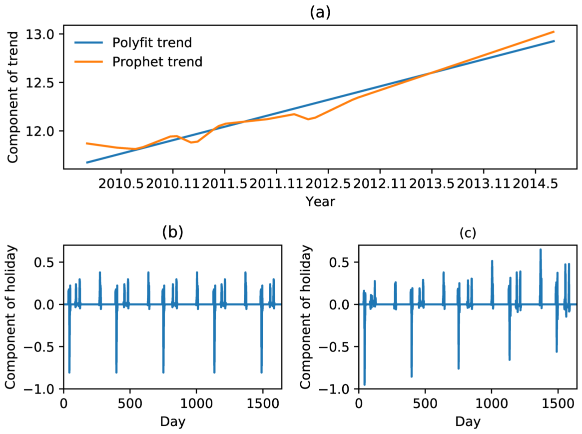

Fig. 4. Yearly and holiday components

3) Holiday components: We finally observe the holiday component, i.e., $h(t)$ in Eq. (1). As shown in Fig. 4b, the holiday components obtained by CG are constants in the training period, i.e., $h(t) = e^{a_h^{i,j}}$. Note that there are 20 holidays in each year. For comparison, as shown in Fig. 4c, the holiday components obtained by EG grows linearly over time in the training period, i.e., $h(t) = e^{a_h^{i,j}+b_h^{i,j}t}$.

D. Fitting and Prediction Results

Fig. 5a and 5b plot the model fitting and prediction results of CG and EG over the whole measurement period, respectively. As shown in Fig. 5a, CG overestimates the holiday traffic from 2010 to 2011, and underestimates it after 2012. The appearance of the problem is because CG models every holiday's component as a constant, which makes the early forecast results exceed the actual values, and the later prediction results less than the real values. For comparison, as shown in Fig. 5b, EG fits and predicts the holiday traffic better.

E. Performance Evaluation Results

Fig. 6 plots the prediction results of all baseline models and EG model, and Table I shows their MREs, REPVs, and REPDs for both non-holiday and holiday traffic. We have the following observations:

1) Prediction performance of non-holiday traffic: We first compare the prediction performance of all models for non-holiday traffic. As shown in Fig. 6, STL-EST, STL-ARIMA and Holt-Winters all underestimate the non-holiday traffic. For comparison, both EG and CG models have better performance in predicting non-holiday traffic. Specifically, as shown in the column *Non-Holiday* of Table I, the MREs of EG and CG models on non-holiday traffic are 0.060 and 0.057, respectively, meaning they have similar prediction accuracy for non-holiday traffic. For comparison, the MREs of ARIMA, ETS and Holt-Winter are 0.123, 0.186, and 0.140, respectively. They are considerably higher than those of EG and CG models. Thus, both CG and EG models are more accurate than ARIMA, ETS and Holt-Winter for non-holiday traffic prediction.

2) Prediction performance of holiday traffic: We then compare the prediction performance of all models for holiday traffic. We first compare the prediction performance of EG and CG with other three baseline models. As shown in Fig. 6, STL-EST, STL-ARIMA and Holt-Winters still underestimate the holiday traffic. Not only in non-holidays, both EG and CG models also have better performance in predicting holiday traffic. For instance, as shown in the column *Labor Day - MRE* of Table I, the MREs of EG and CG models on Lab Day traffic are 0.145 and 0.199, respectively. For comparison, the MREs of ARIMA, ETS and Holt-Winter are 0.459, 0.523, and 0.496, respectively, which are considerably higher than those of EG and CG. The results of other holiday periods are similar. Thus, both CG and EG models perform better than ARIMA, ETS and Holt-Winter for holiday traffic prediction.

We then compare the prediction performance of EG and CG models for holiday traffic. As shown in Fig. 6, CG also underestimates the holiday traffic. For comparison, it seems that EG predicts the holiday traffic more accurately. In order to clearly compare the prediction results of EG and CG, Fig. 2 plots the prediction results for each holiday of EG and CG models. Specifically, as shown in Table I, the MRE, REPV, and REPD of EG are always lower than those of CG, respectively. For instance, the MRE for Spring Festival of EG is 0.18, which is (0.3-0.18)/0.3 = 40% lower than that of CG. Similarly, the REPDs and REPVs for Spring Festival of EG are 0.087, which is (0.212-0.087)/0.212 = 59% lower than those of CG. The results of National Day and Ching Ming Festival holiday periods are similar. For instance, the heaviest traffic usually occurs on Oct. 1st in a year. As shown in Table I, the REPV for National Day holidays of EG is 0.07, which is (18.7-7)/18.7 = 62.6% lower than those of CG.

VII. CONCLUSION

In this paper, based on a long-term large-scale highway network traffic volume measurement data, we conduct a comprehensive measurement analysis of the traffic volume growth pattern in the network and propose an Exponential-Growth holiday component traffic prediction model (EG), which models the holiday component with exponential growth. Experimental results show that the model considerably improves the holiday traffic prediction accuracy compared with the existing models. In our future work, we will evaluate the traffic's stationarity etc.

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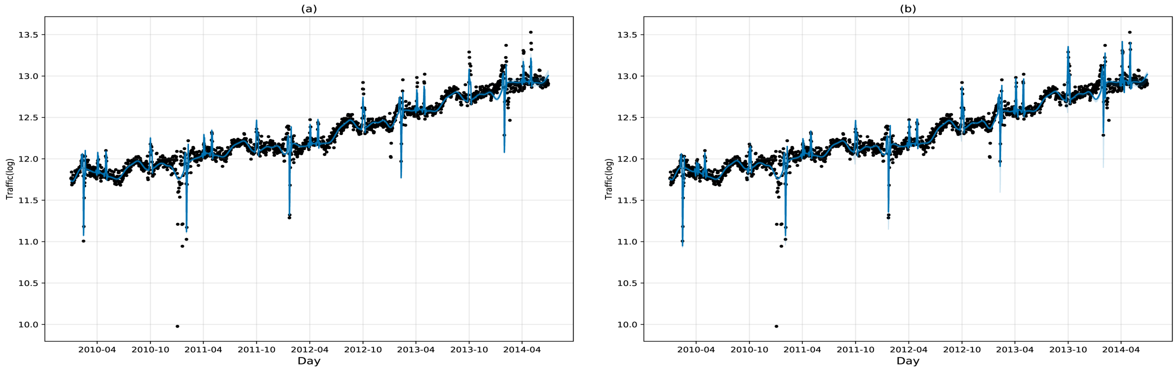

Fig. 5. Modeling and prediction results (from 2013.7 to 2014.6) : (a) CG model, (b) EG model

TABLE I
FITTING AND PREDICTION ACCURACY

Period	Non-Holiday	Spring Festival			Ching Ming Festival			Labor Day			National Day		
Metric	MRE	MRE	REPD	REPV	MRE	REPD	REPV	MRE	REPD	REPV	MRE	REPD	REPV
EG	0.060	0.180	0.087	0.087	0.045	0.117	0.117	0.145	0.1148	0.234	0.098	0.07	0.07
CG	0.057	0.300	0.212	0.212	0.143	0.124	0.124	0.199	0.269	0.269	0.167	0.187	0.187
STL-ARIMA	0.123	0.319	0.468	0.435	0.382	0.380	0.372	0.459	0.447	0.447	0.275	0.346	0.346
STL-ETS	0.186	0.367	0.515	0.484	0.448	0.444	0.436	0.523	0.502	0.502	0.305	0.369	0.369
Holt-Winter	0.140	0.418	0.409	0.491	0.444	0.521	0.441	0.496	0.357	0.488	0.317	0.409	0.399

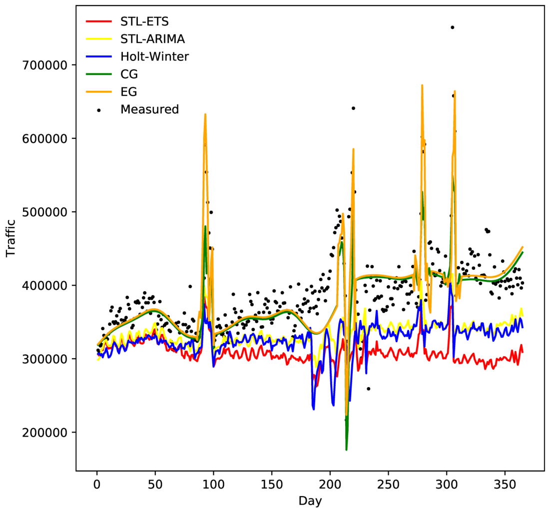

Fig. 6. Prediction result

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APPENDIX

```
model {
k ~ normal(0, 5);
b ~ normal(0, 5);
delta ~ double_exponential(0, tau);
beta ~ normal(0, sigma);
y ~ normal((k + A * delta) .* t + (m + A * gamma) +
    L .* b .* t + X * beta, sigma);
}
```