Development of Dynamic Platoon Dispersion Models for Predictive Traffic Signal Control

Luou Shen, Ronghui Liu, Zhihong Yao, Weitiao Wu, Hongtai Yang

Abstract—**As the development of traffic detection technology, recent research is directed to a new generation of signal control system supported by new traffic data. One of these directions is dynamic predictive control by incorporating short-term prediction capability. This paper focuses on investigating of dynamic platoon dispersion models which could capture the variability of traffic flow in a cross-sectional traffic detection environment. The dynamic models are applied to predict the evolution of traffic flow, and further used to produce signal timing plans that account not only for the current state of the system but also for the expected short-term changes in traffic flows. We investigate factors affecting model accuracy including time-zone length, position of upstream traffic detection equipment, road section length, traffic volume, turning percentages, and computation time. The impact of these factors on the model performance is illustrated through a simulation analysis, and the computation performance of models is discussed. The results show that both the dynamic speed-truncated normal distribution model (DNDM) and dynamic Robertson model (DRM) with dynamics outperform their respective static versions, and that they can be further applied for dynamic control.**

Index Terms—**Traffic Signal; Cross-Sectional Traffic Detection Environment; Dynamic Platoon Dispersion Model; Flow Distribution; Predictive Control.**

I. Introduction

TRAFFIC flows are separated by intersections and formed into platoons along urban streets. Because of different traveling speeds, vehicle operating conditions, and driver behaviors, platoons disperse along the street when moving downstream. Such a phenomenon is called platoon dispersion.

When traffic detection is deployed at certain cross-section location along the road, it is called cross-sectional traffic detection environment. Traffic detectors are widely implemented at stop-line and upstream cross-sections to support traditional actuated and responsive control. Such detectors generally record vehicles' existence and passage information. Here, we propose that vehicles' speed data can be collected at upstream cross-section as a new function of the cross-sectional traffic detection environment. Furthermore, based on the flow information gathered at the upstream cross-section, the arriving flow distribution at downstream stop-line can be predicted using platoon dispersion models which is a central part of the new generation of dynamic predictive traffic signal control system. As reported in COP [1], ALLONS-D [2], LOTC [3], and studies by Gomes [4] and Tan [5] these algorithms are based on the prediction of flow arrivals at stop-line.

Most of the conventional platoon dispersion models are developed for offline applications, as their parameters is calibrated using historically collected static data. Traffic signal control strategies based on static traffic data are not able to respond timely to disruptions of traffic flow and to anticipate changes in the operating environment. As a result, they do not pre-emptively consider any change in the constituting signal timing plans. There have been studies [6-8] which used the historical average speed assumption of traffic flow for real-time applications. However, this is unrealistic since vehicles' different traveling speeds lead to platoon dispersion, especially in under-saturated traffic conditions.

Recent development in Vehicle Infrastructure Integration (VII) [9-11] technology based on wireless communication between vehicle and infrastructure offers a new way for traffic detection. This new type of traffic detection is a floating environment, which uses two wireless communication channels to collect continuously (actually in small time interval) both the traffic data and the positioning data between floating vehicles and fixed-location communication center. While, comparing to this under developing floating traffic detection environment, in cross-sectional traffic detection environment, vehicles positioning is not needed since the location of the detection equipment is already known.

Therefore, this study particularly investigated the dynamic platoon dispersion models in a cross-sectional traffic detection environment which can be achieved, for example, by using VII technology. Based on this environment, dynamic predictive signal control can be achieved by applying dynamic predictive strategies. Furthermore, the cross-sectional traffic detection environment could provide additional data such as the traffic turnings after vehicles have passed the stop-line cross-section and the vehicle delays between the upstream and stop-line cross-sections. For example, the city of Chongqing, China has installed Radio Frequency Identification (RFID) detection roadside units (RSUs) at more than 900 cross-sections, and electronic license place has been mandatorily installed for all

Manuscript received on July, 2016; revised on March, 2017; November, 2017.

This work was supported by the Cultivation Program for the Excellent Doctoral Dissertation of Southwest Jiaotong University (A0920502051703-2).

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local vehicles. As only part of the new generation of the traffic signal control system, this paper focuses on the development of dynamic platoon dispersion models in the cross-sectional traffic detection environment, other topics will be examined at next step.

The remaining parts of the paper are organized as follows: first, literature review is presented; second, dynamic platoon dispersion models are proposed and methods for parameter calibration are developed; then, factors affecting the performance of models are assessed in a microscopic traffic simulation environment, and the computation performance of models is discussed; and finally, conclusions are provided and future work is discussed.

II. LITERATURE REVIEW

The diffusion or spreading effect of the traffic platoon as it moves downstream along the urban street was pioneered by Pacey [12], and the experimental verification was conducted under moderate traffic volumes. Grace and Potts [13] further investigated this macroscopic model with the assumption that the speeds of the vehicles in the platoon follow a normal distribution. Later, Hiller and Rothery [14] proposed a delay minimization model using the concept of a cyclic traffic platoon profile. With the data collected by Hiller and Rothery, Robertson [15] developed a platoon dispersion model formulated in a recursive fashion, laying the foundation of TRANSYT and TRANSYT-7F, and was later used in SCOOT [16], SATURN [17], and TRAFLO [18]. Seddon [19] reported that Robertson's model was equivalently based on shifted geometric distribution of travel time. Giving a different view, Tracz [20] and Polus [21] reported that the distribution of vehicle's travel time is not always a shifted geometric distribution as in Robertson's model, but is more consistent with a normal, lognormal, or a gamma distribution. Yu [22] presented a methodology to calibrate Robertson's model with the information of link travel time. Farzaneh et al. [23] proposed a method to effectively consider the influence of speed variability in the calibration process of the Robertson's model using historical data. Day and Bullock [24] discussed the calibration of Robertson's model parameters by using the high-resolution signal event data but in a post-event fashion. In a recent study, Bie et al. [25] analyzed the impact of the number of lanes on the parameters of the static version of Robertson' model. Shen and colleagues [26-28] proposed platoon dispersion models with truncated normal distribution of speed, and mixed Gaussian distribution for mixed traffic flow. However, all these models are developed and calibrated with offline data. For online applications, dynamic models are needed to capture the changing traffic flow.

The real-time data collected in the traffic detection environment [9] provides opportunities for predictive signal control, which was not possible with data from traditional traffic detectors. This environment includes onboard units (OBUs) and roadside units that communicate with vehicles using technology such as Dedicated Short-Range Communications [10]. The OBUs serve as virtual detectors in the traffic stream. The data that RSUs could collect include vehicles' identification number (ID), speed, timestamp when the information was collected, and the position of the RSUs. The RSUs can be deployed close to upstream intersection at the outgoing approach, at intersection stop-line, or even at several cross-sections along the road section.

By making use of the speed data recorded at upstream cross-section during a specified rolling time window, dynamic platoon dispersion models can be established to predict the future arrival distribution of traffic flow at downstream stop-line. Therefore, short-term future vehicle arrivals could be estimated based on real-time information of the current conditions in addition to the historical data.

III. DYNAMIC PLATOON DISPERSION MODELS

In this section, we first introduce the concept of a dynamic time window for generating the distribution of traffic characteristics. We will then present two dynamic platoon dispersion models, as adapted from two established static models.

A. *Time window*

The parameters of static traditional platoon dispersion model are calibrated using offline data. On the contrary, dynamic models reflect the varying characteristics of traffic flow, which can be achieved by updating the parameters of flow conditions in a small moving time window. There are three typical classes of time window: front-, middle-, and back-positioned windows, as shown in Fig.1. For a current time t_u, and time window length of T, the corresponding three time windows positioning classes are: $[t_u - T, t_u]$, $[t_u - 0.5T, t_u + 0.5T]$, and $[t_u, t_u + T]$. The model parameters at time t_u are then calibrated based on the data collected in the corresponding time window through statistical computing.

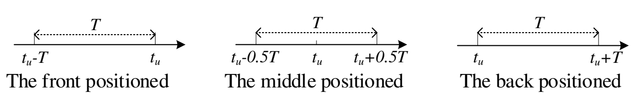


Fig. 1. Three typical time window classes.

Naturally, when the aggregating time window is too long, it misses out the varying conditions of traffic flow; on the other hand, too short a time window can't capture sufficient samples to ensure reliable statistical results. Since the traffic detection environment could collect and transmit real-time data in a small time step, such as 1-3 s, moving horizon method can be adopted to update the parameters by including the latest data. The middle- and back-positioned classes cannot be applied with full data for those most current time steps since the data for the future period of $[t_u - 0.5T, t_u + 0.5T]$, $[t_u, t_u + T]$ is not available. This situation and method for selecting the best time window class are further discussed in the later sections.

B. *A dynamic speed-truncated normal distribution model (DNDM)*

We consider a traffic detection environment whereby the cross-section is set at an upstream location x_u as shown in Fig.2, from where individual vehicle's speed is collected. Based on such information, models can be developed to predict the arrival distribution at a downstream location x_d (Fig. 2). Other than assuming that vehicles travel at constant speed along the road section, the speeds are assumed to follow a truncated normal distribution for DNDM, which has the probability density function as follows:

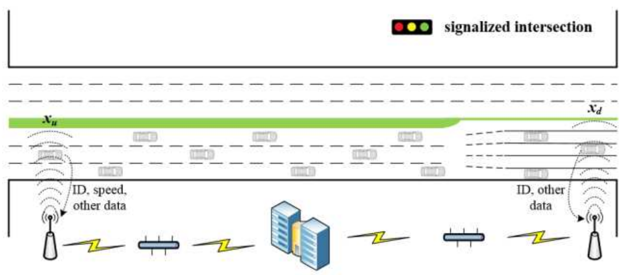


Fig. 2. Diagram of the cross-sectional traffic detection environment.

$$f_{t_u}(v) = \frac{c}{\sqrt{2\pi}} exp\left[-\frac{\left(v-u_{t_u}\right)^2}{2\sigma_{t_u}^2}\right], \quad v_{min} \le v \le v_{max} \tag{1}$$

where c is the coefficient of truncated distribution, u_{t_u}, σ_{t_u}, v_{min}, and v_{max} are the average speed, the mean square deviation of speed, the minimum, and maximum speed at time t_u over time window T, respectively.

If there are total N vehicles passing the upstream cross-section during time window T, then the parameters in Eq.(1) can be estimated using the following formula:

$$u_{t_u} = \frac{1}{N}\sum_{i=1}^{N} v_i \tag{2}$$

$$\sigma_{t_u}^2 = \frac{1}{N}\sum_{i=1}^{N}\left(v_i - u_{t_u}\right)^2 \tag{3}$$

$$v_{min} = \min_{1\le i\le N} v_i \tag{4}$$

$$v_{max} = \max_{1\le i\le N} v_i \tag{5}$$

$$c^{-1} = \int_{v_{min}}^{v_{max}} \frac{1}{\sqrt{2\pi}} exp\left[-\frac{\left(v-u_{t_u}\right)^2}{2\sigma_{t_u}^2}\right] dv \tag{6}$$

where v_i is the spot speed of vehicle i passing the cross-section during the time window. Eq.(6) can be solved using the nature characteristic equation of probability density function: $\int_{v_{min}}^{v_{max}} f_{t_u}(v) = 1$.

With the above dynamically calibrated model parameter values, and following the method proposed in literature [26] the upstream flow at time t_u can be estimated to arrive at the downstream location x_d according to the following conditions:

a) If $\frac{\Delta x}{v_{min}} \le \frac{\Delta x}{v_{max}} + \Delta t$,

$$q_d(x_d, t_u, t_d) = \begin{cases} 0, & t_d < \frac{\Delta x}{v_{max}} \vee t_d > \frac{\Delta x}{v_{min}} + \Delta t \\ q_u(x_u, t_u)\int_{\frac{\Delta x}{\Delta t}}^{v_{max}} f_{t_u}(v)dv, & \frac{\Delta x}{v_{max}} \le t_d < \frac{\Delta x}{v_{min}} \\ q_u(x_u, t_u)\int_{v_{min}}^{v_{max}} f_{t_u}(v)dv, & \frac{\Delta x}{v_{min}} \le t_d < \frac{\Delta x}{v_{max}} + \Delta t \\ q_u(x_u, t_u)\int_{v_{min}}^{\frac{\Delta x}{t_d-\Delta t}} f_{t_u}(v)dv, & \frac{\Delta x}{v_{max}} + \Delta t \le t_d < \frac{\Delta x}{v_{min}} + \Delta t \end{cases} \tag{7}$$

b) If $\frac{\Delta x}{v_{min}} > \frac{\Delta x}{v_{max}} + \Delta t$,

$$q_d(x_d, t_u, t_d) = \begin{cases} 0, & t_d < \frac{\Delta x}{v_{max}} \vee t_d > \frac{\Delta x}{v_{min}} + \Delta t \\ q_u(x_u, t_u)\int_{\frac{x}{\Delta t}}^{v_{max}} f_{t_u}(v)dv, & \frac{\Delta x}{v_{max}} \le t_d < \frac{\Delta x}{v_{max}} + \Delta t \\ q_u(x_u, t_u)\int_{\frac{x}{\Delta t}}^{\frac{\Delta x}{t_d-\Delta t}} f_{t_u}(v)dv, & \frac{\Delta x}{v_{max}} + \Delta t \le t_d < \frac{\Delta x}{v_{min}} \\ q_u(x_u, t_u)\int_{v_{min}}^{\frac{\Delta x}{t_d-\Delta t}} f_{t_u}(v)dv, & \frac{\Delta x}{v_{min}} \le t_d < \frac{\Delta x}{v_{min}} + \Delta t \end{cases} \tag{8}$$

where q_u and q_d are the upstream and downstream flow rates, respectively, Δt is time interval and $\Delta x = x_d - x_u$.

The aggregated arriving flow distribution is computed by accumulating the arriving flows at downstream for all upstream departing flows.

$$q_d(x, t_d) = \sum_{t_u = x/V_{max}}^{t_u = x/V_{min}} q_d(x, t_u, t_d) \tag{9}$$

where V_{min} and V_{max} are the minimum and maximum speed of the road section, respectively, which refers to the minimum and maximum travel time along the road section.

C. A dynamic Robertson model (DRM)

Similar to the development of dynamic speed-truncated normal distribution model, DRM is formed from traditional static Robertson model. Following literature [19], the static Robertson platoon dispersion model can be presented as:

$$q_d(x_d, t_d) = \sum_{t=t_a}^{\infty} F(1-F)^{t-t_a} q_u(x_u, t_d - t) \tag{10}$$

where,

$$F = \frac{1}{1 + \alpha\beta t_M} \tag{11}$$

where t_a is the minimum travel time, F is a smoothing factor, α is the platoon dispersion coefficient, β is the travel time factor, and t_M is the average travel time.

F and t_a are usually estimated using historical data. The rolling horizon method is a natural choice for modeling dynamic traffic flow. Therefore, these parameters become time-dependent variables F_t and $t_a(t)$ at time t.

The departing traffic flow distribution $q_u(x_u, t_u)$ at time t_u has dynamic parameters of F_{t_u} and $t_a(t_u)$. In what follows, we discuss how to estimate those parameters in real-time manner. Referring to the Robertson model, the arriving flow distribution at downstream is expressed as:

$$q_d(x_d, t_u, t_d) = \begin{cases} 0, & t_d < t_a(t_u) \\ q_u(x_u, t_u) F_{t_u} \left(1 - F_{t_u}\right)^{t_d - t_a(t_u)}, & t_d \geq t_a(t_u) \end{cases} \tag{12}$$

The rational of the DRM model can be illustrated in Fig.3, which shows how an upstream departing flow profile is discretized and then used to produce the downstream arriving flow distribution.

At the downstream stop-line, the arriving traffic flow distribution can be expressed as the sum of the discretized flow distributions as follows:

$$q_d(x_d, t_d) = \sum_{t_u=0}^{\propto} q_d(x_d, t_u, t_d) \tag{13}$$

Eqs.(12) and (13) can be transformed into Eq.(14), and the model becomes a dynamic model whereby the model parameters vary with time. We term it a dynamic Robertson model (DRM) of platoon dispersion.

$$q_d(x_d, t_d) = \sum_{t=0}^{\propto} G_{t_u}(t) q_u(x_u, t_d - t) \tag{14}$$

where,

$$G_{t_u}(t) = \begin{cases} 0, & t < t_d - t_a(t_u) \\ F_{t_u}\left(1 - F_{t_u}\right)^{t - t_a(t_u)}, & t \geq t_d - t_a(t_u) \end{cases} \tag{15}$$

where F_{t_u} and $t_a(t_u)$ are the dynamic parameters of upstream flow at time step t_u ($t_u = t_d - t$).

In a cross-sectional traffic detection environment, a vehicle's spot speed at the upstream cross-section x_u at time t_u can be detected and we note it v_i. If there are N passing vehicles in time window T, the parameters in Eq. (15) can be estimated as follows:

$$t_M = \frac{1}{N} \sum_{i=1}^{N} \frac{\Delta x}{v_i} \tag{16}$$

$$t_a(t_u) = \beta t_M \tag{17}$$

$$F_{t_u} = \frac{1}{1 + \alpha t_a(t_u)} \tag{18}$$

where according to TRANSYT-7F manual [29, 30], β is usually set as 0.8, and α is set based on the traffic flow characteristics, and in central business district (CBD) it is 0.5.

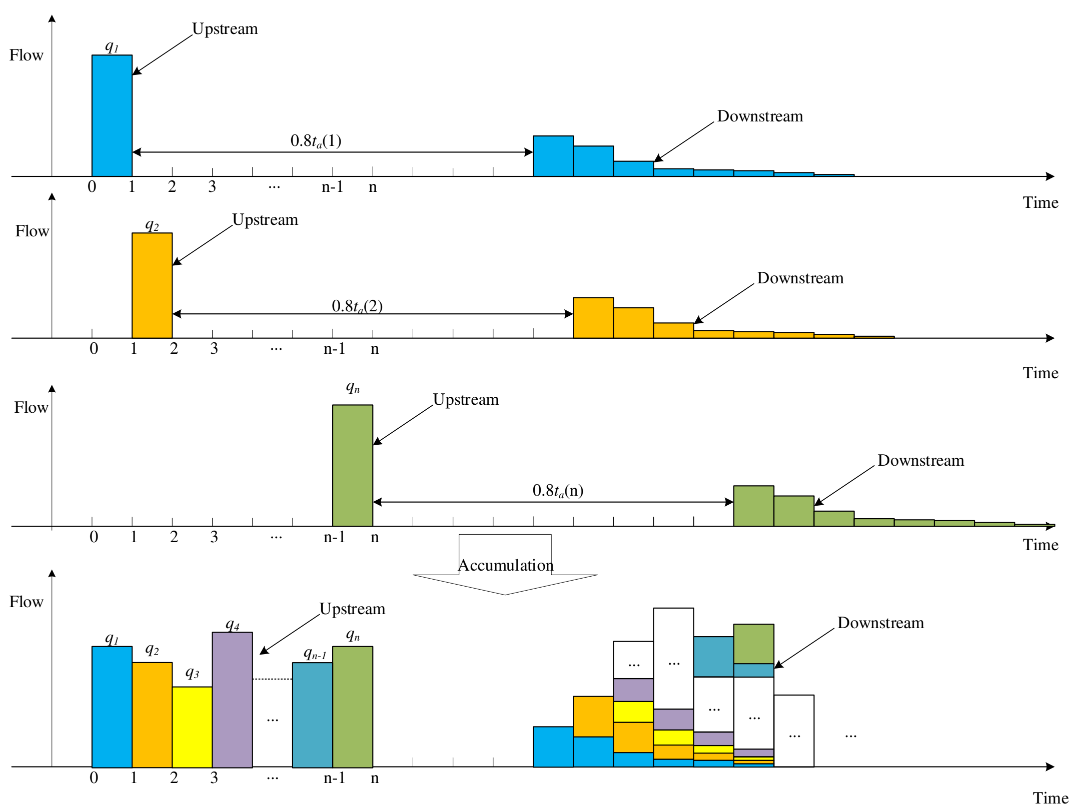


Fig. 3. Discretized platoon dispersion in DRM.

D. A dynamic average speed model (DAM) and a constant speed model (CM)

In the DAM, the i^{th} vehicle's speed is assumed as the average speed of vehicles in time window T. The average speed can be estimated by following the DNDM in a similar way.

While, in the CM, the i^{th} vehicle's speed is assumed as its spot speed at the upstream traffic detection section, and will keep constant till reaching the stop-line. Therefore, the CM has both dynamic and static feature.

E. A static Robertson model (SRM)

Different to the DRM, in the SRM, the two main model parameters: minimum travel time $t_{\min}$ and smoothing factor F are estimated using historical data [23-25] which was usually collected at field in a certain day.

IV. EVALUATION OF THE CONTRIBUTING FACTORS

In this section, we assess the proposed dynamic truncated normal distribution model (DNDM) and dynamic Robertson model (DRM) and compare them with the dynamic average speed model (DAM), the constant speed model (CM) and static Robertson model (SRM). The model parameters of the DAM are estimated using the process mentioned earlier, while the CM can be applied in both offline and dynamic modes. The SRM is already discussed in before sections.

To find out the best traffic detection environment settings, the impact of factors on the model accuracy is evaluated through a simulation analysis. These factors include: the length of the time window, the cross-section location of upstream RSU, the length of the road section, and two traffic condition factors: the volume level and the turning percentage.

A. Simulation model

1) Development of cross-sectional traffic detection environment

The cross-sectional traffic detection environment is modeled in microscopic traffic simulation software PTV Vissim [31]. Fig. 4 shows the testing road network. It includes an upstream signal intersection (node A) which is set as actuated control in order to create the randomness of traffic flow due to variable cycle length, at a downstream signalized intersection (node B), and the road section in between. The downstream signal intersection is set to always run in green light for the study approach in order to obtain vehicle's arrival time as shown in Fig.4.

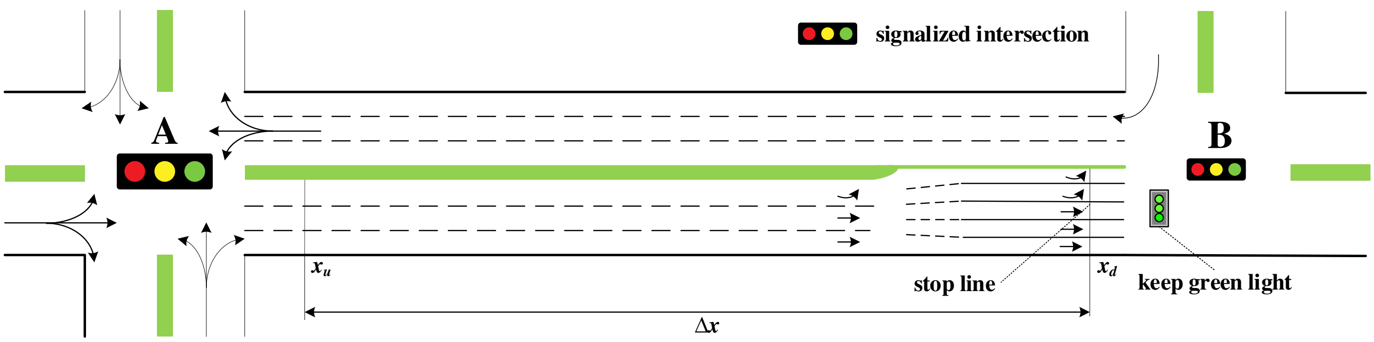


Fig. 4. The testing cross-sectional traffic detection environment.

To collect the traffic data, RSUs are deployed at two cross-sections: one immediately downstream of Node A at location x_u, and the other on approaching the downstream Node B at x_d. As shown in Fig.4, a typical urban arterial section was modeled with three lanes in one direction. The actuated signal control is applied to the intersection A according to the changing traffic flow conditions. As a typical case, the intersection A has four approaches and each has three turning movements: left-turn, through and right-turn. The approach of intersection B includes three through lanes, two left-turn lanes, but no right-turn lane, which creates a relatively convenient condition in this study.

Since the purpose of this study is to capture the arriving flow distribution at downstream stop-line, the signal for the study approach at intersection B is set as always green. Here, it is not necessary to consider the vehicle queueing although the queueing can be estimated using queueing theory or shockwave theory.

The upstream detectors at location x_u are used to record the simulated vehicle's ID and spot speed data through Vissim COM interface [31, 32]. The detectors at downstream stop-line x_d are used to collect the vehicle's ID only. The distance between the two cross-sections is the travel length Δx. By tracking the vehicles' ID, and comparing the time-stamps, the travel time and turning directions can be easily obtained.

2) Simulation environment setting

In Vissim, the simulation time step is set as 1 s, and the simulation period is 4200 s including a warm-up period of 300 s, three 900 s periods with three different levels of traffic volume, and a traffic dissipation period of 300 s.

3) Performance evaluation index

Model performance can be evaluated by comparing the predicted and the actual arriving flow distributions. Usually, the root mean square errors (RMSE) are used for distribution comparison, but it is affected by the traffic volume value. Therefore, when comparing different traffic volumes, the coefficient of variation (without unit) is a better choice. But the number of time intervals in the field observation and calculated number of time intervals in the models are different [25], So the comparison is only made during the same time intervals. A more accurate definition for this index is the range of coefficient variation (RCV), and the formula is shown as follows:

$$RMSE = \sqrt{\frac{1}{K}\sum_{i=0}^{K}\left[q_p^{d*}(i) - q_a^{d*}(i)\right]^2} \tag{19}$$

$$RCV = \frac{RMSE}{\frac{1}{2K}\sum_{i=0}^{K}\left[q_p^{d*}(i) + q_a^{d*}(i)\right]} \tag{20}$$

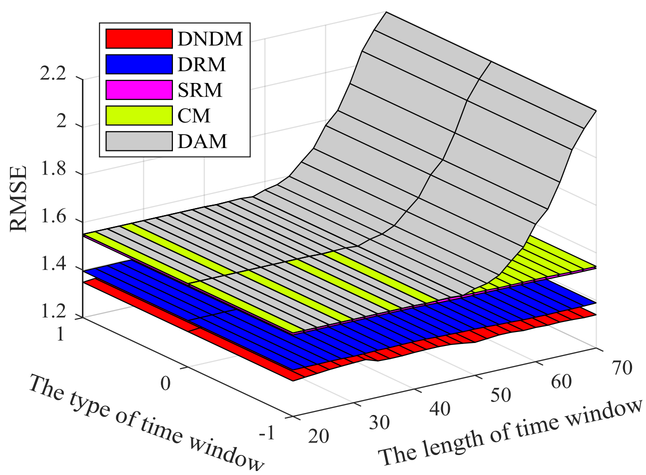
where K is the predicted time range, $q_p^{d*}(i)$ and $q_a^{d*}(i)$ represent the predicted and actual number of arriving vehicles during a small time unit, such as 5 s, respectively.

RMSE is selected as the performance index when traffic volume is fixed, while both the RMSE and RCV are used for evaluating the impact of varied traffic volumes and turning percentages.

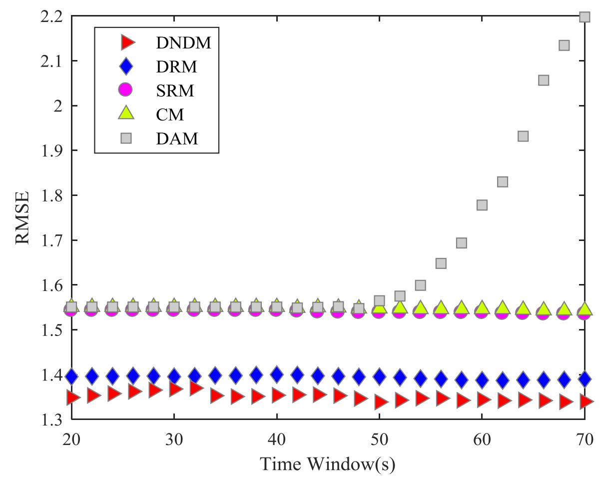
B. *Simulation analysis*

1) *Time window selection*

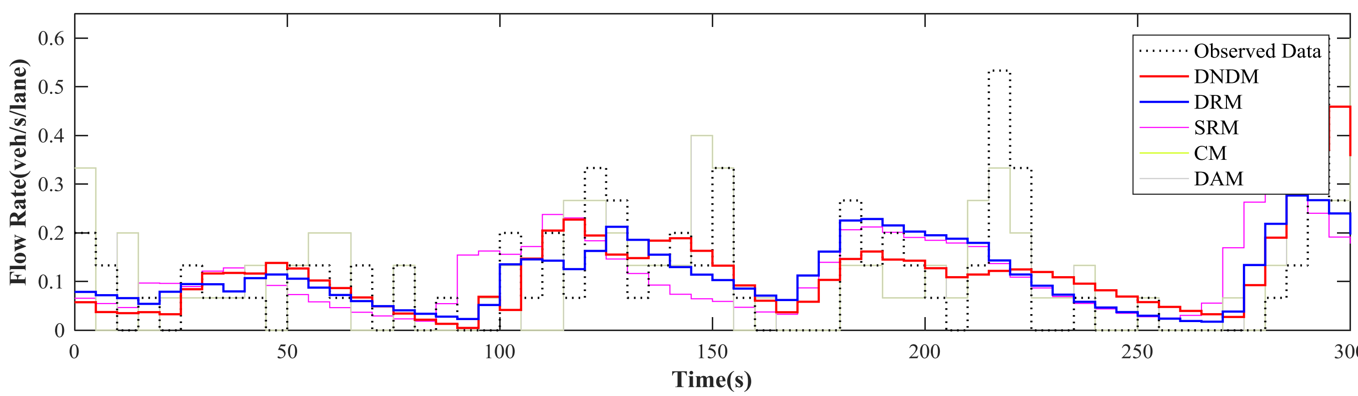
Dynamic platoon dispersion model reflects the dynamic characteristic of traffic flow by separating the time into small time windows. Therefore, theoretically the time window should be set as small as possible to capture the variability of traffic flow. However, as discussed earlier, the number of vehicles should be large enough to ensure statistical significance. Since the distance between two adjacent signal intersections is mostly in the range between 250 and 1500 m in the real world, a wide range of the potential time window is chosen as 20-70 s. Within this range, simulation analysis is carried out to explore the optimal time window length. Besides, five platoon dispersion models are evaluated for different time window lengths, and the previous defined performance index of RMSE is used for comparison as shown in Fig.5.



a) The RMSEs of different time window class and length.



b) The RMSEs of different time window lengths for the front-positioned class.



c) The arrival flow rate of the downstream intersection.

Fig. 5. The performance of five models for different time windows (in Fig.5a, -1 means the front-positioned time window class, 0 means the middle-positioned class, 1 means the back-positioned class; the time interval is 5 s and the time window is 50 s).

Results in Fig.5a show that the difference among the three time window classes is small. Considering the real-life situation that the future data is not available for the middle-and back-positioned classes, the front-positioned time window class $[t_u - T, t_u]$ is chosen for further analysis. Meanwhile, the dynamic truncated normal distribution model has the smallest RMSE when compared with other models, which appears to provide the best prediction accuracy as shown in Fig.5b. When the length of the time window is less than 50 s, the difference of RMSE is negligible for different time windows. When the length is greater than 50 s, RMSE increases significantly for the dynamic average speed model. Since the length of the time window cannot be too short or too long, the final length of the time window is set as 36 s considering that the data updating step is 2 s and it is suitable for the simulation experiment analysis, which is used in the following analysis.

2) Location of upstream cross-sectional traffic detection

As for the base case, the length of the road section is set as 750 m, and traffic volume as 500 veh/h/lane. In the field, vehicles usually start up when the signal light turns to green, and then accelerate to the normal speed after passing the intersection some distance along the outgoing approach. The distance ranges from 10 to 80 m from the intersection to the outgoing approach, which is analyzed to check its influence on the model performance. The results are listed in Table I, and Fig. 6 shows the performance of the five models.

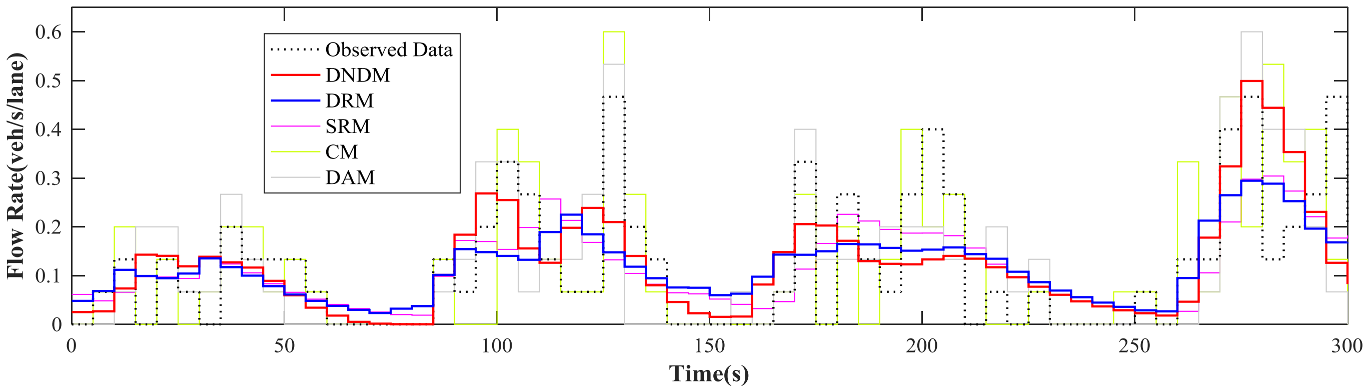


Fig. 6. The arrival flow rate of the downstream intersection (the time intervals is 5 s and the location of upstream cross-section at upstream is 30 m).

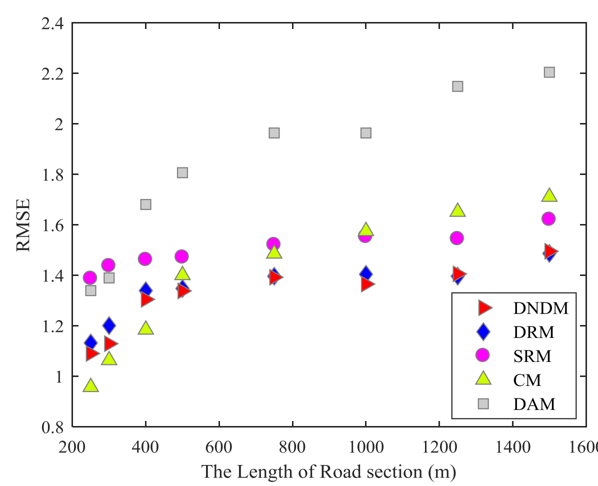
TABLE I
THE RMSES FOR DIFFERENT LOCATIONS OF UPSTREAM CROSS-SECTION AT UPSTREAM

The location of upstream cross-section (m)	DNDM	DRM	SRM	CM	DAM
10	1.3564	1.3161	1.3480	1.5230	1.9471
20	1.3836	1.3521	1.3876	1.4715	1.9516
30	1.3503	1.3439	1.3796	1.5072	1.9303
40	1.3335	1.3311	1.3628	1.4869	1.8592
50	1.3077	1.3040	1.3384	1.4173	1.7797
60	1.3169	1.3232	1.3522	1.3792	1.7907
70	1.2865	1.3145	1.3393	1.3529	1.6985
80	1.2939	1.3271	1.3669	1.3545	1.7358
Average	1.3286	1.3265	1.3593	1.4366	1.8366

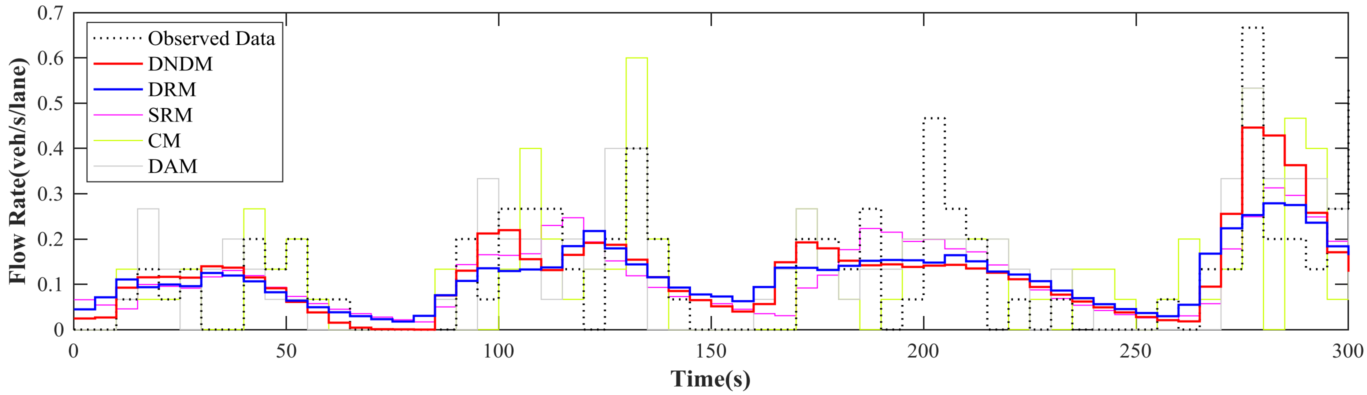
The data in Table I shows that the RMSE decreases as the distance increases for all five models except for the location of 50 and 70 m. This is because it requires some distance for vehicles to accelerate to their expected speed from upstream stop-line, and merging of traffic flows from different tuning directions usually occurs at the beginning of the outgoing approach. Meanwhile, the scenario with the distance of 70 m has the smallest RMSE when compared with other distances, indicating it has the highest prediction accuracy. Therefore, the distance of 70 m is suitable for deployment of RSU. In terms of model performance, DNDM usually performs better than other models for all distances.

3) Length of the road section

As for the upstream cross-section location set at 70 m, and volume level at 500 veh/h/lane, model performance is analyzed for different lengths of road section: 250 m, 300 m, 400 m, 500 m, 750 m, 1000 m, 1250 m, and 1500 m. Their corresponding RMSE index is presented in Fig. 7.



a) The RMSEs of different lengths of road section.



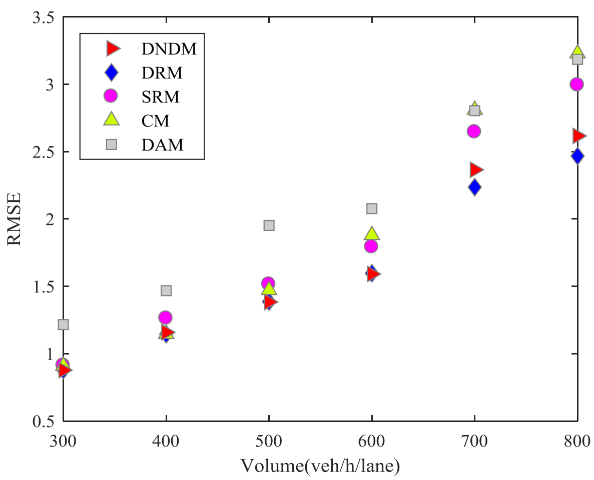
b) The arrival flow rate of the downstream intersection.

Fig. 7. The performance of five models for different lengths of road section (the time interval is 5 s and the length of road section is 750 m).

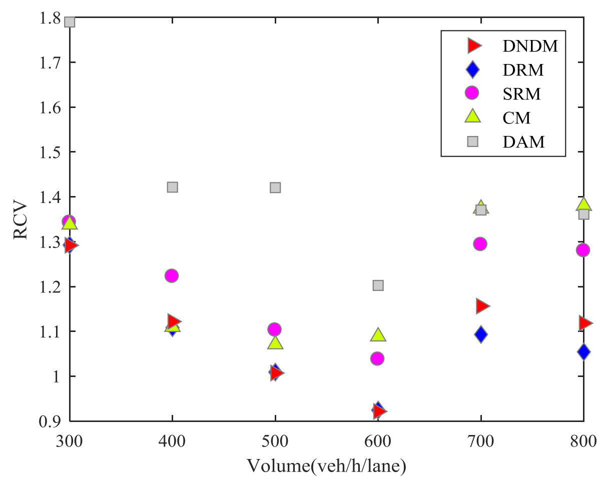
Two patterns can be easily concluded from Fig. 7a: DNDM and DRM always perform well for all length scenarios except for the length less than 400 m; as for length shorter than 400 m, the static speed model has a slightly smaller RMSE when compared with DNDM and DRM. This is reasonable since vehicles have less flexibility to change speed along a shorter road section. However, when the distance between two intersections becomes shorter, it is recommended to apply coordinated signal timing strategy.

4) Volume level

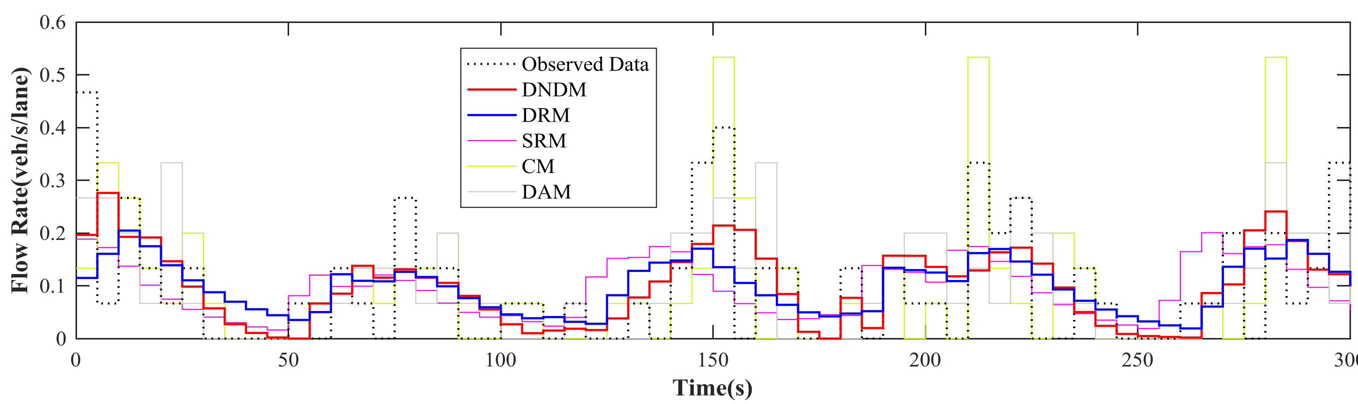
With fixed upstream cross-sectional traffic detection location at 70 m, different volume levels are also investigated. Five sceneries, 300 veh/h/lane, 400 veh/h/lane, 500 veh/h/lane, 600 veh/h/lane, 700 veh/h/lane, and 800 veh/h/lane, are created to assess the model performance. Fig. 8 shows the performance of the five models at different volume levels.



a) The RMSEs of different traffic volume levels.



b) The RCVs of different traffic volume levels.



c) The arrival flow rate of the downstream intersection.

Fig. 8. The performance of five models for different traffic volume (the time interval is 5 s and the volume is 400 veh/h/lane).

The data in Fig.8a shows that the RMSEs of all five models increase with traffic volume. However, Fig.8b shows the RCVs decrease with traffic volume (300-700 veh/h/lane) before reaching the lowest point when the volume is 500-600 veh/h/lane, and then starts to increase. But when the volume reaches 800 veh/h/lane (i.e., close to oversaturated traffic condition), the RCVs begins to decrease. This suggests that the RCVs have different behavior for oversaturated traffic condition. Meanwhile, all models present better performance for middle traffic volume level and the DNDM outperforms the other models.

5) Turning direction

Different turning directions normally exist at an intersection. However, the turning direction information is not available based on upstream cross-sectional traffic detection data. Therefore, it is necessary to examine the model performance for downstream traffic flows turning at different directions. With the fixed length of road section of 750 m, by tracking the vehicles' ID in the traffic detection environment, traffic flow turning direction can be obtained when vehicles cross the stop-line. Table II presents the RMSE and RCV values for different turning directions.

TABLE II
THE RMSES FOR DIFFERENT TRAFFIC DIRECTIONS

Metric	Direction	DNDM	DRM	SRM	CM	DAM
RMSE	Left Turns	0.7788	0.7893	0.8199	0.8597	0.8623
	Through	0.9856	0.9735	1.0208	1.0384	1.0415
	Mixed	1.3836	1.4002	1.5147	1.4715	1.4862
RCV	Left Turns	1.4487	1.4407	1.5242	1.6758	1.6758
	Through	1.1546	1.1858	1.2902	1.2912	1.2912
	Mixed	0.9862	1.0191	1.1246	1.1304	1.1304

Table II shows that the RMSE of left-turn traffic is always smaller than that of through traffic. This is because the left-turn traffic volume is lower than the through traffic volume as concluded in previous section. However, the RCV is always larger for the left-turn traffic than the through traffic. This is because the left-turn traffic needs the additional maneuver of merging into the storage bay. This suggests that setting a cross-section at the beginning of the turning bay may lead to better prediction.

6) Computation performance

In this section, we discuss the complexity of the five algorithms. First, we theoretically analyze the complexity of those algorithms. Assuming the number of vehicles, the length of time window, the length of road segment, minimal and maximal travel speed are N, T, L, V_{min}, and V_{max}, respectively. From the Eqs. (1-18), we can get the complexity of five algorithms, as shown in Table III.

TABLE III
THE COMPLEXITY FOR DIFFERENT ALGORITHMS

Models	Complexity
DNDM	$O(N \cdot T \cdot (L/V_{min} - L/V_{max}))$
DRM	$O(N \cdot T \cdot (L/V_{min} - L/V_{max}))$
SRM	$O(N \cdot (L/V_{min} - L/V_{max}))$
CM	$O(N)$
DAM	$O(N \cdot T)$

From Table III, we know the complexity of DNDM is the same as DRM, and the complexity of CM is the smallest. The five models are implemented in the MATLAB, and the computational times are discussed below.

Those scenarios mentioned in the section of *Location of upstream cross-sectional traffic detection* are chosen to compare the computation efficiency of different models. The computation time of the five models is recorded on a computer with an Intel Core5 @ 3.30GHz with 8GB RAM PC, and shown in Table IV.

TABLE IV
THE COMPUTATIONAL TIME (10^{-3}S) FOR DIFFERENT MODELS

Scenario	DNDM	DRM	SRM	CM	DAM
1	2.8474	0.1139	0.0958	0.0002	0.0272
2	2.8035	0.1144	0.0917	0.0001	0.0261
3	2.7727	0.1116	0.0925	0.0002	0.0261
4	2.8388	0.1119	0.0916	0.0001	0.0256
5	2.9197	0.1126	0.0925	0.0002	0.0263
6	2.8065	0.1131	0.0919	0.0003	0.0251
7	2.9279	0.1130	0.0924	0.0002	0.0251
8	2.9662	0.1115	0.0918	0.0002	0.0253
Average	2.8603	0.1127	0.0925	0.0002	0.0258

Note: The prediction time interval is 200 seconds in Table III.

As shown in Table IV, the computation time of all dynamic platoon models is longer than that of static models. The computation time of the DNDM is at least twenty times higher than that of the other models since it contains many integral functions. The DRM has similar computation time as the SRM, while, DRM presents smaller prediction error as shown in the above analysis. Therefore, the DRM is recommended for future test. Compared with other models, both CM and DAM have shorter computation time since they only contain some simple geometric calculations.

This means that the computation time of all models is less than 0.005 s, which proves its feasibility to be applied in the dynamic predictive signal control systems.

V. CONCLUSIONS AND FUTURE WORK

In this paper, a cross-sectional traffic detection environment is proposed for the very first time which is easy for field application as the electronic plates have already been mandatorily installed in a few China metro cities; later, two dynamic platoon dispersion models are developed in the cross-sectional traffic detection environment: a dynamic speed-truncated normal distribution model, and a dynamic Robertson model. The models make use of dynamic out-flow profiles from an upstream node, available from the cross-sectional traffic detection environment, to predict a dynamic arrival profile of traffic to a downstream node. Meanwhile, the paper provides the model formulations and methods for estimating the dynamic model parameters.

The cross-sectional traffic detection environment and the dynamic platoon dispersion models make it possible for signal control system to have short-term prediction capability which contributes to a new generation of signal control which is the dynamic predictive signal control system.

We also evaluate the sensitivities of the factors affecting the model performance in a simulation environment. A summary of the findings and conclusions is listed below:

1. The range of 20-50 s for the time window of DNDM shows better performance, and 36 s is recommended.

2. The distance of 50-80 m is suitable for the location of upstream cross-sectional RSU.

3. Both DNDM and DRM have the best performance when

the road section is longer than 400 m, and static speed model is superior to other models when the road section is shorter than 400 m.

4. Dynamic platoon dispersion models work well under middle-level volume.

5. The performance of dynamic platoon dispersion models in the upstream cross-section RSU shows lower accuracy for left-turning movement than for through movement.

6. The computation time of all models is less than 0.1 s with the prediction time interval as long as 200 s, which can meet the requirement for application in dynamic predictive signal control.

We have demonstrated the potential application of the DNDM and DRM in a dynamic predictive signal control system. Meanwhile, future work should consider studying the sensitivity of measurement errors and how these factors affect results, multi-cross-sectional traffic detection and feedback strategy (by tracking vehicles' ID) to improve prediction accuracy, model calibration using field data, and a mixture of traffic detection methods before full "market penetration" of VII technology.

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