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Real-Time Detector-Free Adaptive Signal Control with Low Penetration of Connected Vehicles

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Abstract

Most of the existing connected vehicle (CV)-based traffic control models require a critical penetration rate. If the critical penetration rate cannot be reached, then data from traditional sources (e.g., loop detectors) need to be added to improve the performance. However, it can be expected that over the next 10 years or longer, the CV penetration will remain at a low level. This paper presents a real-time detector-free adaptive signal control with low penetration of CVs ($\leq$ 10%). A probabilistic delay estimation model is proposed, which only requires a few critical CV trajectories. An adaptive signal control algorithm based on dynamic programming is implemented utilizing estimated delay to calculate the performance function. If no CV is observed during one signal cycle, historical traffic volume is used to generate signal timing plans. The proposed model is evaluated at a real-world intersection in VISSIM with different demand levels and CV penetration rates. Results show that the new model outperforms well-tuned actuated control regarding delay reduction, in all scenarios under only 10% penetrate rate. The results also suggest that the accuracy of historical traffic volume plays an important role in the performance of the algorithm.

Driven by the rapid development of connected vehicle (CV) technologies, we are on the cusp of a new revolution in transportation safety and mobility on a scale not seen since the introduction of automobiles a century ago. To evaluate the CV technologies in real-world environments, U.S. Department of Transportation (USDOT) has initialized a number of deployment projects including Safety Pilot Model Deployment project in Ann Arbor, Michigan (*1*), CV pilot deployment projects (https://www.its.dot.gov/pilots/), and Smart City Challenge (https://www.transportation.gov/smartcity). Through these projects, thousands of vehicles and hundreds of intersections have/will be equipped with dedicated short-range communication (DSRC) devices, which enable vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communications to improve safety, mobility and sustainability.

Traffic signal control system, as one of the critical components of the urban transportation operations, can also benefit from the CV technology. Through V2I communications, the traffic control system receives vehicle trajectories from nearby CVs to make control decisions. Compared with traditional data from fixed-location infrastructure-based sensors, CV data provide much more information and have high potential in improving signal operations. A number CV-based signal control and performance estimation models have been proposed (*2–8*). However, results from existing studies have shown that minimum required penetration rates vary from different applications, but typically 20–30% penetration rate is necessary (*9*). If the critical penetration rate cannot be reached, then data from traditional sources (e.g., loop detectors) need to be added to improve the performance (*10*). Some studies intended to characterize individual vehicle behaviors through limited CV trajectories. For example, Goodall et al. estimated unequipped vehicle location (*5*), and Feng et al. inferred both location and speed of unequipped vehicles (*3*). Sun and Ban attempted to reconstruct the entire trajectory of unequipped vehicles (*11*). From a traffic signal control point of view, aggregated performance measures such as volume, queue length, travel time, and delay are sufficient to optimize traffic signals. Although these aggregated metrics can be

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easily derived from individual vehicles,, it requires more information and therefore higher penetration rates. A systematic review of adaptive signal control with CVs can be found in Jing et al. (*12*).

Despite substantial efforts in investing and developing CV technologies in the past decade, over the next 10 years or longer the CV penetration rate is expected to remain at a low level. Therefore, optimizing traffic signals with low penetration rates of CVs is essential and will make an immediate impact on the state of the practice.

To the best of the authors' knowledge, there are only a few studies that have focused on a low-penetration environment. A study from Day and Bullock (*9*) proposed a proof-of-concept study to optimize signal offsets with limited CV market penetration. The penetration rates used in the paper were from 0.1% to 50%. However, instead of focusing on real-time implementation, their analysis periods were set to 3 h (offline) and 15 min (online). The selected analysis period may be sufficient for offset adjustment as offset may not change much over a few cycles. However, for real-time adaptive signal control, traffic conditions change significantly within 15 minutes. Moreover, the data used in this study were sampled from loop detectors, and does not represent real CV trajectory. Recent work done by Zheng and Liu utilized aggregated CV trajectory data to estimate traffic volumes (*13*). The model was formulated as a maximum likelihood estimation problem and solved by expectation maximization algorithm. The overall penetration rates varied from 3% to 12% at different approaches and time of day, and the mean absolute percentage error (MAPE) of the estimated volume was about 10%. However, this method cannot be directly implemented for real-time signal operations because the trajectory data need to be aggregated over days.

This paper extends the study by Zheng and Liu by combining both historical and real-time trajectory data to perform detector-free adaptive signal control. A simple probabilistic model is applied to estimate cycle-by-cycle vehicle arrival times and delays based on estimated average historical volume and a limited number of observed critical CV trajectories. Then a dynamic programming (DP)-based adaptive signal control algorithm is applied to generate the optimal signal plan, using estimated vehicle delay as the objective function. The proposed model is tested in software-in-the-loop (SIL) simulation with various low penetration rates (10%, 5%, 2%, and 0%) and demand levels at a real-world intersection. Results are compared with well-tuned actuated signal control.

The rest of this paper is organized as follows. The next section describes the methodologies for CV trajectory-based delay estimation and adaptive signal control models. Simulation results and discussions are then presented, and conclusions and areas for further research are provided in the final section.

Methodology

Before presenting the method, Figure 1 shows the CV trajectories in one lane under 10% penetration rate with a demand level of 700 veh/h/ln, which represent the raw data used in this paper. The figure shows that some CVs passed the intersection without stop while others stopped in the queue for the red signal. Some of the vehicle trajectories are only partial because of lane changes. Note

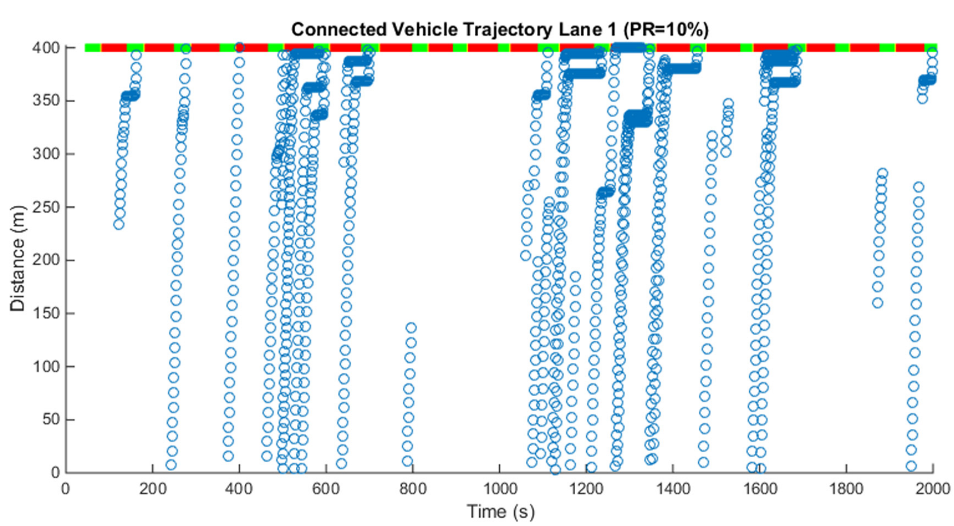

Figure 1. Illustration of CV trajectories under 10% penetration rate.

that during most of the cycles only one or two CVs were observed, and during some cycles there was no CV at all.

Vehicle Delay Estimation

The core idea of using limited trajectories to estimate delay is to utilize critical CV information. Critical CVs are defined as the last stopped CV and the first non-stopped CV. The last stopped CV provides a lower boundary of queue length, whereas the first non-stopped CV provides an upper boundary because the queue has to be fully discharged before the arrival of the non-stopped CV. For those cycles that do not have any observed CV, an average hourly volume is used to generate vehicle arrival and departure times for delay estimation. The hourly volume can be estimated from the aggregation of historical CV trajectory data (*13*). It was assumed the vehicle arrivals follow Poisson process with mean arrival rate λ. The cumulative number of arrivals during time interval t is expressed as $N(t) \sim \text{Poisson}(\lambda t)$.

Four cases are identified according to the existence of observed CVs as shown in Figure 2.

Case 1: No Observed CV. If no CV is observed during the entire cycle (Figure 2*a*), the only information that can be utilized is the average volume estimated by historical data. Given cycle length C, the total number of vehicles arrive within the cycle $n = \lambda C$, which is the mean of the Poisson distribution. Total vehicle delay D is the summation of delay from each vehicle:

$$D = \sum_{i=1}^{round(n)} D_i \tag{1}$$

Delay of each vehicle is expressed by the following equation:

$$D_i = t_i^d - t_i^e - t_f \tag{2}$$

where t_i^d is the departure time of vehicle i, t_i^e is the entrance time of vehicle i, and t_f is the free flow travel time from entrance location d_e to the intersection. Free flow travel time is assumed to be the same for all vehicles. The entrance location is defined based on the communication range (e.g., 300 m).

The departure time of each vehicle is calculated based on the entrance time, free flow speed, signal timing, and vehicle position in the queue:

$$t_i^d = \max(t_g + t_{sl} + i^* s_f, t_i^e + t_f) \tag{3}$$

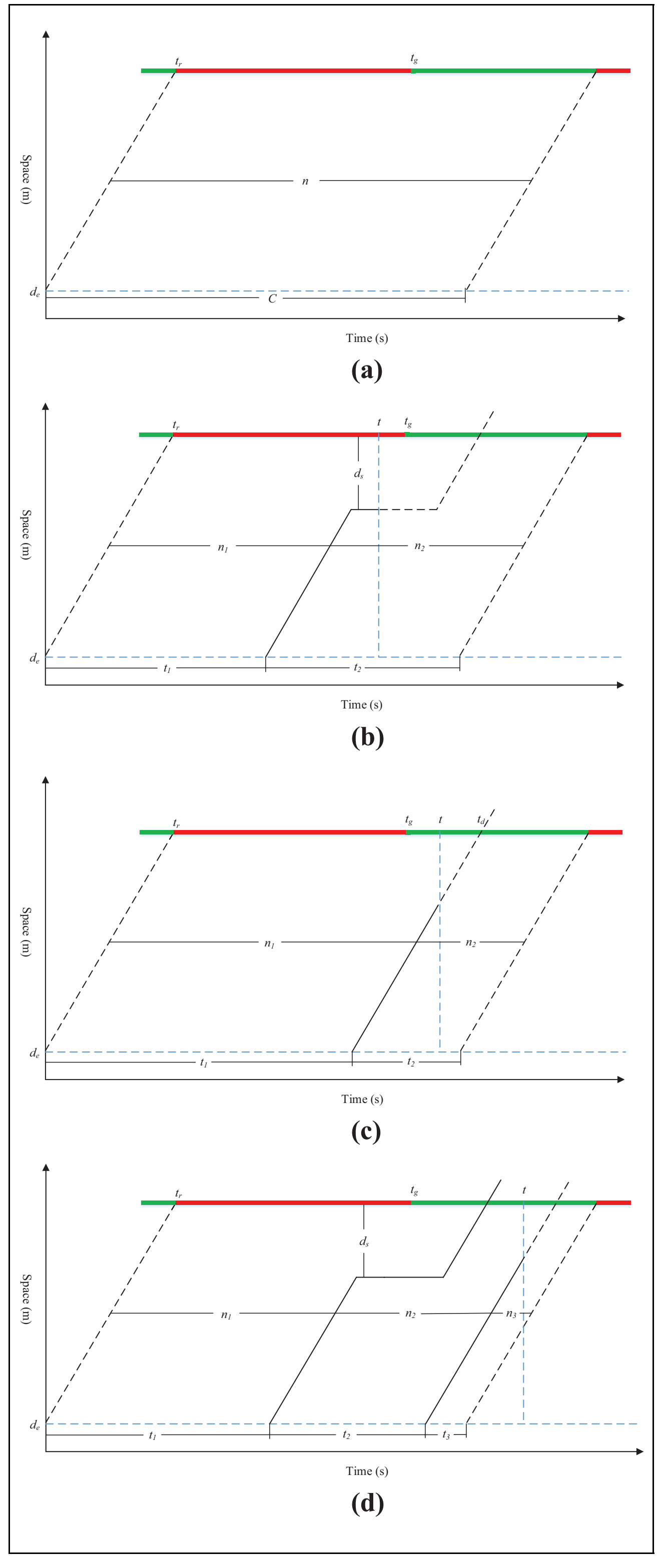

Figure 2. Four scenarios based on critical CV trajectory: (*a*) no CV; (*b*) only stopped CV; (*c*) only non-stopped CV; (*d*) both stopped and non-stopped CV.

where t_g is the green start time, t_{sl} is the start-up lost time, and s_f is the saturation headway (e.g., 2 s/veh). We do not consider lane change so that the i^{th} vehicle approaching the intersection is also the i^{th} vehicle in the queue.

Given the cumulative number of arrivals n during interval C, the event occurrence time (entry time of each individual vehicle) $t_1^e, \ldots t_n^e$ have the same distribution as the order statistics corresponding to n independent random variables uniformly distributed within the interval $(0,C)$ (*14*). The entrance time of each vehicle can be expressed as:

$$t_i^e = t_r - t_f + CU_{(i)} \tag{4}$$

where t_r is red start time and $U_{(i)}$ is i^{th} order statistics from a standard uniform distribution. It can be proved that i^{th} order statistics of the standard uniform distribution follows a beta distribution $U_{(i)} \sim B(i, n+1-i)$ (*14*). The mean of the beta distribution is used to present arrival times of each vehicle:

$$U_{(i)} = i/(n+1) \tag{5}$$

Combining Equations 1–5, total delay can be calculated.

Case 2: Only Stopped CV. If only stopped CVs are observed during a cycle, then the cycle time is divided into two intervals (Figure 2*b*). The first interval is the time period from the entry time of the first stopped vehicle to the entry time of the stopped CV (t_1), and the second interval is the time period after the entry time of the stopped CV until the last vehicle that passes during the green time (t_2), with $t_1 + t_2 = C$.

All vehicles that enter during t_1 are stopped vehicles, as the stopped CV provides a lower boundary of the queue. Based on the location of the stopped CV, the total number of stopped vehicle n_1 can be estimated, assuming vehicle length is uniform and known:

$$n_1 = round\left(\frac{d_s}{l}\right) \tag{6}$$

where d_s is the stopping distance of the CV and l is the average vehicle length.

The number of vehicles that enter during t_2 is estimated based on the average arrival rate because no more CV information is available. That is $n_2 = \lambda t_2$. The departure time of each vehicle during t_1 and t_2 is calculated using Equations 7 and 8, respectively. Vehicles arrive during t_1 must depart at saturation flow rate because they are all in the queue. Vehicles arrive during t_2 may pass the intersection without stop if they arrive after the queue is fully discharged:

$$t_i^d = t_g + t_{sl} + i^* s_f \quad i \le n_1 \tag{7}$$

$$t_i^d = \max(t_g + t_{sl} + i^* s_f, t_i^e + t_f) \quad n_1 < i \le n_1 + n_2 \tag{8}$$

The entry time and delay calculation are similar to Case 1.

Case 3: Only Non-Stopped CV. If only non-stopped CVs are observed during the cycle, then the cycle time is also divided into two intervals (Figure 2*c*). The first interval is the time period from the entry time of the first stopped vehicle to the entry time of the non-stopped CV (t_1), and the second interval is the time period after the entry time of the non-stopped CV until the last vehicle that passes during the green time (t_2), with $t_1 + t_2 = C$.

The non-stopped CV provides an upper boundary of the queue. Unlike stopped CV, it only gives the maximum possible number of vehicles entered during t_1, because the queue can be cleared before the arrival of the non-stopped CV. The maximum possible number of vehicles is calculated as:

$$n_{\max} = \left(t_d - t_g - t_{sl}\right)/s_f \tag{9}$$

where t_d is the departure time of the non-stopped CV. The number of actual vehicles arrived during t_1 can be calculated as the summation of conditional probabilities:

$$n_1 = \sum_{i=1}^{round(n_{\max})} i^* P(X = i | X \le round(n_{\max})) \tag{10}$$

where $X \sim \text{Poisson}(\lambda t_1)$. The total estimated delay of vehicles entered during t_1 is the summation of total delays of all possible numbers of entered vehicles multiplied by the corresponding probability:

$$D_1 = \sum_{j=1}^{round(n_{\max})} \left\{ P(X = j | X \le round(n_{\max})) \sum_{i=1}^{j} D_{i,j} \right\} \tag{11}$$

where $D_{i,j}$ is the delay of vehicle i given total j vehicles enter during t_1. The calculation of $D_{i,j}$ for each vehicle is similar to Equations 3–5. The number of vehicles that enter during t_2 is estimated based on the average arrival rate as in Case 2. Note that since the queue is already fully discharged before the non-stopped CV, vehicles that enter after the CV do not cause any delay.

Case 4: Both Stopped and Non-Stopped CV. In this case, both the lower boundary and the upper boundary of vehicle queue are provided by the stopped CV and non-stopped CV, respectively (Figure 2*d*). Therefore, the cycle time is divided into three intervals. The first interval is the time period from the entry time of first stopped vehicle to the entry time of the non-stopped CV (t_1). The second interval is the time period from the entry time of the stopped CV to the entry time of the non-stopped CV (t_2), and the third interval is after the entry time of the non-stopped CV until the last vehicle that passes during the green period (t_3), with $t_1 + t_2 + t_3 = C$. It is easy to see that delay estimation of the three intervals are included in previous three cases. To avoid redundancy, the detailed calculation is skipped.

If multiple stopped and non-stopped CVs are observed within one cycle, only the last stopped CV and the first non-stopped CV are utilized because they represent the critical information.

Adaptive Signal Optimization

The adaptive control algorithm is adapted from previous research by Feng et al. (*3*). The algorithm generates an optimal signal phase sequence and duration using a two-level optimization model. The model is based on DP and can apply different objective functions, including total delay minimization and total queue length minimization. In this paper, only total delay minimization is chosen as the objective.

The algorithm uses an arrival table as the input to the optimization model. The arrival table is a two-dimensional matrix with time and phase. The value of each cell is the number of vehicles that will arrive at the stop-bar at time point t requesting phase p. It is generated based on CV trajectory data at the time of executing the signal optimization. The original model adds all queuing vehicles to the first line of the arrival table, which does not consider accumulative delay generated by already stopped vehicles. Delay of all vehicles is calculated from the time point when the signal optimization is conducted. In the proposed delay estimation model, entry times of each individual vehicle are generated so that the arrival time of each vehicle at the stop-bar can be calculated. As a result, the accumulative delay of each queuing vehicle can be obtained. A new arrival table is constructed to incorporate the delay from vehicles that already stopped before the planning time.

Simulation Results and Discussion

To test the proposed models, a SIL simulation framework is designed and implemented with VISSIM microscopic simulation software. The SIL simulation architecture is shown in Figure 3.

CVs in VISSIM simulation network generate basic safety messages (BSMs) at a frequency of 10 Hz and broadcast to the Data Processor module. This module also requests Signal Phasing and Timing (SPaT) data from the Econolite ASC/3 virtual controller. Processed CV trajectory and signal information are then sent to the delay estimation module. This module generates the arrival table and sends to the adaptive control algorithm, which is responsible for producing optimal signal timing plan with the objective to minimize total vehicle delay. The optimal signal plan will be converted into a series of control commands by the Signal Controller Interface module and control virtual signal controllers in VISSIM.

A real-world intersection at Huron Pkwy and Plymouth Rd in Ann Arbor, Michigan is modeled in VISSIM 9. The intersection geometry and signal phasing are shown in Figure 4.

To evaluate the proposed delay estimation model, the VISSIM model is run for 1 h, and all vehicle trajectories are recorded and served as the ground truth. The traffic signals are under actuated control so that the cycle lengths and phase splits change over time. Figure 5

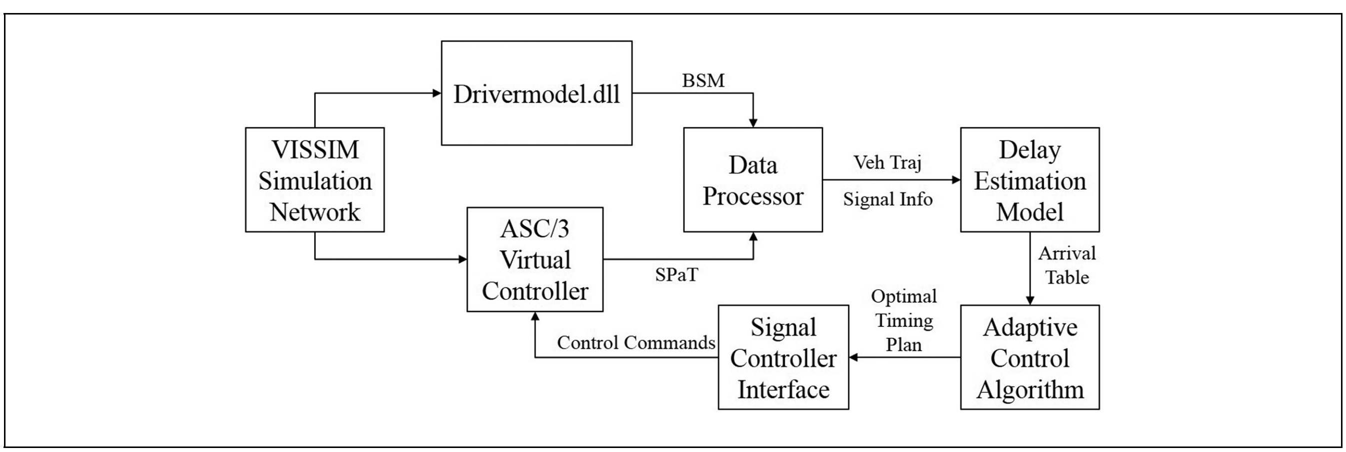

Figure 3. Software-in-the-loop simulation architecture.

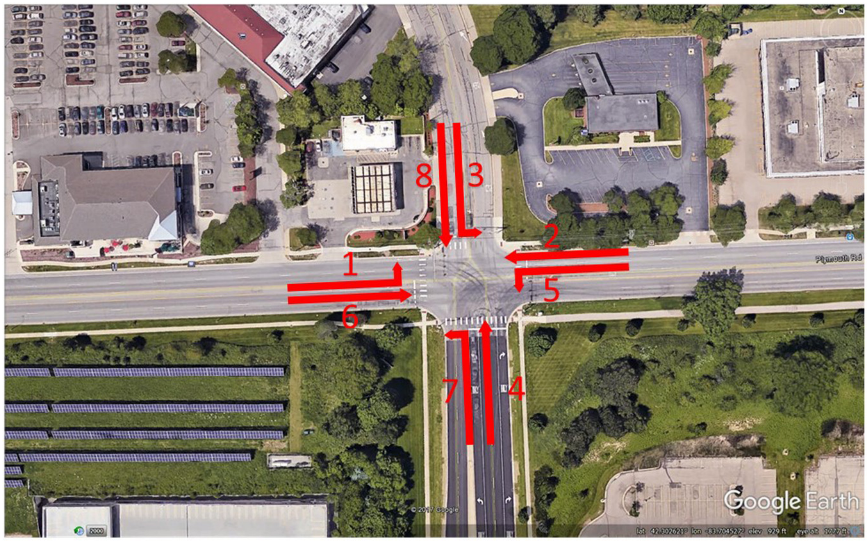

Figure 4. Geometry and signal phasing at Huron Pkwy & Plymouth Rd intersection.

shows the comparison of the estimated total vehicle delay and the actual vehicle delay of Phase 6 by lane with 10% penetration rate. There are total 31 full cycles operated within 1 h.

To further quantify the accuracy, the MAPE was calculated for the estimated delay using the following equation:

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\frac{\left|D_i^e - D_i^t\right|}{D_i^t} \tag{12}$$

where N is the total number of cycles, D_i^e is the estimated vehicle delay of cycle i, and D_i^t is the actual vehicle delay of cycle i.

Under 10% penetration rate, the MAPE for Lane 1 and Lane 2 are 18.99% and 14.56%, respectively. If two lanes are combined together, the MAPE for Phase 6 is 14.30%. The model was also tested under 0% penetration rate, under which only hourly volume is used to generate vehicle arrivals (i.e., always in Case 1 because of no observed CV). The MAPE for Lane 1 and Lane 2 are 32.60% and 28.65%, respectively. If two lanes are combined together, the MAPE values for Phase 6 is 30.49%. The result indicates that if only hourly volume is used as input for the delay estimation model, the estimated delays in each cycle significantly differ from the actual delays. From Figure 5*c*, it can be seen that the vehicle delay of each cycle varied from less than 500 veh·s to over 2000 veh·s. Estimation using only 10% CV's data can reduce the MAPE significantly, from more than 30% to less than 15% percent. This suggests that just a few critical CV trajectories are needed to improve the vehicle delay estimation to a relatively accurate level.

As the delay estimation algorithm generates individual vehicle arrival times, an arrival table can be easily constructed and served as the input to the adaptive control algorithm. Two scenarios with two different demand levels and four penetration rates are evaluated. Scenario 1 assumes that the estimated hourly volume of each phase (or average arrival rate λ) is accurate. Scenario 2 assumes the estimated hourly volume of each phase has 10% error, which is more realistic based on field data (*13*). Scenario 2 adds 10% of demand on phase one to four and deducts 10% of demand on phase five to eight. The objective of such adjustment is to maximize the disturbance on the signal timing. Two demand levels are considered as medium (critical v/c ratio 0.82) and congested (critical v/c ratio 0.93) traffic conditions. Four penetration rates under evaluation are: 10%, 5%, 2%, and 0%. Under 0% penetration rate, the adaptive control basically becomes a fixed-time signal plan, which is generated by the hourly volume (always Case 1 in delay estimation algorithm). The traffic demands used in each scenario are summarized in Table 1. Note that the estimated hourly volume with 10% error is only used in the delay estimation model. The vehicle inputs in the VISSIM model are the same for the two scenarios, which is the actual hourly volume.

A total duration of 3900 s is executed in VISSIM simulation for each scenario, each demand level, and each penetration rate, with 300 s of warm-up period and 3600 s of data collection time. To capture the stochastic demand pattern, each simulation run is repeated with

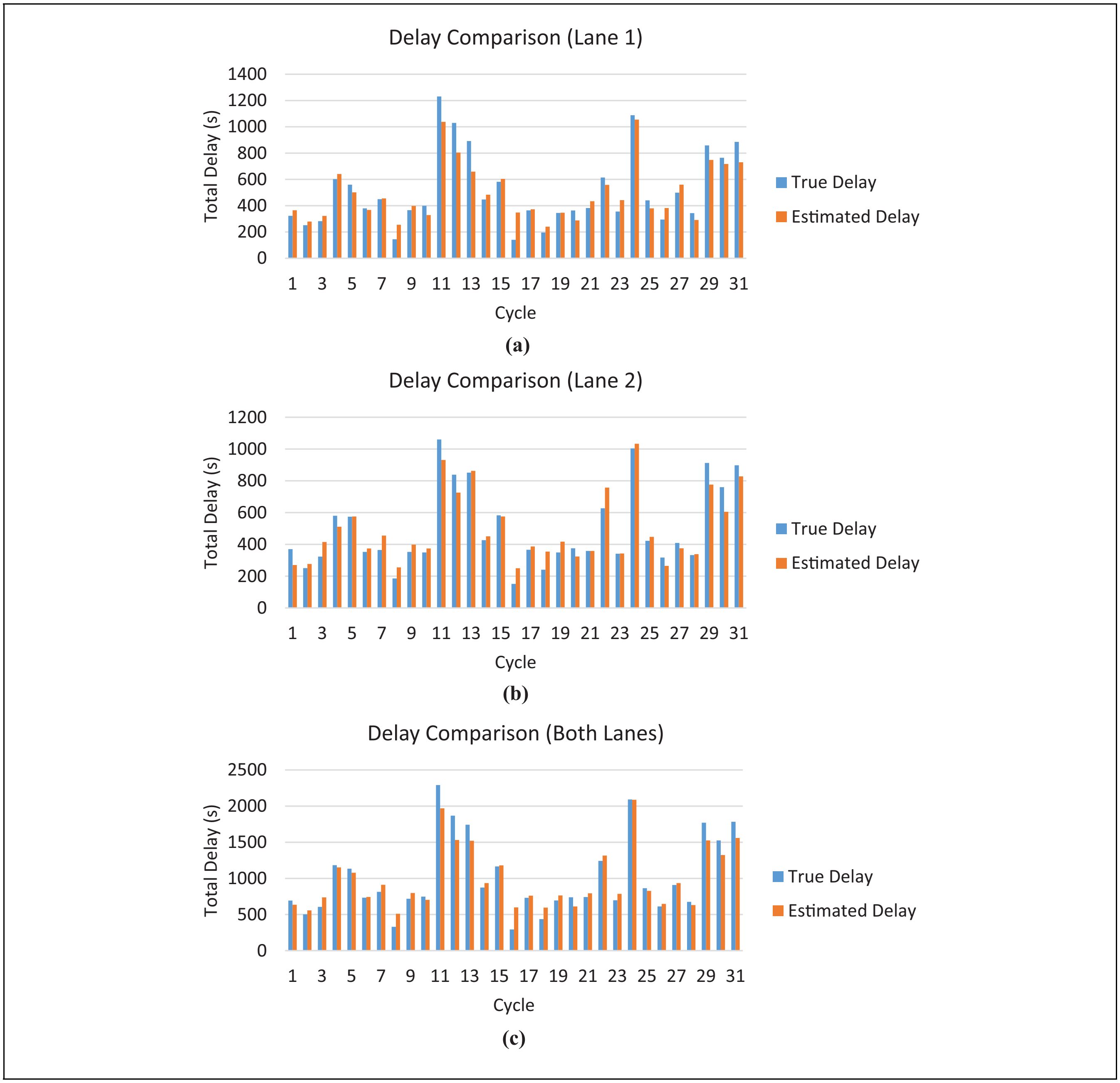

Figure 5. Estimated vehicle delay under 10% penetration rate: (*a*) lane 1; (*b*) lane 2; (*c*) combination of both lanes.

Table 1. Traffic Demands of Each Phase under Two Scenarios and Two Demand Levels

Unit: veh/h/ln	P1	P2	P3	P4	P5	P6	P7	P8
Medium demand (Scenario 1)	187	675	133	450	150	656	150	333
Medium demand (Scenario 2)	206	742	146	495	135	591	135	300
Congested demand (Scenario 1)	212	765	167	525	170	744	175	417
Congested demand (Scenario 2)	233	841	182	577	153	670	157	375

five random seeds. The results are compared with a well-tuned fully actuated control, in which the minimum green time, maximum green time, yellow interval, and all red clearance interval are set to be the same as in the adaptive control algorithm. The unit extension time of the actuated control is set to 1.6 s, which is obtained by

Table 2. Total Vehicle Delay in Seconds under Medium Demand Level

Random seed	1	2	3	4	5	Average (SD)	Delay reduction
Scenario 1: accurate hourly volume estimation							
10% PR	143336	152534	135818	151338	137554	144311 (7674)	5.23%
5% PR	148165	157135	141530	158741	149372	150988 (7034)	0.84%
2% PR	168963	190877	152779	178334	168224	171835 (14046)	−12.84%
Actuated	145736	162606	150933	158352	143770	152279 (8070)	N/A
Scenario 2: 10% hourly volume estimation error							
10% PR	144404	155736	143002	155517	149726	149677 (5983)	1.71%
5% PR	157791	168744	146392	159259	151568	156750 (8447)	−2.94%
2% PR	164093	182495	145614	170820	164004	165405 (13386)	−8.62%
Actuated	145736	162606	150933	158352	143770	152279 (8070)	N/A

Note: SD = standard deviation.

Table 3. Total Vehicle Delay in Seconds under Congested Demand Level

Random seed	1	2	3	4	5	Average (SD)	Delay reduction
Scenario 1: accurate hourly volume estimation							
10% PR	227684	248169	222959	260393	231441	238129 (15656)	16.33%
5% PR	240871	258387	222687	260856	231085	242777 (16692)	14.70%
2% PR	259532	281069	240524	280446	242579	260830 (19631)	8.35%
0% PR	327241	367273	288306	344282	261268	317674 (42731)	−11.62%
Actuated	256728	305282	279268	330017	251736	284606 (33074)	N/A
Scenario 2: 10% hourly volume estimation error							
10% PR	252124	282365	243068	279463	258485	263101 (17189)	7.56%
5% PR	267432	283013.	242671	271912	249347	262875 (16577)	7.64%
2% PR	270629	339032	254176	317639	281232	292541 (34897)	−2.79%
0% PR	346828	380832	356243	442983	313010	367979 (48470)	−29.29%
Actuated	256728	305282	279268	330017	251736	284606 (33074)	N/A

Note: SD = standard deviation.

the recommendations from Signal Timing Manual (*15*). Tables 2 and 3 show the delay comparison under two demand levels.

The following observations are made by analyzing the results:

1. When the penetration rate is 10%, the proposed model outperforms well-tuned actuated control in all cases. The total vehicle delay is decreased by 16.33% under congested demand level with accurate volume estimation. Under medium demand

level with 10% volume estimation error, the vehicle delay is still reduced by 1.71%. As the penetration rate decreases, the total delay tends to increase.

2. The hourly volume estimated from historical data has a significant impact on the performance. Under same demand level and same penetration rate, the results with 10% volume estimation error are all worse than no error in volume estimation. When the algorithms are executed under low penetration rates, it is common that no CV is observed within the entire cycle. Then the hourly volume serves as the only data for determining the phase duration.
3. Besides penetration rate, the absolute number of observed CVs is also crucial to the performance of the algorithm. This explains why the algorithm performs better under congested demand level than medium demand level with the same penetration rate. Under congested demand level with accurate volume estimation, even 2% penetration has a delay reduction of 8.35%. However, under medium demand level with accurate volume estimation, model performance with 5% penetration rate is almost the same as actuated control.
4. Vehicle delays with 10% and 5% penetration rates under congested demand level are similar, in both scenarios. This indicates that a few critical vehicle trajectories are enough to make an accurate estimation of vehicle delay. Higher penetration rates only bring marginal benefits.
5. When the algorithm is executed under 0% penetration rate, the adaptive control becomes a fixed-time control. Because no CV trajectory is available, the control decision is made only based estimated hourly volume, which is a set value. The results under such conditions are significantly worse than other cases, which supports a well-accepted argument that fixed-time control cannot accommodate short-time demand fluctuation, even if the average volume is accurate. Moreover, under congested demand level, the intersection under fixed-time control may enter oversaturated condition as a result of demand fluctuation, and the delay increases significantly. On the other hand, actuated and adaptive control can handle the demand fluctuation better and prevent the intersection entering the oversaturated condition.

Conclusion and Further Research

This paper presents a detector-free real-time adaptive signal control model in a low CV penetration environment. Critical CVs were defined, which referred to the last stopped CV in the queue and the first non-stopped CV that passed the intersection. They provided the lower and upper boundaries of queue length, respectively. Based on critical CV information, a simple delay estimation model was proposed. Then the model was integrated with an adaptive control algorithm to generate optimal signal plans with the objective of minimizing vehicle delay. Microscopic simulation results showed the proposed model worked well under 10% penetration rate in all scenarios. Compared with well-tuned actuated control, the total delay reduction can reach as much as 16.3%.

The new model has two significant advantages. First, it does not require any data from infrastructure-based sensors, which usually have considerable high installation and maintenance costs. Second, it only needs at most 10% CV penetration rate, so that it can be implemented at an early stage of CV deployment. For example, the Ann Arbor Connected Vehicle Test Environment (AACVTE) project is targeting to equip up to 5,000 vehicles in the next few years, which accounts for about 5% of total vehicles in Ann Arbor metro area (https://www.its.dot.gov/research_archives/safety/aacvte.htm). The proposed model has great potential to be implemented at real-world intersections in the near future.

One direction for further research is to extend the current model to a corridor level, where the vehicle arrivals may not be Poisson distributed, and signal coordination needs to be considered. One of the difficulties lies in the determination of platoon size and speed on coordinated phases to dynamically update offset and split. In addition, the current model relies on the estimated average volume from historical data as the first step. It would be very interesting to develop an integrated platform that combines the volume estimation algorithm, as in Zheng and Liu (*13*), and the real-time adaptive signal control together so that the estimated volumes can be updated dynamically when new CV trajectories become available.

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Author Contributions

The authors confirm contribution to the paper as follows: study conception and design: Yiheng Feng, Jianfeng Zheng, Henry Liu; data collection: Yiheng Feng; analysis and interpretation of results: Yiheng Feng, Jianfeng Zheng; draft manuscript preparation: Yiheng Feng, Jianfeng Zheng, Henry Liu. All authors reviewed the results and approved the final version of the manuscript.

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