

Estimation of Performance Metrics at Signalized Intersections Using Loop Detector Data and Probe Travel Times

Qijian Gan, Gabriel Gomes, and Alexandre Bayen

Abstract—This paper introduces a simple but practical approach that uses both loop detector data and probe travel times for computing the *vehicle hours traveled* (VHT), average delay, and *level of service* (LOS) for signalized intersections. The goal is to improve upon the state-of-the-practice method outlined in the *highway capacity manual* (HCM) by incorporating additional travel time measurements from probe vehicles or vehicle re-identification systems. The proposed methodology is designed to work under a variety of traffic conditions, including states of congestion in which the HCM methodology is not reliable. Our analysis is then tested using simulation of an arterial site in Arcadia, CA, USA. The results suggest that the proposed methodology performs better at the approach level than at the lane group level. Population size and probe penetration rate are two key parameters in the estimation. Either a large population size or a high penetration rate is required in order to produce reliable estimates of VHT, delay, and LOS. Results also show that the proposed methodology only requires 7% of the penetration rate to outperform the HCM methodology.

Index Terms—Loop detector data, probe travel time, highway capacity manual, VHT, delay, level of service.

I. INTRODUCTION

THE evaluation of performance metrics for urban networks is an important task for both urban planners and traffic operators. In the planning context, metrics are used to estimate the impacts of proposed long-term projects at the neighborhood or city level. The criteria used in California for evaluating these projects have recently shifted with *State Bill 743* (2013). This bill seeks to upgrade the process for evaluating transportation projects under the *California Environmental Quality Act* (CEQA) such that it aligns with the broader goal of reducing environmental impacts, specifically

Manuscript received May 11, 2016; revised November 10, 2016 and January 25, 2017; accepted January 28, 2017. The Associate Editor for this paper was I. Papamichail.

Q. Gan is with the Institute of Transportation Studies, University of California at Irvine, Irvine, CA 92697 USA (e-mail: qgan@uci.edu).

G. Gomes is with the Partners for Advanced Transportation Technology, University of California at Berkeley, Berkeley, CA 94720 USA (e-mail: gomes@path.berkeley.edu).

A. Bayen is with the Department of Electrical Engineering and Computer Sciences, University of California at Berkeley, Berkeley, CA 94720 USA, also with the Department of Civil and Environmental Engineering, University of California at Berkeley, Berkeley, CA 94720 USA, and also with the Institute of Transportation Studies, University of California at Berkeley, Berkeley, CA 94720 USA (e-mail: bayen@berkeley.edu).

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Digital Object Identifier 10.1109/TITS.2017.2666143

by reducing greenhouse gas emissions. The guidelines that have emerged from this process [1] argue against the use of the *Level Of Service* (LOS), which grades the network performance into different scales (E.g., *Table I*), as a guiding metric, and for alternatives such as *Vehicle Miles Traveled* (VMT) and *Vehicle Hours Traveled* (VHT), which take into account more details of drivers' travel behaviors. Among the stated reasons for this is the fact that LOS forecasts tend to favor development in lightly populated areas over urban areas and city centers. Standard LOS evaluations fail to promote mode shifts away from cars and into cleaner alternatives such as bikes, buses, and walking. It is also argued that delay-based metrics in general are not adequate for evaluating projects that involve changes in trip lengths. It is possible, for example, to decrease average delay while increasing travel times, if trips are made longer. Hence, the trend in urban planning is currently towards aggregate metrics such as VHT and VMT, and away from delay-based metrics such as LOS.

The case is somewhat different in the short-term operations context. Here the objective is to use performance metrics to evaluate an intersection or a group of intersections in order to improve their signal control settings. In this context, trip lengths are largely fixed - some portion of drivers may be coaxed into taking a different route, but only by increasing the delay on their nominal route. Thus, it can be argued that, at the operations level, the goals of greenhouse gas reduction and delay reduction are aligned.

The calculation of delay and LOS at urban intersections has been improved over the years, from the traditional Webster's calculation [2] to the *Incremental Queue Accumulation* (IQA) method [3], and is well documented in the *Highway Capacity Manual* (HCM) [4]. However, using field observations from six signalized intersections, studies in [5] concluded that the new HCM method still provides unreliable estimates of delay. Therefore, the aim of this article is to investigate the extent to which the estimation quality of delay, LOS and VHT can be improved by using travel time samples from onboard devices such as smartphones.

Several technologies now exist that enable the collection of travel times in urban settings. These include toll tag readers, bluetooth devices, and smartphones. Additionally, travel times can be obtained through vehicle re-identification techniques, such as that of [6]. The availability of probe devices is growing rapidly. It was reported in [7] that as of July 2015, 68% of American adults own a smartphone. The potential for

using probe data to infer traffic states has been established. Herrera *et al.* [8] found that a 2 – 3% penetration rate of cell phones is sufficient to provide accurate measurements of speeds on a freeway. Patire *et al.* [9] further confirmed that relatively low penetration rates for GPS-based probes are sufficient to significantly improve the estimation of traffic states on freeways. However, fewer studies have been conducted to assess the ability of doing estimation with varying penetrations of probe data on local streets. The existence of signalized intersections on these streets, along with the complexities of urban routing, makes it likely that a higher rate of probes will be needed.

In the estimation of travel times, some studies were concerned with fitting the parameters of a candidate model, e.g., a mixture Gaussian in [10] and a model derived from traffic theory in [11]. While these serve useful purposes, for example for the route selection problem, the goals of the present effort only require the estimation of the mean of travel times, and thus a more simple non-parametric approach is sought. Zhang *et al.* in [12] proposed new aggregating and sampling methods to process the GPS data for the estimation of travel times and speeds. However, due to the low penetration rate of probe vehicles, it is impossible to compute more aggregated metrics such as VHT solely through probe travel times. Bhaskar *et al.* in [13] further fused loop detector with probe vehicle data in order to obtain the statistics (average and quantile) of travel times. However, such a method is difficult to implement in the field since it requires detector counts from the two link boundaries. Ban *et al.* in [14] used travel time samples to estimate the queuing delay patterns and queue lengths. However, the assumptions made in that study either can be easily violated (e.g., uniform arrivals and no spill-back) or can not be satisfied (e.g., known signal settings and high penetrations) in the field.

This article introduces a method for combining travel time samples with loop detector counts to estimate VHT, delay, and LOS. The method is contrasted with the formulas of the HCM [4], which take lane group volumes, queues, capacities, and signal parameters as inputs. These formulas are provided in Section II. Section III presents the proposed method. The framework for studying the method and comparing it to the HCM formulas is described in Section IV. This framework consists of a micro-simulation model built with the Aimsun software [15]. The model covers 11 intersections along streets running parallel to the eastbound I-210 freeway in Arcadia, California. The analysis of the simulation results is provided in Section V. The article ends with conclusions and future research directions.

II. THE HCM METHOD

The method currently used by both urban planners and traffic engineers to calculate delay and LOS is that of the HCM. This method, illustrated in Figure 1, requires information about the geometric design, traffic demands (forecasts in the planning case), and signal settings. The details of the calculations are provided below. These are applied for comparison to our proposed method in Section III.



Fig. 1. HCM procedure for calculating delay and LOS.

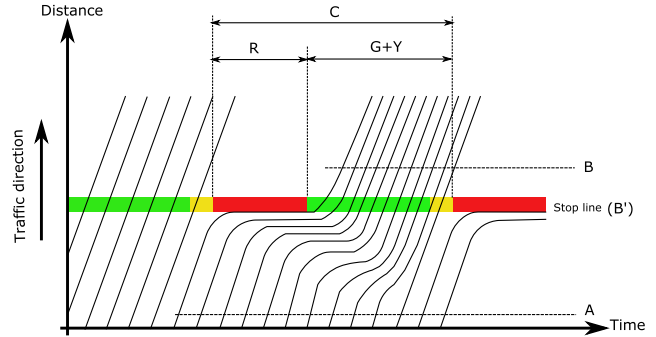


Fig. 2. Trajectories of vehicles approaching a signalized intersection.

A. HCM Delay Calculations

Figure 2 illustrates the trajectories (solid lines) of vehicles approaching a signalized intersection. The intersection is controlled by fixed time traffic signals with sequences of green, yellow, and red phases. Point A is the location where a vehicle first begins to decelerate as it approaches the queue, while point B is the location where it has accelerated to its original speed after exiting the queue [2]. Conceptually, the delay experienced by a vehicle is measured between point A and point B. However, in the HCM, the control delay is measured differently, which only takes into account the delay between point A and the stop line (point B') (See Exhibit 31-5 in [4]).

The HCM identifies three components of delay: uniform delay (d_1), incremental delay (d_2), and initial queue delay (d_3). The average delay for the lane group, d_g , is computed as the sum of these three parts:

$$d_g = d_1 + d_2 + d_3. \quad (1)$$

The uniform delay represents the delay computed under an idealized assumption of uniform arrivals. It can be computed using the Incremental Queue Accumulation (IQA) method in [4], which is provided below.

$$d_1 = \frac{0.5 \sum_{i=1} (Q_{i-1} + Q_i) t_{t,i}}{qC}, \quad (2)$$

with

$$t_{t,i} = \min\{t_{d,i}, Q_{i-1}/w_q\}, \quad (3)$$

where

- $t_{t,i}$: duration of trapezoid or triangle in interval i (sec),
- $t_{d,i}$: duration of time interval i during which the arrival flow-rate and saturation flow-rate are constant (sec),
- Q_i : queue size at the end of interval i (veh),
- v : demand flow rate (veh/hr),
- q : arrival flow rate = $v/3600$ (veh/sec),
- w_q : queue change rate (veh/sec),
- C : the cycle length (sec).

The second component (d_2) accounts for delay caused by random arrivals or oversaturation during the analysis period. This component is calculated with,

$$d_2 = 900 T \left((X - 1) + \sqrt{(X - 1)^2 + \frac{8kIX}{cT}} \right), \quad (4)$$

where

- T : duration of the analysis period (hr),
- X : volume-to-capacity (v/c) ratio,
- c : capacity (veh/hr),
- k : parameter that depends on controller settings,
- I : adjustment factor that accounts for the effect of an upstream signal on vehicle arrivals.

The selection of T typically ranges from 15 minutes to one hour, during which traffic conditions are assumed to remain steady. The selection of k varies from 0.04 to 0.5. For pretimed, coordinated, and “recall-to-maximum” phases, a value of $k = 0.5$ is recommended. The selection of I is typically within [0.09, 1]. A value of $I = 1$ is used for isolated intersections, while smaller values are recommended for interacting intersections.

A third component d_3 is included whenever a queue exists at the beginning of the analysis period. This term is calculated with,

$$d_3 = \frac{3600}{vT} \left(t_A \frac{Q_b + Q_e - Q_{eo}}{2} + \frac{Q_e^2 - Q_{eo}^2}{2c} - \frac{Q_b^2}{2c} \right), \quad (5)$$

with

$$Q_e = Q_b + t_A(v - c), \quad (6)$$

$$Q_{eo} = \begin{cases} 0 & \text{if } v < c \\ T(v - c) & \text{otherwise,} \end{cases} \quad (7)$$

$$t_A = \begin{cases} \min\{Q_b/(c - v), T\} & \text{if } v < c \\ T & \text{otherwise,} \end{cases} \quad (8)$$

where

- t_A :duration of unmet demand in the analysis period (hr),
- Q_b :initial queue at the beginning of the analysis period (veh),
- Q_e :queue at the end of the analysis period (veh),
- Q_{eo} :queue at the end of the analysis period when $v \geq c$ and $Q_b = 0$ (veh).

The average delays for approach a (d_a) and for intersection i (d_i) are calculated by aggregating the lane group ones,

$$d_a = \frac{\sum_{g \in \mathcal{X}_a} d_g v_g}{v_a},$$

$$d_i = \frac{\sum_{a \in \mathcal{X}_i} d_a v_a}{\sum_{a \in \mathcal{X}_i} v_a}. \quad (9)$$

Here \mathcal{X}_a is the set of lane groups belonging to approach a , \mathcal{X}_i is the set of approaches belonging to intersection i , and $v_a = \sum_{g \in \mathcal{X}_a} v_g$ is the volume on approach a .

TABLE I
LOS CRITERIA FOR SIGNALIZED INTERSECTION IN THE HCM

LOS	Average delay (sec/veh)
A	≤ 10
B	(10, 20]
C	(20, 35]
D	(35, 55]
E	(55, 80]
F	≥ 80

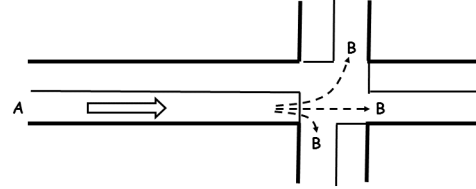


Fig. 3. Measurement of link travel times.

Once the average delays for lane groups, approaches, and intersections are calculated, the corresponding LOS's can be found using the lookup table provided in Table I.

B. Commentary

Although the HCM delay estimation methodology is widely used by traffic engineers and has been tested and validated in numerous field studies, there are several limitations that are worth noting. First, the method requires a large amount of information regarding the geometric design, signal timing parameters, demand volumes, estimated capacities, and even estimated queues. This makes its application time consuming and error prone. Second, the delay calculation for actuated traffic signals is very complicated since the cycle lengths and green times depend on arrival patterns and may vary during the analysis period. Third, the formulas assume that traffic conditions in the downstream of the intersection are clear. For this reason the results become less reliable when queue spillback occurs. Finally, the methodology assumes that lane groups exist independently of one another, such that their delays can be computed separately with simple equations. Hence, interaction between different lane group movements for the same approach is not considered.

III. THE PROPOSED METHOD

In this section, we propose a new method for computing link delays and VHTs that makes use of travel time measurements obtained from probe vehicles or by some re-identification technique. As illustrated in Figure 3, it is assumed that travel times are collected for some portion of the vehicle population from the entrance of an approach section (point A) to the exit of the intersection (points B). The goal is to combine this data with existing loop detector measurements so as to obtain estimates of delay and VHT.

Figure 4 illustrates the proposed method. The inputs are volumes obtained from mid-block loop detectors, the set of travel time samples, and the geometric characteristics of the intersection, specifically the segment lengths and free-flow

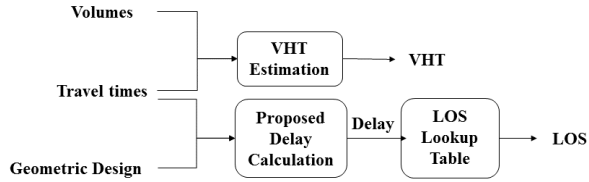


Fig. 4. The proposed method to calculate VHT, delay, and LOS.

speeds (or, equivalently, the free flow travel times). The mid-block volumes and the probe travel times are provided to the VHT estimation algorithm. This component does not require system parameters. Delay is calculated directly from the sampled travel times and the free flow travel time. Delay is then used in Table I to obtain LOS. Further details are provided below.

A. Travel Time Measurements

Travel time measurements are taken from the beginning of one road segment (point A) to the beginning of the next road segment (points B), as shown in Figure 3. Thus the measurements capture the free-flow travel time, plus the delays induced by the traffic signal and by congestion spilling back from downstream segments. As a result, neither the details of the signal controller nor the presence of downstream congestion need to be provided to the estimator, since both of these are recorded in the travel time measurements.

We assume that travel times are recorded over some given period of time T (15 minutes, for example) in some portion of a network. We use n to denote the total number of arrivals to points B during this period. The set of travel times is denoted as $tt = \{tt_i\}_{i=1..n}$, where tt_i is the individual travel time of vehicle i . We assume that only a small portion p (the penetration rate) of these are observed. The number of collected samples, \bar{n} , is a binomial random variable with n trials and probability p , i.e., $\bar{n} \sim B(n, p)$. The set of observed travel times $\bar{tt} = \{tt_i\}_{i=1..\bar{n}} \subseteq tt$.

B. VHT Estimation

VHT is typically defined as the time spent by vehicles in some portion of a transportation network during some given period of time. This concept can be applied to any portion of the network: a lane group, a road segment, an intersection, etc. Here we will adopt a slightly different definition of VHT as the total time spent by vehicles who *exit* the study area during the given time interval. The two concepts are illustrated in Figure 5. These definitions are similar whenever vehicle trips do not start or end within the study area, and the observation time period is sufficiently large. The ground-truth VHT thus can be expressed as,

$$\begin{aligned} \text{VHT} &= \sum_{i=1}^n tt_i \\ &= n \times \text{mean}(tt). \end{aligned} \quad (10)$$

As illustrated in Figure 5, n is the number of vehicles exiting the study area during the sample time, and tt is the

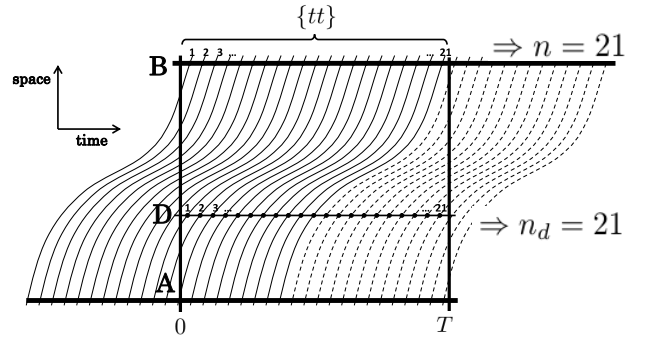


Fig. 5. Two definitions of VHT calculation. The standard definition is the sum of the horizontal lengths of trajectories within the box, while our alternative definition is the sum of the horizontal lengths of solid trajectories, which cross point B during the observation period. The loop detector is placed at point D.

corresponding set of travel times and $\text{mean}(tt)$ is its average. Since n and tt can be defined for a lane group or an approach, Eq. (10) can be used to calculate the VHT at the lane group or the approach level.

The proposed strategy for estimating VHT is to approximate the two terms in Eq. (10) using the available measurements. Specifically we use the vehicle count of the mid-block loop detectors as a proxy for n , and the mean of the reported travel times as an estimate of the average travel time. Thus we obtain the following estimator for VHT,

$$\hat{\text{VHT}} = n_d \times \text{mean}(\bar{tt}), \quad (11)$$

where n_d is the total number of vehicles observed by the mid-block detectors (shown in Figure 5) during time interval T .

Despite its simplicity, this estimator has some useful properties. First, the fact that it is non-parametric implies that it does not rely on the assumptions of any particular model. This is in contrast to the HCM methodology which has assumptions on vehicle's arrival patterns, traffic conditions, etc. This property allows the estimator to adapt to changing conditions with little or no additional tuning. Given the required measurements of travel time, Eq. (11) is valid for any signal control algorithm (fixed-time or actuated). It is also valid over a range of demands and queueing states, as long as the mid-block loop detector provides a good estimate of the number of trips completed during the time interval T . Second, the precision of the estimator is in a direct relation with the availability of probe data, which is likely to increase in the coming years. In Section V we investigate the dependency between estimation error and penetration rate. Finally, if we assume n_d to provide a good estimate of the total number of completed trips, then the estimator will be consistent, meaning that it will converge to the true VHT as the penetration rate reaches 100%. One can observe in Figure 5 that n_d becomes a better representation of the number of trips as the length of the observation time increases.

C. Delay Estimation

Delay for a vehicle is defined as the difference between its actual travel time and its free flow travel time,

$$d_v = tt_v - tt_f, \quad (12)$$

where the subindex v represents the vehicle. The free flow travel time tt_f assumes that the vehicle is not delayed by traffic or the signal. It is typically calculated as the ratio of the length of the segment to the free-flow speed. Here we assume that the free-flow speed is given and equal for all vehicles in the segment. In this case the lane group and approach delays (per vehicle) can be expressed as,

$$d_g = \text{mean}(tt_g) - tt_f, \quad (13)$$

$$d_a = \text{mean}(tt_a) - tt_f, \quad (14)$$

where tt_g and tt_a are the collection of travel times for vehicles in the lane group and the approach segment respectively. These definitions imply the following relationship between the lane group delay and the approach delay,

$$n_a d_a = \sum_{g \in \mathcal{X}_a} n_g d_g, \quad (15)$$

where n_g is the number of trips completed for lane group g , and $n_a = \sum_{g \in \mathcal{X}_a} n_g$ is the number of completed trips for the approach.

Delays are estimated similarly to VHT, by taking the sample mean of travel times recorded for either the lane group or the approach,

$$\hat{d}_g = \text{mean}(\bar{t}t_g) - tt_f, \quad (16)$$

$$\hat{d}_a = \text{mean}(\bar{t}t_a) - tt_f. \quad (17)$$

These are both consistent and unbiased estimators of delay, as they are sample means taken from the underlying delay distribution. Also, the sample mean has the property of being the minimum variance estimator amongst all linear estimators of the mean, regardless of the underlying distribution (assuming i.i.d. samples). This fact provides important support for the use of non-parametric estimators for this purpose.

The estimated LOS is obtained by evaluating Table I using estimated delay values.

IV. STUDY FRAMEWORK

The goals of the experiments are i) to test the various assumptions that have been made in constructing the VHT and delay estimators, ii) to assess the performance of the estimators under various traffic scenarios, iii) to compare the performance with the HCM methodology, and iv) to study the dependency of the estimation error on the penetration rate of probe data. To do this it is necessary to collect a "ground truth" set of travel times. For this we used a micro-simulation model, as described next.

A. Study Site

The experiments were done using an Aimsun model of Huntington Dr. and Colorado Blvd. in Arcadia, California. These two streets run parallel to the I-210 freeway and have been extensively studied as possible detour routes for corridor management [16]. The model includes eleven signalized intersections, of which six were chosen for detailed study: @San

Clara St., @Santa Anita Ave., @1st Ave., @2nd Ave., @Gateway Dr., and @5th Ave. (see Figure 6). Table II provides additional parameters used in the calculations: link lengths (L_l) and free-flow speeds (v_f) per intersection approach.

Lane group is defined as the set of traffic movements sharing the same lanes. Thus, an approach in which all movements share all lanes is considered to have only one lane group. An approach in which left-turns, through movements, and right-turns are segregated into different lanes is considered to have three lane groups. The lane group information is also provided in Table II.

The simulation model includes fixed-time signal controllers with protected left turns for all intersections. The specific settings (green times, offsets, etc.) were modified from the original values in order to produce a variety of queuing conditions. A common cycle length of 120 seconds was applied to all intersections. Yellow and all-red times were set to 3 seconds and 2 seconds respectively. Detailed signal settings are provided in Table II.

The network was initially empty, and the model was run over the four-hour afternoon peak period, from 4:00 PM to 8:00 PM. At the sources, demands were updated every five minutes. Vehicles were generated with constant headways and assigned into the network with if the downstream link had sufficient space to accommodate them; otherwise, queues would form at the sources. A Python script was written to collect detailed trajectories for all vehicles in the network during the simulation, which were used to form the set of "ground truth" data.

B. Experimental Design

The steps of the experiments are as follows,

- 1) *Travel times.* For an approach link i , the number of vehicles that exited the intersection during period k after transiting through the whole link was determined through the trajectory data set. The corresponding travel times and vehicle movement information were collected and organized into the sets indexed by k and i , i.e., $\{tt\}_{k,i}$. The set $\{tt\}_{k,i}$ can be used for the study at the approach level, while it can be used for the lane group level if vehicle movement information is also used.
- 2) *Loop detector data.* The mid-block loop detectors were placed in the middle of the links. Synthetic measurements were gathered for each lane group in every approach link and were aggregated into constant observation periods. The period was selected to be 15 minutes, i.e., $T = 15$, since it is a conventional setting in traffic studies, e.g., in [4].
- 3) *Ground truth calculations.* True values of VHT and delay were computed from the synthetic data for all lane groups, approaches, and intersections that were considered. The delays were used to find ground truth LOS values from Table I.
- 4) *HCM estimates.* The signal settings, geometric designs, and demand volumes were used in Eqs. (1) through (8) and Table I to calculate HCM estimates of delay and LOS for all lane groups and for each 15-minute period.



Fig. 6. Six selected signalized intersections along the Huntington Dr. in the City of Acadia, CA.

TABLE II
INTERSECTION GEOMETRIC DESIGN AND SIGNAL SETTINGS FOR THE SIX SIGNALIZED INTERSECTIONS

Intersection	Approach	L_l (ft)	v_f (mph)	Lane Group ID	No. of lanes	Phase ID	Green Time (sec)
@5th Ave.	Eastbound	624	30.00	1: L	1	1	25
				2: T & R	2	2	35
	Southbound	589	30.00	1: L	1	3	10
				2: T & R	1	4	30
	Westbound	477	30.00	1: L	1	1	25
				2: T	2	2	35
				3: R	1	2	35
	Northbound	565	30.00	1: L	1	3	10
2: T & R				1	4	30	
@Gateway Dr.	Eastbound	578	30.00	1: L	1	1	15
				2: T	2	2	60
	Southbound	473	30.00	1: L	1	3	30
				2: R	1	3	30
	Westbound	623	30.00	1: T & R	2	2	60
@2nd Ave.	Eastbound	964	30.00	1: L	1	1	20
				2: T	2	2	30
				3: R	1	2	30
	Southbound	717	30.00	1: L	1	3	25
				2: T & R	2	4	25
	Westbound	578	30.00	1: L	1	1	20
				2: T	2	2	30
				3: R	1	2	30
Northbound	495	30.00	1: L	1	3	25	
			2: T & R	2	4	25	
@1st Ave.	Eastbound	848	30.00	1: L	1	1	15
				2: T & R	2	2	45
	Southbound	195	30.00	1: L	1	3	15
				2: T & R	1	4	25
	Westbound	964	30.00	1: L	1	1	15
				2: T & R	2	2	45
	Northbound	346	30.00	1: L	1	3	15
				2: T & R	1	4	25
@Santa Anita Ave.	Eastbound	1048	30.00	1: L	1	1	15
				2: T	2	2	35
				3: R	1	2	35
	Southbound	734	30.00	1: L	2	3	20
				2: T	2	4	30
				3: R	1	4	30
	Westbound	849	30.00	1: L	1	1	15
				2: T	2	2	35
				3: R	1	2	35
	Northbound	1506	30.00	1: L	2	3	20
2: T				2	4	30	
3: R				1	4	30	
@Santa Clara St.	Eastbound	380	30.00	1: L	1	1	43
				2: T	2	1	80
	Southbound	717	30.00	1: R	2	3	30
				1: T	2	2	32
	Westbound	1046	30.00	2: R	1	2	32
				1: L	1	3	30
	Northbound	1953	30.00	2: T	2	3	30
				3: R	2	3	30

Note: L: left turn; T: through; and R: right turn. "1: L" means the left-turn movement is defined as lane group 1.

These were aggregated using Eq. (9) to the approach and intersection levels. Here the demand volume is computed as the arrival rate at the entrance of each approach

segment. Such a measurement is a good proxy for the actual demand when no queue spills back to the entrance point and the analysis time period is long enough. For

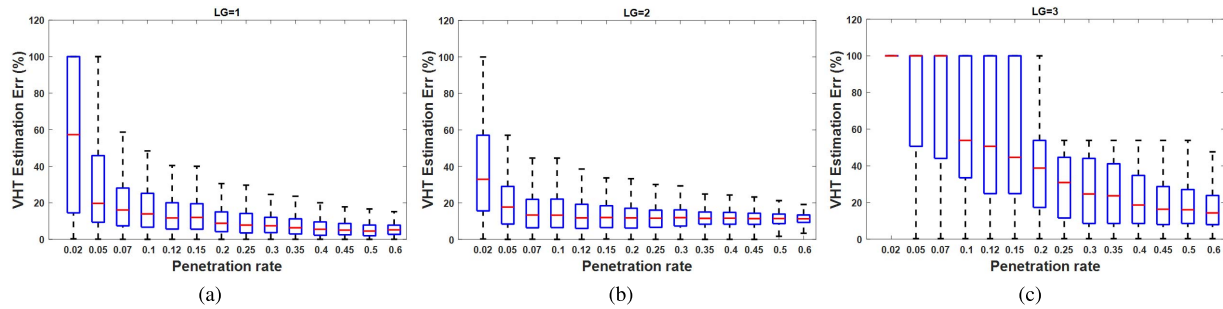


Fig. 7. Lane group based VHT estimation errors in the eastbound direction of the intersection at Santa Anita Ave. from 4:15 PM to 4:30 PM. The population size is 45 for Left turn, 88 for Through, and 7 for Right turn. Penetration rates greater than 0.6 are not shown in this figure. (a) Eastbound: Left turn. (b) Eastbound: Through. (c) Eastbound: Right turn.

real-world applications, the mid-block detector counts can be used as the demand volumes.

- 5) *Sampled travel times.* Vehicles that report travel times are sampled from the whole population in the network at a penetration rate p . The sampling follows a Binomial distribution, i.e., $\bar{n} \sim B(n, p)$, where n is number of unique vehicles in the network, and \bar{n} is the number of sampled vehicles. Then the set of sampled travel times $\{\bar{t}\}_{k,i}$ is formed using these sampled vehicles.
- 6) *Estimates of VHT, delay, and LOS.* Lane group VHT and delay estimates were computed with Eqs. (11) and (16) for all lane groups and time intervals. There are two possible methods for estimating VHT and delay for an approach. The first is to aggregate the lane group VHTs to the approach level and apply Eq. (9) to get the approach delay. The other is to directly take the mean of the collected travel times for the approach and apply Eqs. (11) and (17) to get the approach VHT and delay. The former is only possible if lane-by-lane counts with exclusive traffic movements are available, which is not always the case. Here we consider both of these possibilities. Estimated LOS values were found using Table I.
- 7) *Errors calculations.* Steps 5) and 6) were repeated 500 times for each penetration rate, and for 18 different penetrations rates in $[0,1]$. The selected penetration ratios are listed in Figure 9. Deviations of the various estimates from the ground truth values were computed using the MAPE (Mean Absolute Percentage Error) metric.

V. RESULTS

In this section, we compare the errors obtained with the proposed method to those of the HCM.

A. VHT Estimation Errors

1) *Lane Group Based:* Figure 7 provides box plots of lane group based VHT estimation errors under different penetration rates of probe vehicles. The selected approach is the eastbound direction of the intersection at Santa Anita Ave, which consists of three different lane groups. We select the time period from 4:15PM to 4:30PM instead of from 4:00PM to 4:15PM because the network was initially empty and needed some

time to warm up. On each box, the central mark indicates the median, and the bottom and top edges indicate the 25th ($y_{25\%}$) and 75th ($y_{75\%}$) percentiles, respectively. The data points that are out of the range, $[y_{75\%} + 1.5 \times (y_{75\%} - y_{25\%}), y_{25\%} - 1.5 \times (y_{75\%} - y_{25\%})]$, are considered as outliers and are not plotted in the figure. The whiskers of each box extend to the most extreme data points not considered as outliers. Analogous plots for other approaches, intersections, and time intervals exhibit similar patterns.

The following observations can be made. First, the estimation error as well as its variance reduces as the penetration rate increases. This is true for all lane groups and population sizes. Second, for a fixed penetration rate, the estimation error reduces as the population size grows. Thus we can identify two important factors for VHT inference: penetration rate and population size. Either a high penetration rate or a large population size is needed to produce good estimates of VHT and delay from sampled travel times.

2) *Approach Based:* Figure 8 provides the box plots of approach based VHT estimation errors for the same intersection and time period. Similar patterns as those in the lane group case are apparent.

In addition, compared with the lane group based case, VHT estimates at the approach level turn out to be more reliable with smaller variance. This can be explained by the fact that a larger number of samples is taken for the approach than for the individual lane-groups, while the travel time patterns are similar across lane groups in the same approach segment.

3) *Impact of Penetration Rates:* Based on the above analysis, we further analyze the impact of penetration rates on the estimation errors. For both lane group and approach based methods, we first group the population size (P.S.) into different bins. Then in each bin, we obtain the average VHT estimation error for each given penetration rate. Figure 9 illustrates the relation between the average VHT estimation error and the penetration rate under different bins of population sizes. Regardless of lane groups, approaches, and population sizes, it is clear to find a monotonic decreasing trend in the estimation error as the penetration rate increases. The improvement is significant especially when the penetration rate is less than 10%. When the penetration rate is 10%, it generally requires more than 80 vehicles (per 15 minutes) for one lane group to guarantee the average estimation error less than 10%. For

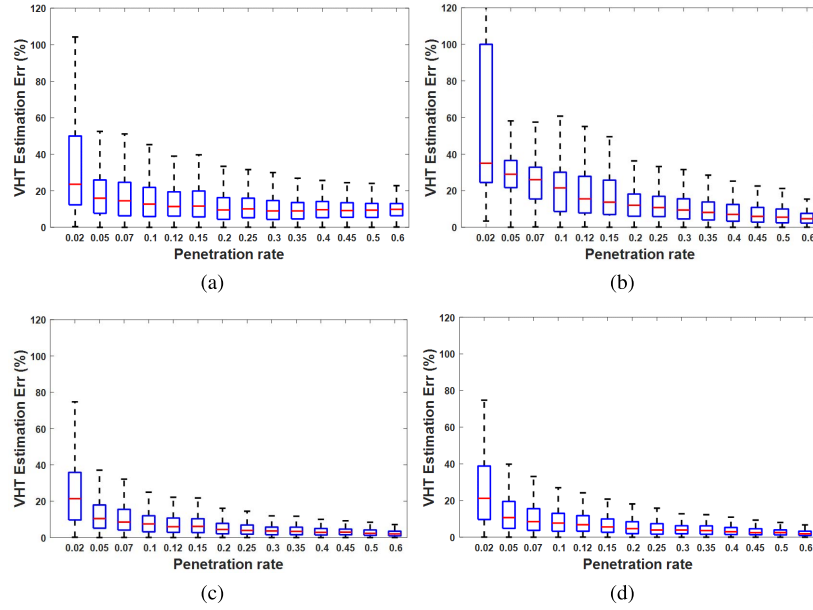


Fig. 8. Approach based VHT estimation errors at the intersection of Santa Anita Ave. from 4:15 PM to 4:30 PM. The population size is 140 for the EB direction, 77 for the WB direction, 170 for the SB direction, and 124 for the NB direction. Penetration rates greater than 0.6 are not shown in this figure. (a) Eastbound. (b) Westbound. (c) Southbound. (d) Northbound.

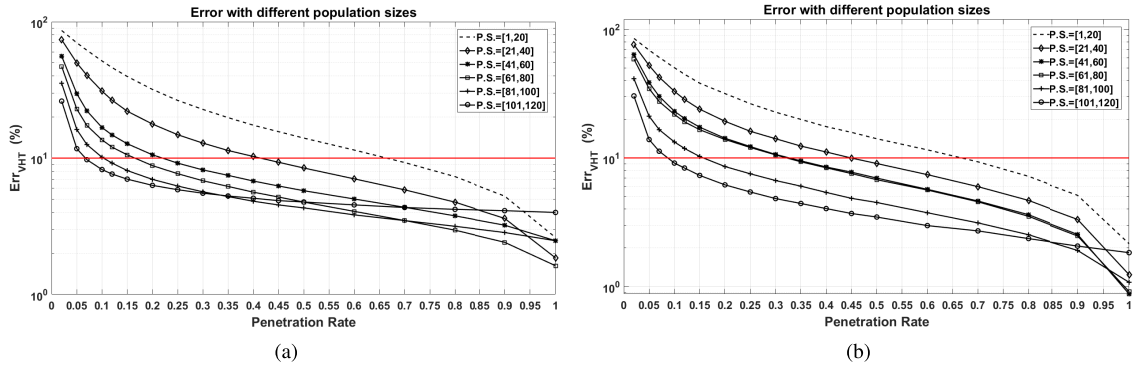


Fig. 9. Relations between VHT estimation errors and penetration rates of probe vehicles under different population sizes (P.S.). (a) Lane group based. (b) Approach based.

the approach based case, it requires more than 100 vehicles (per 15 minutes) to guarantee the same estimation accuracy. However, since it is relatively easier for one approach to satisfy such a requirement, it is better to estimate the performance metrics at the approach level. Note that when the penetration rate reaches one, the VHT estimation error is very small but not zero. That is because the vehicle count from a mid-block detector (\bar{n}) generally has a small deviation from the actual number of vehicles exiting the intersection (n).

B. Delay and LOS Calculation Errors

The ground truth delay is calculated using Eqs. (16) and (17) by replacing the sets of observed travel times \bar{t}_g and \bar{t}_a with the ground truth ones tt_g and tt_a . The HCM delay is calculated using Eqs. (1) to (9). The delay for the proposed method is calculated using Eqs. (16) and (17). The same LOS lookup table (Table I) is used to map the delays to the corresponding LOS's.

1) *Delay*: Figures 10 and 11 provide the lane group based and the approach based delay estimation errors for the intersection at Santa Anita Ave from 4:15PM to 4:30PM. From the figures, it is not surprising to find that the trends are similar to those in Figures 7 and 8 since the delays are calculated from the estimates of average travel times, which are also used in the VHT estimation. As a comparison, we provide the corresponding errors using the HCM delay calculation.

We find that our proposed method requires a sufficiently large population size in order to outperform the HCM method. This is generally true, for example, as shown in Figures 10 and 11. In such a case, a low penetration rate, e.g., 7%-10%, is enough. However, we do find an exception. As shown in Figure 11(d), the northbound direction requires a high penetration rate, e.g., 20%, for the proposed method to outperform the HCM since its estimate is very close to the ground truth value. Such an exception may be caused by the following factors: (i) vehicles in this direction were assigned

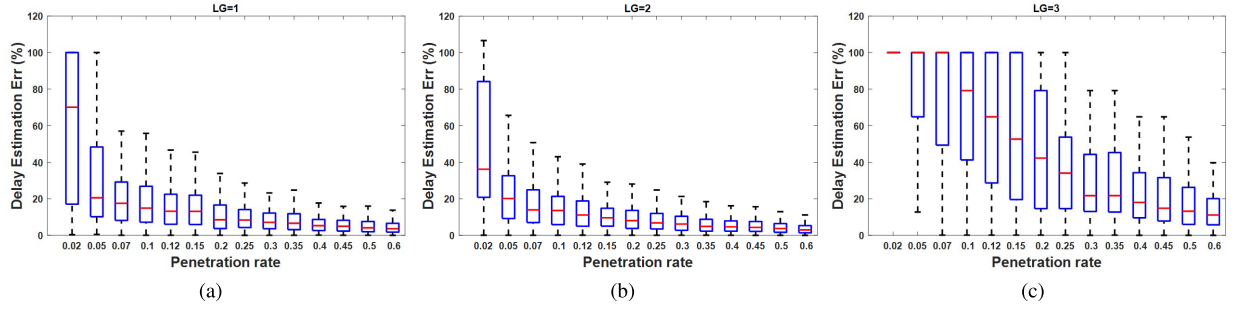


Fig. 10. Lane group based delay estimation errors in the eastbound direction of the intersection at Santa Anita Ave. from 4:15 PM to 4:30 PM. The delay error using the HCM method is: 49.5% for Left turn; 14.9% for Through; and 28.5% for Right turn. Penetration rates greater than 0.6 are not shown in this figure. (a) Eastbound: Left turn. (b) Eastbound: Through. (c) Eastbound: Right turn.

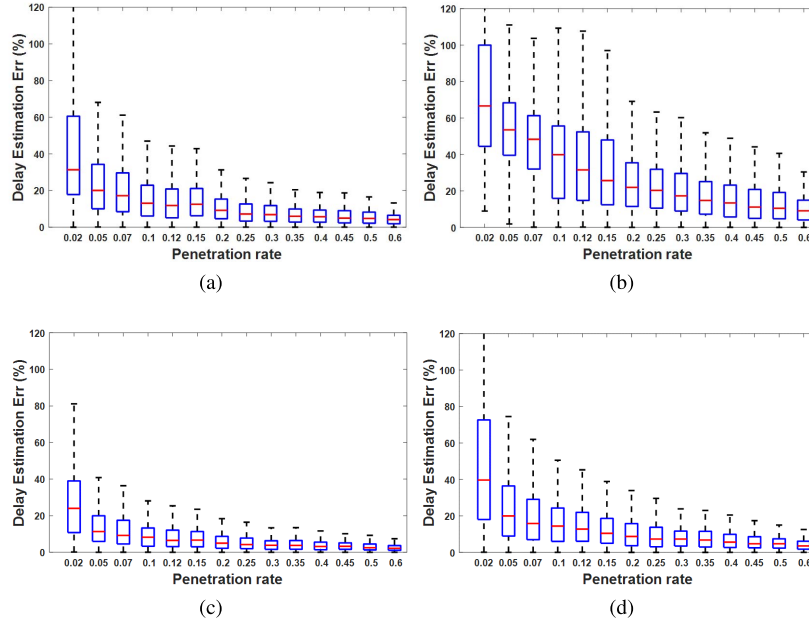


Fig. 11. Approach based delay estimation errors at the intersection of Santa Anita Ave. from 4:15 PM to 4:30 PM. The delay error using the HCM method is: 36.1% for the EB direction; 90.9% for the WB direction; 15.4% for the SB direction; 7.5% from the NB direction. Penetration rates greater than 0.6 are not shown in this figure. (a) Eastbound. (b) Westbound. (c) Southbound. (d) Northbound.

with constant headways from the source, which is consistent with the assumption of uniform arrivals in the HCM method; and (ii) there exists randomness, e.g., sampling of vehicles, in our proposed method, which will also bias our estimation results. Furthermore, we find that when the population size is small, it requires a higher penetration rate to guarantee the estimation accuracy. For example, the right-turn movement in the eastbound direction (Figure 10(c)) has only 7 vehicles, and it requires a penetration rate of more than 30% in order to outperform the HCM method.

2) *LOS*: Table III summarizes the estimation results of approach LOS for all intersections in the whole time period (Totalling 368 samples). Inside the table, confusion matrix and the following statistical metrics are provided for both the HCM and the proposed methods: True Positive Rate (TPR), True Negative Rate (TNR), Precision, Accuracy, and F1 Score. The above metrics can be computed as

$$TPR = \frac{TP}{TP + FN}, \quad (18)$$

$$TNR = \frac{TN}{FP + TN}, \quad (19)$$

$$Precision = \frac{TP}{TP + FP}, \quad (20)$$

$$Accuracy = \frac{TP + TN}{TP + FN + FP + TN}, \quad (21)$$

$$F1 = \frac{2TP}{2TP + FP + FN}, \quad (22)$$

where TP is True Positive, TN is True Negative, FP is False Positive, and FN is False Negative.

From the table, we can find that the HCM method provides poor performance at different levels of LOS's. For example, it only produces 7 out of 30 correct estimates at the LOS of B, and 8 out of 35 correct estimates at the LOS of E. In contrast, we find that when the penetration rate is low, e.g., 2%, the proposed method performs worse than the HCM method, both at the lane group and the approach levels. However, as the penetration rate increases, the estimation gets more accurate. For example, if the penetration rate reaches 7%, the proposed method outperforms the HCM method both at the lane group and the approach levels. Furthermore, we find that the proposed method always performs better at the approach level than the lane group level for any given penetration rate. Note that, even with a high penetration rate, e.g., 10%,

TABLE III
LOS ESTIMATION RESULTS FOR ALL INTERSECTIONS

Total Population		Predicted LOS						Statistical metrics						
		A	B	C	D	E	F	True Positive Rate	True Negative Rate	Precision	Accuracy	F1 Score		
HCM Method	Actual LOS	A	0	0	0	0	0	0	NA	NA	NA	NA	NA	
		B	0	7	0	23	0	0	0.23	0.97	0.44	0.91	0.30	
		C	0	8	18	32	0	0	0.31	0.94	0.50	0.84	0.38	
		D	0	1	18	115	19	10	0.71	0.66	0.63	0.68	0.66	
		E	0	0	0	11	8	16	0.23	0.91	0.22	0.85	0.22	
		F	0	0	0	3	10	69	0.84	0.91	0.73	0.89	0.78	
Lane Group Level	pr=2%	Actual LOS	A	0	0	0	0	0	0	NA	NA	NA	NA	NA
			B	26	4	0	0	0	0	0.13	0.72	0.04	0.67	0.06
			C	15	29	14	0	0	0	0.24	0.79	0.18	0.70	0.20
			D	9	60	63	31	0	0	0.19	0.89	0.57	0.58	0.29
			E	0	5	3	23	4	0	0.11	0.98	0.44	0.90	0.18
			F	0	0	0	0	5	77	0.94	1.00	1.00	0.99	0.97
	pr=5%	Actual LOS	A	0	0	0	0	0	0	NA	NA	NA	NA	NA
			B	20	10	0	0	0	0	0.33	0.93	0.31	0.89	0.32
			C	6	20	32	0	0	0	0.55	0.76	0.30	0.73	0.39
			D	6	2	74	81	0	0	0.50	0.92	0.83	0.73	0.62
			E	0	0	1	17	17	0	0.49	1.00	0.94	0.95	0.64
			F	0	0	0	0	1	81	0.99	1.00	1.00	1.00	0.99
	pr=7%	Actual LOS	A	0	0	0	0	0	0	NA	NA	NA	NA	NA
			B	18	11	1	0	0	0	0.37	0.96	0.44	0.91	0.40
			C	6	13	39	0	0	0	0.67	0.87	0.49	0.84	0.57
			D	5	1	40	117	0	0	0.72	0.94	0.91	0.84	0.80
			E	0	0	0	12	23	0	0.66	1.00	0.96	0.96	0.78
			F	0	0	0	0	1	81	0.99	1.00	1.00	1.00	0.99
	pr=10%	Actual LOS	A	0	0	0	0	0	0	NA	NA	NA	NA	NA
			B	12	18	0	0	0	0	0.60	0.98	0.69	0.95	0.64
			C	4	5	49	0	0	0	0.84	0.95	0.78	0.94	0.81
			D	3	3	14	143	0	0	0.88	0.96	0.94	0.92	0.91
			E	0	0	0	9	26	0	0.74	1.00	0.96	0.97	0.84
			F	0	0	0	0	1	81	0.99	1.00	1.00	1.00	0.99
Approach level	pr=2%	Actual LOS	A	0	0	0	0	0	0	NA	NA	NA	NA	NA
			B	23	7	0	0	0	0	0.23	0.87	0.14	0.82	0.18
			C	15	22	21	0	0	0	0.36	0.70	0.18	0.65	0.24
			D	7	21	85	50	0	0	0.31	0.94	0.79	0.66	0.44
			E	0	0	8	13	14	0	0.40	0.99	0.88	0.94	0.55
			F	0	0	0	0	2	80	0.98	1.00	1.00	0.99	0.99
	pr=5%	Actual LOS	A	0	0	0	0	0	0	NA	NA	NA	NA	NA
			B	19	11	0	0	0	0	0.37	0.94	0.37	0.90	0.37
			C	5	15	38	0	0	0	0.66	0.92	0.59	0.88	0.62
			D	4	4	24	131	0	0	0.80	0.93	0.90	0.88	0.85
			E	0	0	2	14	19	0	0.54	1.00	1.00	0.96	0.70
			F	0	0	0	0	0	82	1.00	1.00	1.00	1.00	1.00
	pr=7%	Actual LOS	A	0	0	0	0	0	0	NA	NA	NA	NA	NA
			B	17	11	2	0	0	0	0.37	0.96	0.44	0.91	0.40
			C	4	7	47	0	0	0	0.81	0.95	0.73	0.92	0.77
			D	2	7	15	139	0	0	0.85	0.95	0.93	0.91	0.89
			E	0	0	0	10	25	0	0.71	1.00	1.00	0.97	0.83
			F	0	0	0	0	0	82	1.00	1.00	1.00	1.00	1.00
	pr=10%	Actual LOS	A	0	0	0	0	0	0	NA	NA	NA	NA	NA
			B	11	18	1	0	0	0	0.60	0.96	0.58	0.93	0.59
			C	1	8	49	0	0	0	0.84	0.96	0.79	0.94	0.82
			D	2	5	12	144	0	0	0.88	0.96	0.95	0.93	0.91
			E	0	0	0	8	27	0	0.77	1.00	1.00	0.98	0.87
			F	0	0	0	0	0	82	1.00	1.00	1.00	1.00	1.00

the proposed method still provides incorrect estimates for some approaches, which is a result of a low population size. For example, at the LOS of D, the proposed method still generates 2 out of 163 LOS estimates of A with $pr = 10\%$ at the approach level.

VI. CONCLUSION

This article has proposed a simple but practical method for computing performance metrics for intersections. Under the assumption that travel time data can be obtained from

a sub-population of vehicles, we proposed to combine the sample mean of travel times with the vehicle count obtained from mid-block loop detectors to obtain an estimate of VHT. This estimator has several advantages as compared to the current state of the practice. First, it is data-driven rather than model-driven and therefore, it does not rely on any modeling assumptions. For this reason it can be applied in a variety of scenarios, including congestion and spillback. It is also very simple to compute as compared to the delay formulas of the HCM. The method also does not require signal timing

parameters to be known. Although the travel time distributions were assumed to be stationary, it remains to be tested whether the method works well under actuated or adaptive signal control. The simple structure of the estimator makes it, in our opinion, a good candidate for deployment, provided the travel times can be obtained.

A microsimulation-based traffic model was used to evaluate the performance of the estimator and compare it to the methodology of the HCM currently used by most traffic analysts in the United States. The simulation model provided a set of ground truth data, on which both methods were applied. The complexities of the travel time distribution produced by the simulator strengthened the case for a data-driven approach. Two possibilities for data collection were considered: lane-group level and approach level, and the results showed that better results were obtained in the latter case. The study also identified the penetration rate of probe vehicles and the population size as the two main factors influencing the estimation error. As a comparison, we first showed that the HCM formulas often failed to produce correct values of LOS (as shown in Table III). Then we showed that when the population size is large, the proposed method only requires 7%-10% of probe vehicles in order to obtain VHT, delay, and LOS estimates that improve upon the HCM. These numbers hold promise for the use of probe data for estimating performance metrics for signalized intersections.

This study considered an ideal case that ignores errors in the measured travel times. This was done for the sake of clarity. However, it is easy to see that because the model is linear, any additional measurement noise will transfer linearly to the estimates. If ground truth travel time measures from real technologies such as Bluetooth, Cell Data Records (CDR), etc. are available in the future, it is interesting to analyze the magnitude and distribution of the measurement errors and the corresponding impact on the proposed estimation method.

ACKNOWLEDGMENT

The authors would like to thank Andrew Campbell and Prof. Alexei Pozdnukhov for the data support. They would also like to thank Francois Belletti and Matthew Wright for their useful comments.

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Qijian Gan received the B.E. degree in automatic control from University of Science and Technology of China in 2009 and the M.S. and Ph.D. degrees in civil engineering from University of California at Irvine (UC Irvine), Irvine, in 2010 and 2014, respectively. He is an Assistant Project Scientist with the Institute of Transportation Studies, UC Irvine. His main expertise includes network traffic flow theory, network modeling and simulation, traffic signal control, and data analysis.



Gabriel Gomes received the B.S. degree in mechanical engineering from Simon Bolivar University, Venezuela, in 1996 and the Ph.D. degree in systems and control theory from Mechanical Engineering Department, University of California at Berkeley, Berkeley, CA, USA, in 2004. He is an Assistant Research Engineer with the California PATH Program, where he focuses on the problems of modeling, control, and simulation of transportation systems.



Alexandre Bayen received the B.E. degree in applied mathematics from École Polytechnique, France, in 1998, and the M.S. and Ph.D. degrees in aeronautics and astronautics from Stanford University, in 1998 and 1999, respectively. He was a Visiting Researcher with the NASA Ames Research Center, from 2000 to 2003. In 2004, he was the Research Director of the Autonomous Navigation Laboratory with the Laboratoire de Recherches Balistiques et Aérodynamiques, Ministère de la Défense, Vernon, France, where he holds the rank of Major. He is the Liao-Cho Professor of Engineering with the University of California at Berkeley, Berkeley, CA, USA, and a Professor of Electrical Engineering and Computer Science, and Civil and Environmental Engineering. He is currently the Director of the Institute of Transportation Studies. He is also a Faculty Scientist of Mechanical Engineering with the Lawrence Berkeley National Laboratory. He has authored two books and over 200 articles in peer-reviewed journals and conferences. He was a recipient of the Ballhaus Award from Stanford University, in 2004, the CAREER Award from the National Science Foundation, in 2009, and he is a NASA Top 10 Innovators on Water Sustainability, in 2010. He was also a recipient of the Presidential Early Career Award for Scientists and Engineers Award from the White House, in 2010, the Okawa Research Grant Award, the Ruberti Prize from the IEEE, and the Huber Prize from the ASCE.