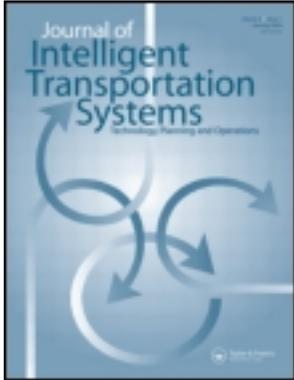


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# Measuring Signalized Intersection Performance in Real-Time With Traffic Sensors

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*Safety and quality of travel on arterial networks tie closely to the performance of signalized intersections. Measures commonly used for intersection performance evaluations are control delay, queue length, and cycle failure. However, these variables are not directly available from typical configurations of traffic sensors designed for intersection signal control. Collecting vehicle control delay data manually for intersection performance measurement has been a task too time-consuming and labor-intensive to be practical. Video image processors (VIPs) have been increasingly deployed for intersection signal control in recent years. This study aims to use the extra detection capabilities of VIPs for performance monitoring at signalized intersections. Most VIPs can support up to 24 virtual loops, but normally less than half of the virtual loops are used. By properly configuring the spare virtual loops and analyzing the loop measurements, intersection performance can be monitored in real time. In this research, we propose an approach for measuring queue length and vehicle control delay at signalized intersections based on traffic count data collected with traffic sensors. This algorithm has been implemented in a computerized system called In-PerforM. The In-PerforM system was evaluated by both field tests and simulation experiments. Although the VIPs' counting errors do affect the accuracy of field test results, we still received encouraging results on queue lengths and control delay measurements in both the field tests and simulation experiments. This demonstrates that the In-PerforM system, and therefore the proposed algorithm, has the potential to be a cost-effective approach for performance measurement at signalized intersections.*

**Keywords** Control Delay; Performance Measurement; Queue Length; Signalized Intersections; Traffic Detector

## INTRODUCTION

There are more than 265,000 signalized intersections in the United States (Institute of Traffic Engineers [ITE], 2004). Qual-

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ity of travel on these roadways ties closely to the performance of signalized intersections. There are several traffic parameters for performance evaluation at signalized intersections (Abu-Lebdeh, Chen, & Benekohal, 2007). In terms of automobile performance measurement, the *Highway Capacity Manual 2010* (Transportation Research Board, 2010) uses control delay and volume-to-capacity ratio to characterize level of service (LOS). Control delay is the part of the total delay that contributes to traffic signal operation of a signalized intersection. In the traditional definition, queue size is the maximum number of vehicles queued during a signal cycle, and queue length is the distance between the stop line and the rear of the stacked queue. In this article, the queue length means the queue size, that is, the number of vehicles in a queue. Cycle failure occurs when a number of queued vehicles cannot enter the intersection due

to insufficient capacity during a signal cycle. These traffic parameters are difficult or even impossible to directly capture by typical configurations of traffic sensors designed for intersection signal control. Collecting vehicle control delay data manually for intersection performance measurement has been a task too time-consuming and labor-intensive to be practical. Therefore, in practice, intersection performance is typically evaluated by using the calculation equations suggested by the *Highway Capacity Manual (HCM)* (Transportation Research Board, 2010). Since these HCM equations are based on certain vehicle arrival patterns and predetermined parameters that may not be appropriate for specific applications, the HCM equation-based calculations may not be accurate enough for traffic operation purposes, unless the inputs to the HCM formulas are accurate or descriptive enough of prevailing conditions (Fambro & Rouphail, 1997).

In recent years, the rapidly developing technologies, especially the information technology, have provided many more opportunity and capacity to solve transportation problems that were difficult to deal with before and to supply better transportation services. Intelligent transportation systems (ITS), which apply advanced sensor, computer, electronics, and communication technologies to improve the transportation system, have gained more and more attention from researchers and are widely applied in many transportation fields (National ITS Architecture Team, 2001). As part of the ITS efforts, video image processors (VIPs) have been increasingly deployed for intersection signal control over the past decade. Most VIPs can support up to 24 virtual loops, but normally less than half of the virtual loops are used. By properly configuring the spare virtual loops and analyzing the loop measurements, intersection performance can be monitored in real time.

In this article, we present innovative algorithms designed for measuring average control delay and queue length at signalized intersections using traffic counts collected from properly configured traffic sensors, such as inductance loops or VIPs. These algorithms are implemented in a computerized system called In-PerforM for measuring the performance of signalized intersections in real time. The article is organized as follows: A brief overview of the state of the art is provided in the second section, followed by a detailed description of the proposed methodology in the third section. In the fourth section, we present the implementation of the proposed algorithms in the prototype In-PerforM system. Then we show field test and simulation test results in the fifth section. In the last section, we conclude the study and recommend future studies.

### STATE OF THE ART

In the past decades, researchers have put their endeavors to monitor freeway traffic performance. Various freeway performance measurement systems were developed and widely implemented in practice. These systems have traditionally relied on

archived ITS data retrieved from fixed sensors. For instance, the California Department of Transportation (Caltrans) developed the Performance Measurement System (PeMS), which provides a comprehensive assessment of freeway performance based on loop detector data (Chen, Karl, Alexander, Pravin, & Jia, 2001). The TranStar system in Houston provided vehicle delays, which were calculated based on travel time data collected by an automatic vehicle identification (AVI) system (Texas Transportation Institute [TTI], 2000).

Recently, more and more research focuses have been shifted to the arterial performance measurement, especially for the signalized intersection performance monitoring. Loop detector data still dominate the traffic detection systems due to their low costs. Numerous studies are conducted to estimate the signalized intersection delay and queue length using loop detection data. Sharma, Bullock, and Bonneson (2007) developed a new technique that calculates vehicle delay and queue length at signalized intersections based on the arrival and departure profiles generated from loop detectors. Calculated delays and queue lengths were compared with manually extracted ground-truth data. The delay calculation error was found to be below 0.7 veh-s and the error for maximum queue length was less than 0.15 on a cycle-by-cycle basis. Texas Transportation Institute developed a traffic signal performance measurement system (TSPMS) using the existing traffic controller and detector data (2005). However, it cannot retrieve queue length directly. As a supplement of PeMS system for Caltrans, Skabardonis and Geroliminis (2008) employed the kinematic wave theory to calculate travel times using loop detector data. Specific treatments were also provided to treat both long queues and queue spillovers. Their developed algorithm has been implemented into PeMS system as the Arterial Performance Measurement System (APeMS).

With the advent of data collection technologies, more and more research studies are stimulated to evaluate the signalized intersection performance measures using various data sources (Ran, Jin, Boyce, Qiu, and Cheng, 2012). Liu and Ma (2008) proposed the SMART-SIGNAL (Systematic Monitoring of Arterial Road Traffic and Signals) system to calculate a rich set of performance measures, such as volumes and queue length. This system requires a data server in each master cabinet and the initial cost for data collection is significant. Based on this system, Liu, Wu, Ma, and Hu (2009) used the high-resolution event data, and applied Lighthill-Whitham-Richards (LWR) shock-wave theory to estimate time-dependent queue length even when the signal links are congested with long queues. Liu and Ma (2009) proposed a virtual probe vehicle model to estimate the time-dependent travel time. Both intersection queue length and travel time were compared with ground truth data with a satisfactory accuracy. Cheng, Qin, Jin, Ran, and Anderson (2011) proposed a cycle-by-cycle queue length estimation approach based on the extracted vehicle trajectory from global positioning system (GPS) data. Ban, Herring, Hao, and Bayen (2009) inferred the sampled travel times between two consecutive locations on arterial streets from mobile sensors to estimate

the delay pattern in the signalized intersection. Using the similar mobile data sets, Ban, Hao, and Sun (2011) introduced two concepts: queue rear no-delay arrival time (QRNAT) and queue front no-delay arrival time (QFNAT). By combining with the shock-wave theory, they were able to estimate queue length in a real-time manner. Smaglik, Sharma, Bullock, Sturdevant, and Duncan (2007) developed an integrated general-purpose data collection module to collect cycle by cycle data based on the actuated traffic controller, and provided quantitative graphs to measure signalized intersection performance. Smaglik, Bullock, and Sharma (2007) also proposed a procedure where the arrival type parameter can be calculated by traffic signal controllers in real time. It provides an easily obtainable measure for quantifying the quality of traffic signal coordination. Following the similar logic, Day, Sturdevant, and Bullock (2010) collected the high-resolution controller data to quantify the signalized arterial capacity, such as degree of intersection saturation, volume-to-capacity ratio, and others. Cheng, Qin, Jin, and Ran (2012) presented the shock-wave approach to estimate queue length using probe trajectories in the signalized intersection. Viti and Zuyleen (2009) applied probabilistic modeling to calculate the distribution of both queues and delays at a signalized intersection. The model result was consistent with the simulated result. These previous studies laid a valuable foundation for the modeling and analysis work of this study. However, most of these algorithms are driven by mathematical equations, such as shock-wave theory, queuing theory, and so on. These well-known theoretical models could capture only a certain amount of facts, since there are several assumptions associated with each model, and these assumptions may not adhere to the reality well due to human factors (Ma, Wu, & Wang, 2012).

Video image processing could be another effective countermeasure to quantify the signalized intersection performance. Several studies have been conducted to collect intersection traffic data based on this technique. A video image processing system, called Spatial Image Processing Traffic Flow Sensor (SPITS), was developed by Higashikubo, Hinenova, and Takeuchi (1997) to detect traffic queue length. SPITS measures a queue length in meters, but cannot provide the number of vehicles in a queue. Fathy and Siyal (1995, 1998) also developed image processing systems to measure volume, speed, vehicle length, and queue length. The profiles used to detect queue length were divided into subprofiles, each with approximately the same length per vehicle, thereby making it possible to estimate the number of vehicles in the queue. Yin, Fan, Liu, and Ran (2004) used virtual loops to measure traffic parameters. The position and size of each loop can be adjusted by users for collecting volume, speed, occupancy, and vehicle classification data. Zheng, Wang, Nihan, and Hallenbeck (2006) developed a video image processing system to detect traffic signal cycle failure by tracking the location of the end of the queue. Gupte, Masoud, Martin, and Papanikolopoulos (2002) proposed a method to track vehicles by matching regions with vehicles in the video stream. Vehicle parameters such as location, length, and speed can be extracted from images captured by a properly

calibrated camera. They also proposed to use a dynamically updated threshold to separate vehicles from the background. In a study conducted by Saito, Walker, and Zundel (2001), average stopped vehicle delays were estimated by image analysis. The total delay was calculated by adding all the stopped vehicle delays in a sampling time interval. The average stopped vehicle delay was then estimated by dividing the total delay by the total volume.

Video-based vehicle detection provides an alternative approach to collect vehicles' speed, queue lengths, and delay in the signalized intersection. In some cases, not every intersection is installed by the loop detectors (Du & Barth, 2005). Video image processing is a surrogate for intersection performance measurement under these circumstances. However, video-based vehicle detection has its inherent disadvantages to extract traffic parameters; for example, occlusion, vibration of cameras, and sensitivity of the environmental factors may impact the accuracy of video detection (Malinovskiy, Wu, & Wang, 2009). Combining traditional inductance loop detection and video-based vehicle detection techniques triggers the emergence of virtual loops (Yin et al., 2004). The merits of virtual loop approach lie in the following two aspects: (a) There are no physical loops embedded in the pavement, which generates no indirect costs, such as maintenance and installation fees. (b) Traffic engineers can easily configure the size and location of virtual loops for data collection. Besides the fundamental traffic parameters, such as vehicle speed and volume, virtual loops should be able to generate more useful information for signalized intersection performance measures. This article aims to propose an effective and efficient approach to measure the intersection delay and queue length.

## METHODOLOGY

This methodology requires vehicle count data but does not require a specific detection system. There are several detection systems that are available for this task, and most of them perform reasonably well and have been commercialized for years. In this study, a Traficon VIP3D.2 detector was chosen to capture the traffic volume and speed data. The reason for using a VIP was because of its extra detection capability, mentioned earlier in the Introduction section. Its flexibility in drawing the virtual loops at desired locations is another attractive aspect for this research. Choosing VIP3D.2 among the available VIP products was that it is one of the most widely used type of VIPs and has been deployed at many locations, including the city of Lynnwood, WA, which supplies traffic data to the research team at the Smart Transportation Applications and Research Laboratory (STAR Lab) of the University of Washington (UW).

Based on the vehicle count data, vehicle queue lengths can be estimated with a model developed in this study. With the estimated queue length, an innovative algorithm can be applied to calculate the corresponding control delays. Consequently,

signal cycle failures can be calculated using the estimated queue length and signal control status data. Signal control status data can be polled from traffic controllers or estimated based on vehicle movements. However, in this study we focus only on queue length and control delay estimates. Signal cycle failure estimation is not covered in this article. Readers interested in our cycle failure research are referred to Zheng et al. (2006) for details.

**Study Site With Traffic Sensor Configuration**

Figure 1 shows the layout of the study site, an intersection approach with four lanes of the following configurations:

1. The right-most lane is a right-turn-only lane and is numbered as Lane 1.
2. The second and third lanes (Lanes 2 and 3) from the right are for through movements only.
3. The left-most lane (or the fourth lane from the right) is a left-turn-only lane (Lane 4).

At this study site, all four lanes are in the same signal phase group; that is, protected left-turn, through, and right-turn movements share the same green signal. Figure 1 also shows the traffic sensor configurations for each lane at the study site. In our method for intersection performance measurement, only vehicle count data are needed from traffic sensors. At this site, these traffic sensors are of the VIP3D.2 type. Actually, any type of traffic sensors, such as inductance loops, infrared detectors, radar sensors, and so on, that can provide reliable count data should work. Each lane has two traffic sensors, with the upstream one called an entry loop and the downstream one called an exit loop. The area between the entry loop and the exit loop is called the measuring zone. Each loop outputs a pulse signal together with a time stamp when a vehicle is detected. The normal distance of the measuring zone is between the stop line and mid block. In the ideal situation, the measuring zone covers all the traffic queues.

The methodology development in this article is based on the layout and sensor configuration at the study site. Although this study site represents a relatively ideal intersection approach layout, the methodology developed in this article can be easily modified and extended for applications in other approach layouts.

**Modeling Queue Length**

Queue length data can be derived from vehicle count data. The analysis starts at the beginning of a red phase  $t_r(1)$ . Assume that the queue length on lane  $i$  at time  $t_r(1)$  is  $Q_i$ , where  $i = 1, 2, 3,$  and  $4$  (lane is numbered from right to left as shown in Figure 1). At the end of the red phase, that is, the beginning of the first green phase  $t_g(1)$ , the entry loops detected that a total

of  $IV_r(1)$  vehicles entered the measuring zone, and the right-turn exit loop detected that  $OV_r(1,1)$  vehicles completed a right turn; hereby the first “1” in  $OV_r(1,1)$  refers to the phase number and the second “1” to the lane number (right lane is numbered as Lane 1). Then a total of  $IV_r(1) - OV_r(1,1)$  vehicles added to the initial queues through the first red phase. Depending on the intended movements (i.e., through, left turn, and right turn), these vehicles enter different queues. For the purpose of queue modeling, it is assumed that a vehicle will follow the lane layout for its intended movement and join the shortest queue whenever choices are available.

Assuming that the right-turn to total volume ratio is  $rr$  and the left-turn to total volume ratio is  $lr$ , the queue lengths at the end of the  $(k + 1)$ th ( $k > 1$ ) red phase are:

Right turn lane:

$$Q_r(k + 1, 1) = Q_g(k, 1) + IV_r(k + 1) \cdot rr(k + 1) - OV_r(k + 1, 1) \tag{1}$$

Through lanes:

$$Q_r(k + 1, 2) = Q_g(k, 2) + IV_r(k + 1) \cdot (1 - rr(k + 1) - lr(k + 1))/2 \tag{2}$$

and

$$Q_r(k + 1, 3) = Q_g(k, 3) + IV_r(k + 1) \cdot (1 - rr(k + 1) - lr(k + 1))/2 \tag{3}$$

Left turn lane:

$$Q_r(k + 1, 4) = Q_g(k, 4) + IV_r(k + 1) \cdot lr(k + 1) \tag{4}$$

where  $OV_r(k + 1, 1)$  represents number of vehicles detected by the exit loop at the right-turn lane during the  $(k + 1)t_h$  red phase and  $IV_r(k + 1)$  represents number of vehicles detected by all entry loops during the  $(k + 1)t_h$  red phase.  $Q_g(k)$  represents the queue length at the end of the  $k$ th green phase and can be calculated as follows:

Right turn lane:

$$Q_g(k, 1) = Q_r(k, 1) + IV_g(k) \cdot rr(k) - OV_g(k, 1) \tag{5}$$

Through lanes:

$$Q_g(k, 2) = Q_r(k, 2) + IV_g(k) \cdot (1 - rr(k) - lr(k))/2 - OV_g(k, 2) \tag{6}$$

and

$$Q_g(k, 3) = Q_r(k, 3) + IV_g(k) \cdot (1 - rr(k) - lr(k))/2 - OV_g(k, 3) \tag{7}$$

Left turn lane:

$$Q_g(k, 4) = Q_r(k, 4) + IV_g(k) \cdot lr(k) - OV_g(k, 4) \tag{8}$$

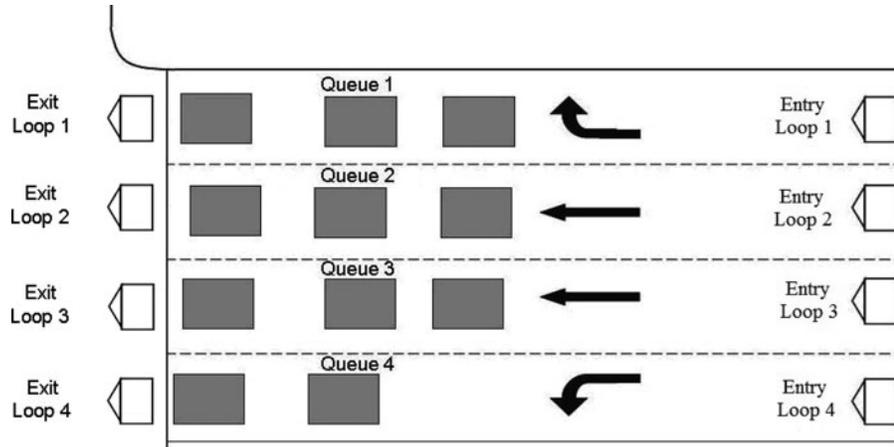


Figure 1 Layout and sensor configuration of the study site.

where  $OV_g(k,i)$  represents number of vehicles detected by the exit loop at lane  $i, I \in [1, 4]$ , during the green phase of interval  $k$  and  $IV_g(k)$  represents number of vehicles detected by all entry loops during the green phase of interval  $k$ . Right-turn and left-turn volume ratios can be estimated with historical data and updated periodically using Eqs. 9 and 10, respectively.

$$rr(k+1) = \frac{OV_r(k, 1) + OV_g(k, 1)}{\sum_{i=1}^4 OV_g(k, i) + OV_r(k, 1)} \quad (9)$$

$$lr(k+1) = \frac{OV_g(k, 4)}{\sum_{i=1}^4 OV_g(k, i) + OV_r(k, 1)} \quad (10)$$

When  $k = 1$ , the queue lengths are:

$$Q_r(1, 1) = Q_1 + IV_r(1) \cdot rr(1) - OV_r(1, 1) \quad (11)$$

$$Q_r(1, 2) = Q_2 + IV_r(1) \cdot (1 - rr(1) - lr(1))/2 \quad (12)$$

$$Q_r(1, 3) = Q_3 + IV_r(1) \cdot (1 - rr(1) - lr(1))/2 \quad (13)$$

$$Q_r(1, 4) = Q_4 + IV_r(1) \cdot lr(1) \quad (14)$$

$$Q_g(1, 1) = Q_r(1, 1) + IV_g(1) \cdot rr(1) - OV_g(1, 1) \quad (15)$$

$$Q_g(1, 2) = Q_r(1, 2) + IV_g(1) \cdot (1 - rr(1) - lr(1)) - OV_g(1, 2)/2 \quad (16)$$

$$Q_g(1, 3) = Q_r(1, 3) + IV_g(1) \cdot (1 - rr(1) - lr(1)) - OV_g(1, 3)/2 \quad (17)$$

$$Q_g(1, 4) = Q_r(1, 4) + IV_g(1) \cdot lr(1) - OV_g(1, 4) \quad (18)$$

As shown in the preceding equations, the initial queue lengths on all four lanes should be known to start the process. Considering that cycle failure does not exist during off-peak hours at most intersections, it can be assumed that  $Q_1 = Q_2 = Q_3 = Q_4 =$

0 if the process is started during off-peak hours. As for the initial turning volume ratios,  $rr(1)$  and  $lr(1)$ , we can estimate values from historical data. The cost for incorrect initial values is diminishing and after first few cycles, the turning volume ratios should adapt to their correct values because these ratios are continuously updated using virtual loop measured volumes.

Although equations are given to only the scenario shown in Figure 1, the same logic can be extended to other scenarios. When shared lanes exist, probability theory can be employed to model the vehicle lane arrivals and real-time feed back information will be needed to tune up the probability models for enhanced accuracy. However, as a study to initiate and demonstrate the idea, this study will not investigate the details of such shared lane scenarios.

If the vehicle queue extends beyond the entry loop, it cannot be estimated accurately. The frequency of such cases depends on the location of the entry loop. Ideally, it is installed at a mid-block location as has been done in the city of Lynnwood to avoid being occupied. The STAR Lab is currently working on a pattern-recognition approach to estimate queue lengths from loops occupied by queued vehicles. This approach will be incorporated in the In-PerforM system to make it more robust to all possible traffic flow conditions.

### Measuring Control Delay

Based on the calculated queue lengths, together with vehicle count data, average control delay can be estimated. Assume the distance from the entry loops to the exit loops is  $L$  and the speed limit on the approach is  $s_{df}$ . The time needed to traverse the length of  $L$  with  $s_{df}$  is

$$tt_{df} = \frac{L}{s_{df}} \quad (19)$$

When a vehicle  $i$  enters the measuring zone, its entry is time-stamped as  $en_i$  and recorded in a log file. Similarly, when a vehicle  $j$  exits the measuring zone, its departure time stamp  $de_j$

is also recorded. By comparing the entry time and the departure time of vehicle  $i$ , its control delay can be calculated as

$$cd_i = de_i - en_i - tt_{df} \quad (20)$$

In reality, however, it is difficult to match the entry and departure time for each vehicle. Therefore, only average control delay data can be collected using this approach.

Assume that we start to collect control delay data at time  $t_0$  when the total number of vehicles in the measuring zone is  $N$ . Because the time when the  $N$  vehicles entered is unknown, we cannot provide control delay measurements for these vehicles. After all the  $N$  vehicles have checked out at  $t_s$ , we can start to calculate control delay. To estimate the average control delay from  $t_s$  to  $t_e$ , we need to know the number of vehicles exited from the detection zone  $N_{de}$ .  $N_{de}$  should be the sum of all the exit-loop detected vehicles from  $t_s$  to  $t_e$ . Then the average control delay of the  $N_{de}$  vehicles can be calculated using Eq. 21:

$$D(t_s, t_e) = \frac{\sum_{i=1}^{N_{de}} (de_{i+N} - en_i)}{N_{de}} - tt_{df} \quad (21)$$

Although the logged  $en_i$  and  $de_{i+N}$  may not be for the same vehicle, mismatch is not an issue for calculating the average control delay as far as all the timestamps of the  $N_{de}$  vehicles are included in the calculation.

### ALGORITHM IMPLEMENTATION

To demonstrate and test the algorithms described in the Methodology section, a prototype system, Intersection Performance Measurement (In-PerforM) system, is developed and tested with field data. This system was evaluated using traffic counts from VIPs, which are increasingly deployed for traffic detection in the field. However, the In-PerforM system is also capable of receiving input data from other traffic sensors, such as inductive loops.

In practice, the existing advance loop or system loop may serve as the entry loop and the presence loop or checkout loop may serve as the exit loop. When VIPs are used for traffic detection as is the case for the study site, the entry loop and the exit loop are very likely on different fields of view. Therefore, the In-PerforM system requires the input from up to two traffic cameras, one at the entrance and one at the exit of the approach. The VIP3D.2 card can process video images from two cameras at the same time and output traffic counts for all the virtual loops in every 5 s. Figure 2 shows a screen shot of the user interface of the VIP3D.2 card. The four black boxes with arrows are virtual loops that count the number of vehicles passing over them in the direction of the arrow.

The In-PerforM system is implemented in Microsoft Visual C#. The computer that runs the In-PerforM system communicates with the VIP3D.2 card through an Ethernet cable. The traffic count data are logged in a Hypertext Markup Language (HTML) file every 5 s. The In-PerforM system then polls the

vehicle count data from the HTML file as soon as a new event is logged. Using the algorithm introduced in the Methodology section, the queue length and control delay data can be estimated. Figure 3 shows a snapshot of the user interface, with output and input data presented, of the prototype In-PerforM system.

In addition to traffic counts from the entry and exit loops, traffic signal control event data are also needed. There are two ways to acquire the traffic signal status data. The first one is to estimate the traffic signal status based on the video data. There are no extra hardware requirements in the method. When through or left-turn vehicles start to move from still at the stop bar, then we know green signal is initiated. When they start to stop from motion, then it is the moment that green signal expires. The second one is to acquire real-time high-resolution detector-event data from traffic cabinets for the In-PerforM system, and it is implemented in this study (Wang, Wu, Ma, & Corey, 2011). With an Ethernet I/O device that collects high-resolution event data from the back panel of the cabinet, the event data, which include voltages changes in traffic signal lights and traffic sensors, are transmitted to the Traffic Management Center through fiber optics in real time. They are stored in binary format in a Microsoft SQL Sever database hosted at the STAR Lab, and can be accessed by the In-PerforM system in real time. Figure 4a shows the configuration interface. Figure 4b shows the status of each signal. Figure 4c shows the verification process with the detector and traffic signal statuses visualized by a computer program for comparison with real-time traffic video.

### TESTS AND DISCUSSION

#### Test With Field Data

The study site was chosen as the northbound approach of the intersection of SR 99 and 200th Street SW, Lynnwood, WA. This intersection is one of the busiest in the city of Lynnwood. The city of Lynnwood has installed traffic cameras at both the stop line and an upstream location to monitor and control traffic. Two videocassette recorders (VCRs) were used to record traffic video for the field test. About 100 min of data was recorded during afternoon peak hours.

The recorded video data were used as field data inputs to the VIP3D.2 card at the STAR Lab. The queue length and control delay measured by the In-PerforM system were compared with the ground-truth data extracted manually. The ground-truth data of control delay were collected using field measurement technique by Currin (2012). The test results are summarized in Table 1. Error is defined as the difference between the measured value and the ground-truth value.

We can see that traffic volumes were undercounted at both the entry and exit loop locations. A  $t$ -test was conducted to evaluate the difference between the VIP reported volumes and the ground-truth volumes. A  $t$ -ratio value of  $-6.04$  was obtained

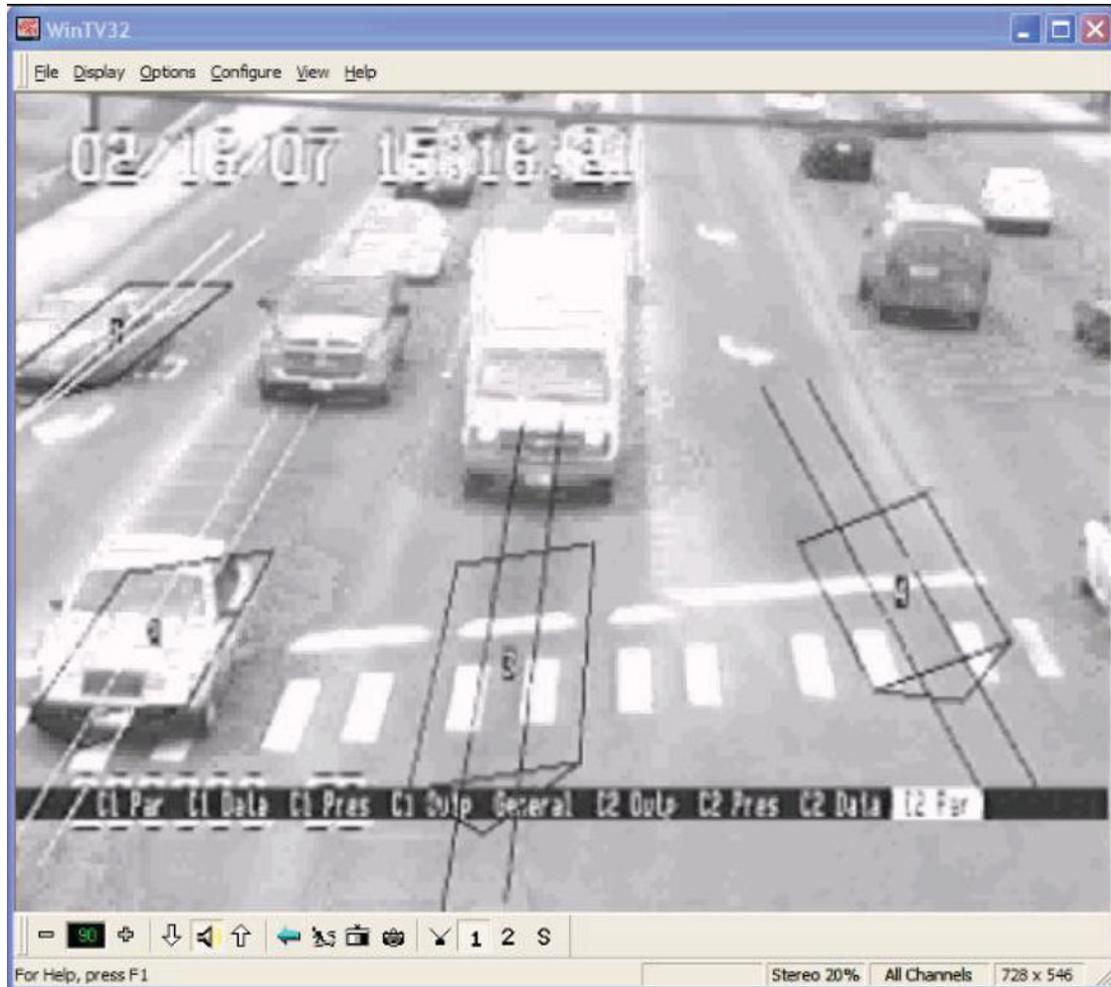


Figure 2 Screen shot of the user interface of VIP3D.2 card (color figure available online).

for the  $t$ -test between the detected entrance volume and the corresponding ground-truth volume sequences. Similarly, the  $t$ -test between the VIP detected exit volume and the ground-truth exit volume series resulted in a  $t$ -ratio of  $-4.70$ . With the critical  $t$ -ratio of  $2.02$  for the degree of freedom ( $df$ ) =  $39$  and the significance level  $p = .05$ , we identified that the VIP card used for this test significantly undercounted vehicles. The reason for the undercount errors was not clear. It could be caused by vehicle occlusions or the detection algorithm implemented in the VIP card. Such count errors inevitably affected the estimation accuracy of queue lengths and control delay. However, we would be interested to see whether the degraded estimation accuracy is still acceptable in practice.

The test results showed that the estimated queue length was also underestimated compared to the ground-truth queue lengths, with a  $t$ -ratio of  $-4.04$ , larger than the critical  $t$ -ratio of  $2.02$ . Consequently, the control delays were underestimated as well, with a  $t$ -ratio of  $-11.24$ , way above the critical  $t$ -ratio of  $2.02$ , when compared with the ground-truth control delays. However, when comparing the average values of the estimated

variables and the ground-truth data, the performance of the In-PerforM system is definitely acceptable. The average queue length provided by the In-PerforM system was  $9.9$  vehicles, only  $0.9$  vehicles lower than the ground-truth data, with a standard deviation of  $1.43$  vehicles. This reflects a relative error of  $8\%$ , which is good enough for practice in most cases. Similarly, the average control delay estimated by the In-PerforM system was  $42.6$  s/veh, which is  $3$  s/veh or  $7\%$  shorter than the ground-truth control delay of  $45.6$  s/veh, with a standard deviation of  $1.72$  vehicles. Considering the randomness in vehicle arrival from cycle to cycle, such accuracy in control delay estimates is sufficient from practical perspective and would still predict the right level of service in most cases.

The delay calculated by the HCM2010 method is  $30.9$  s/veh. The number is lower than the ground truth  $45.6$  s/veh. The reason why the HCM2010 method underestimates the control delay in this particular case study might result from multiple reasons. One potential reason might be that the field test site is close to several small businesses areas and drivers tend to have a longer startup time. Another potential reason might be because

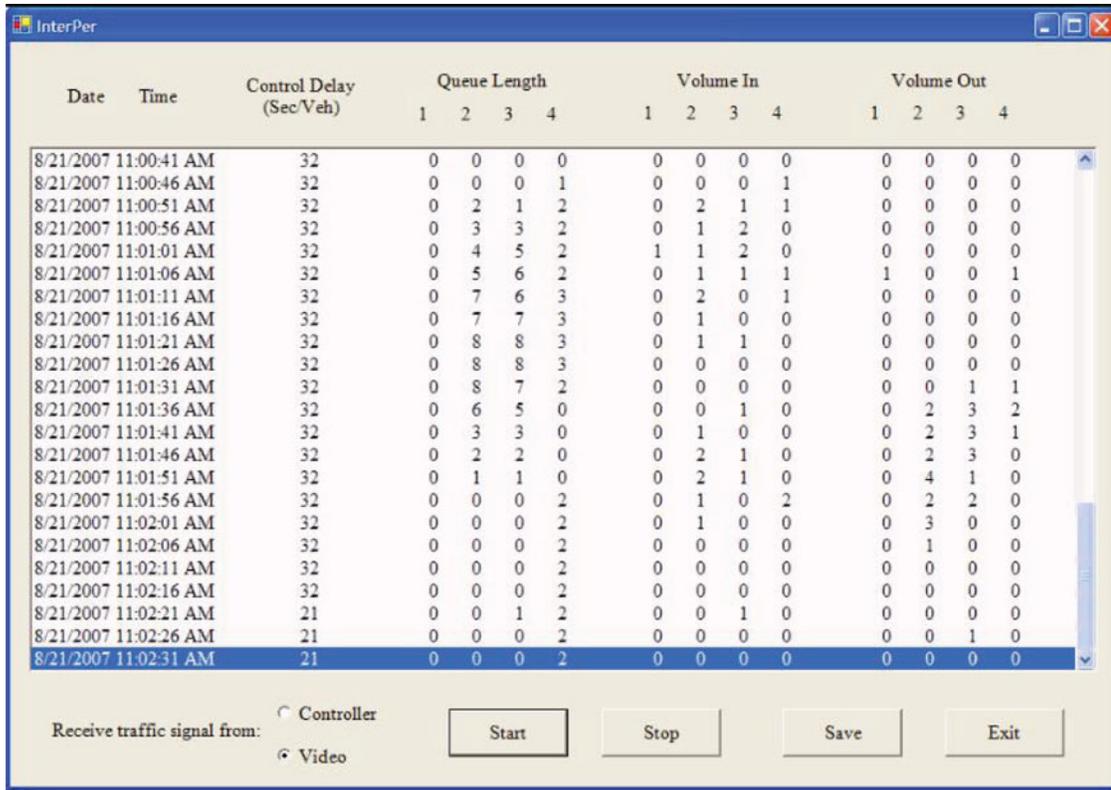


Figure 3 User interface of the prototype In-PerforM system (color figure available online).

the HCM2010 method does not fully capture the behaviors of the drivers in the field test site.

**Test on Simulated Data**

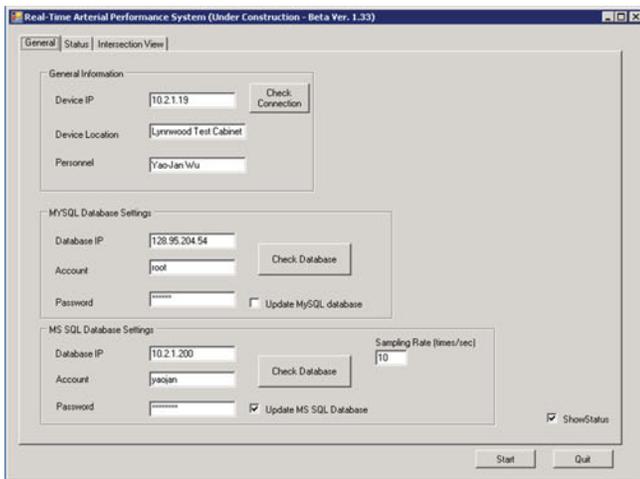
The test with field-collected data showed that the queue length and control delay estimation algorithms are practical but their performance depends largely on the accuracy of traffic counts. Since the traffic sensor undercounted vehicle volumes, the accuracy of our algorithms may have been underestimated in the field test. To test the algorithms with ideal sensor inputs, a simulation model was developed using the VISSIM simulation tool. VISSIM is a microscopic step and driver behavior-based traffic simulation tool, employed widely by transportation modelers and researchers. More details of the tool can be found in the *VISSIM User Manual* (PTV 2007).

Since VISSIM tracks each vehicle’s movement in the simulation model, it can measure control delays nearly perfectly. It can also provide the physical lengths of vehicle queue as “queue length.” Since the proposed method counts queue lengths as number of vehicles in the measuring zone, the definition of queue length is different and conversion of the physical vehicle queue length in distance to number of vehicles in the queue is necessary before comparison can be made. According to Wang and Nihan (2003), the majority of vehicles traveling in west

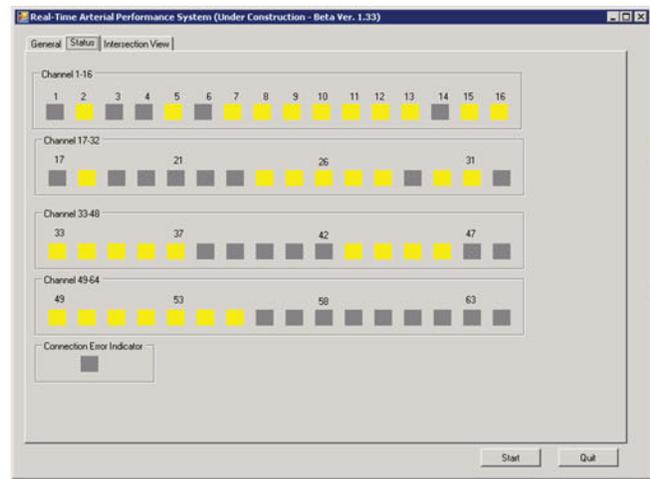
Washington are vehicles that are shorter than 12.2 m (or 40 ft) and the mean length for these short vehicles is 5.5 m (or 18.0 ft). Assuming a standstill net distance of 0.5 m (or 1.6 ft), a vehicle takes roughly 6.0 m (or 19.6 ft) in a queue. Queue length in number of vehicles can be resulted from dividing the VISSIM produced queue length by 6.0 m (or 19.6 ft). Even after the conversion, there is still some difference between the VISSIM measured queue length in number of vehicles and the calculated queue length from the proposed algorithm because the latter one includes not only stopped vehicles but also moving vehicles in the measuring zone. Therefore, attention must be paid when making comparisons between the simulation results and calculation results.

The simulation model was calibrated using field observed data. Readers are referred to Wang, Hallenbeck, Zheng, Zhang, Ma, and Corey (2008) for details of the calibration process. Forty-five signal control cycles were simulated in this experiment. In total, five simulation runs were conducted, with each run using a different random seed. Table 2 shows the test results of the queue length and control delay from the simulation experiments. The ground truth values in Table 2 were directly provided by or converted from the VISSIM’s delay and queue length evaluation tools. We also set up vehicle counting detectors in the simulation model. The vehicle counts provided by VISSIM were saved in a data file and postprocessed with our queue length and control delay estimation algorithms. That is,

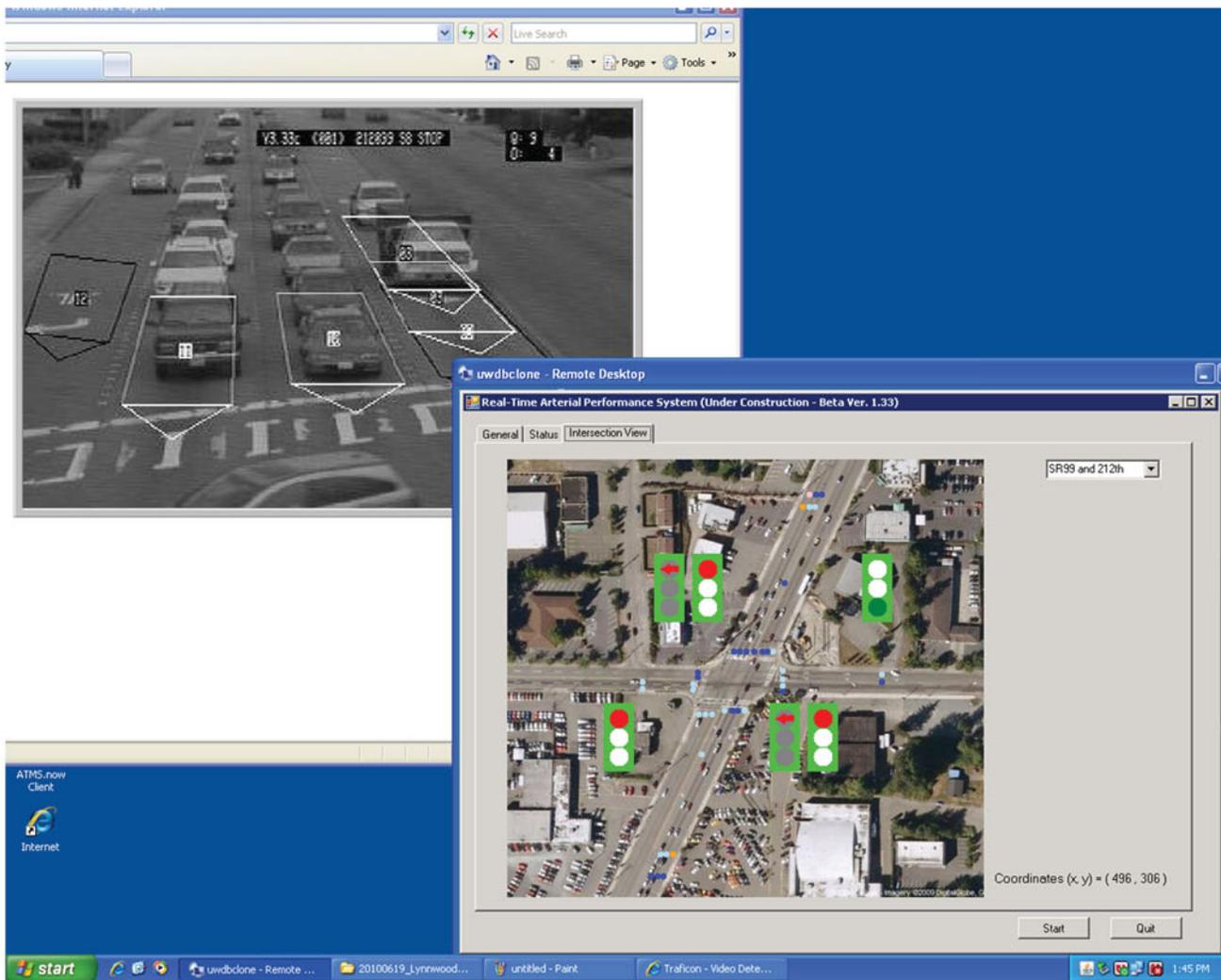
Downloaded by [University of Arizona] at 18:51 24 November 2013



(a)



(b)



(c)

Figure 4 Software development: (a) main interface, (b) signal status, and (c) visualization and verification (color figure available online).

**Table 1** Test results of the In-PerforM system.

Signal cycle	Volume in			Volume out			Queue length (veh)			Control delay (s/veh)		
	Measured	Ground truth	Error	Measured	Ground truth	Error	Measured	Ground truth	Error	Measured	Ground truth	Error
1	54	57	-3	54	56	-2	11	12	-1	32	35	-3
2	33	36	-3	35	35	0	8	9	-1	21	22	-1
3	40	47	-7	45	47	-2	10	11	-1	28	32	-4
4	42	48	-6	47	47	0	11	11	0	35	40	-5
5	37	52	-15	52	52	0	8	11	-3	30	32	-2
6	52	58	-6	57	58	-1	9	11	-2	28	33	-5
7	66	70	-4	65	69	-4	11	12	-1	23	25	-2
8	37	37	0	44	38	6	10	10	0	42	43	-1
9	41	43	-2	42	42	0	10	11	-1	25	28	-3
10	46	47	-1	40	48	-8	11	11	0	32	33	-1
11	33	36	-3	34	34	0	11	10	1	43	48	-5
12	66	70	-4	55	69	-14	10	12	-2	31	34	-3
13	35	36	-1	33	39	-6	7	10	-3	50	54	-4
14	29	30	-1	30	30	0	9	10	-1	80	82	-2
15	55	60	-5	57	57	0	9	11	-2	36	37	-1
16	39	40	-1	31	44	-13	10	11	-1	50	53	-3
17	38	48	-10	46	48	-2	13	11	2	74	77	-3
18	64	65	-1	62	65	-3	10	11	-1	41	43	-2
19	40	40	0	35	38	-3	10	11	-1	54	57	-3
20	45	46	-1	40	48	-8	11	11	0	64	68	-4
21	47	49	-2	40	49	-9	10	11	-1	45	48	-3
22	41	53	-12	50	53	-3	9	11	-2	49	58	-9
23	41	43	-2	24	43	-19	12	11	1	67	70	-3
24	34	35	-1	34	35	-1	12	10	2	90	91	-1
25	47	48	-1	47	48	-1	11	11	0	34	36	-2
26	46	58	-12	55	58	-3	8	12	-4	23	24	-1
27	35	38	-3	38	38	0	8	10	-2	41	46	-5
28	43	57	-14	55	57	-2	10	11	-1	45	46	-1
29	49	50	-1	50	50	0	10	11	-1	37	37	0
30	50	55	-5	54	55	-1	10	12	-2	39	42	-3
31	47	47	0	42	47	-5	10	11	-1	49	53	-4
32	32	36	-4	35	36	-1	12	10	2	39	44	-5
33	80	83	-3	76	83	-7	11	12	-1	38	41	-3
34	8	8	0	6	8	-2	3	3	0	13	15	-2
35	57	57	0	50	57	-7	11	11	0	37	40	-3
36	59	62	-3	45	62	-17	13	12	1	85	90	-5
37	53	55	-2	51	55	-4	9	12	-3	37	40	-3
38	47	51	-4	49	51	-2	10	11	-1	37	41	-4
39	29	34	-5	33	34	-1	8	10	-2	29	31	-2
40	49	50	-1	41	49	-8	8	11	-3	49	54	-5
Average	44.7	48.4	-3.7	44.5	48.3	-3.8	9.9	10.8	-0.9	42.6	45.6	-3.0
STD	12.63	13.19	3.95	12.41	13.03	5.11	1.80	1.45	1.43	17.51	17.86	1.72

the calculated results were from the proposed algorithm using data produced by the virtual entry and exit loops in the simulation model.

A *t*-test was also conducted to evaluate the difference between the algorithm produced queue lengths and simulation model measured queue lengths. The *t*-ratio was -9.27 with the critical *t*-ratio of 2.02 for *df* = 43 and *p* = .00. This indicates that the two series of queue length data are statistically different. As mentioned earlier, the difference in queue lengths was caused by the definition disparity of queue length rather than measurement error. A ground-truth queue length shows the number of vehicles stopped before the red light, while, in the queue length estimation algorithm, a queue length is referred to

as the number of vehicles added to the measuring zone during the red signal indication, regardless of vehicle speeds. Therefore, the ground-truth queue lengths are typically slightly lower than the measured queue lengths. Based on Table 2, the mean of the measured queue lengths is 1.6 vehicles or 14% higher than that of the ground-truth queue lengths, with a standard deviation of 1.2 vehicles. However, the correlation coefficient between the two series data sets is .969, showing that the measured queue lengths are great indicators for the ground-truth queue lengths.

The simulation result of control delays also showed that the control delay estimation algorithm is robust in measuring intersection LOS. On average, the control delay measured by the proposed algorithm is 56.7 s/veh, 1.9 s/veh or 3%

**Table 2** Test results of simulated data.

Signal cycle	Queue length		Control delay		Signal cycle	Queue length		Control delay	
	Measured	Ground truth	Measured	Ground truth		Measured	Ground truth	Measured	Ground truth
1	14	15	38.4	36.1	24	11	9	79.7	72.3
2	15	14	45.2	43.2	25	12	11	53.9	50.6
3	11	11	61.3	59.0	26	10	7	48.5	48.3
4	9	8	58.5	56.5	27	9	7	79.1	78.4
5	13	11	76.3	72.3	28	6	5	47.2	45.5
6	15	13	42.2	41.6	29	6	4	49.5	49.0
7	20	19	106.8	103.7	30	4	3	16.8	15.1
8	7	7	25.1	24.8	31	16	14	98.9	98.1
9	19	17	29.6	28.6	32	10	10	41.5	40.8
10	12	10	32.5	30.3	33	9	7	48.9	46.9
11	13	13	42.3	40.3	34	21	17	43.5	42.2
12	4	4	29.5	28.8	35	17	12	105.8	103.0
13	6	5	30.4	29.4	36	18	15	106.9	106.2
14	21	18	48.9	47.7	37	16	14	75.2	73.3
15	17	16	42.5	41.8	38	14	12	66.7	65.8
16	13	12	37.5	36.4	39	16	12	99.9	99.5
17	16	13	46.3	45.0	40	14	13	83.6	80.2
18	10	8	18.1	17.3	41	16	14	94.4	91.2
19	9	8	62.3	61.4	42	14	12	69.1	62.6
20	2	2	13.5	8.5	43	17	16	72.8	71.4
21	16	15	64.5	62.1	44	15	13	37.3	36.5
22	15	13	72.5	70.2	45	13	11	17.2	15.7
23	14	12	90.4	88.8	Average	12.8	11.2	56.7	54.8
					STD	4.6	4.2	26.1	25.8

longer than the ground-truth control delay of 54.8 s/veh, with a standard deviation of 1.5 s/veh. Also, the two result series have a correlation coefficient of .998, indicating that the proposed control delay estimation algorithm works really well when vehicle arrival and departure data can be accurately collected from the entry and exit loops.

## CONCLUSIONS

Signalized intersection performance plays a vital important role for safety and quality of travel on arterial networks. However, to collect intersection performance information, such as vehicle control delay and queue length, is a time-consuming and labor-intensive task. In this article, a comprehensive strategy has been developed and implemented in the In-PerforM system to quantitatively measure intersection performance in real-time with traffic count data collected with traditional traffic sensors. The strategy contains two algorithms for measuring important performance parameters for signalized intersections including average control delays and queue lengths.

Based on the traffic count data and detector actuation time stamps collected at the entrance and exit of the measuring zone, the queue length estimation algorithm estimates the number of vehicles on each lane inside the measuring zone during the red signal indication. With the estimated queue length, the control delay estimation algorithm calculates the corresponding vehicle delays due to signal control. Both algorithms have been implemented in the In-PerforM system using Microsoft Visual C#.

The In-PerforM system was tested using both field data and simulation data. The field test results showed that the estimated queue lengths and control delays were slightly lower than the ground truth data. These errors were largely due to count errors with the VIPs used in this study. On average, the estimation error for control delay was about 3 s/veh or 7% of the ground-truth control delay. In practice, estimation error of control delay in a couple of seconds per vehicle range is certainly acceptable. Its impact on determination of the intersection's LOS would be marginal. To further evaluate the performance of the proposed control delay estimation algorithm, simulation experiments were conducted. The simulation tests showed that the algorithm is reliable and robust in measuring intersection performance under the tested conditions. The queue length measured in the simulation model was also lower than the ground truth value due to the definition disparity of queue length rather than measurement error. The measured queue lengths are strongly correlated to the ground-truth queue lengths with a correlation coefficient of .969, indicating that a measured queue length (maximum number of vehicles in the measuring zone) using the proposed algorithm is a great indicator for the actual queue length (maximum number of stopped vehicles). The average of control delay measured with the proposed algorithm using simulation data was 56.7 s/veh, which is only 3% longer than the average control delay of 54.8 s/veh from the ground truth data in the simulation experiments. The proposed algorithms have been proven to be reasonably accurate when detector errors are eliminated. The In-PerforM system is more affordable

for deployment when compared with other systems or methods developed by previous studies for performance measurements at signalized intersections.

Compared with the traditional *Highway Capacity Manual* (HCM)-based intersection performance calculation methods, this proposed algorithm is more accurate and can be implemented in a real-time manner. This methodology does not require a specific detection system, and only relies on traffic count data collected with traditional traffic sensors (e.g., video image processors). Although the current algorithms were developed based on the relatively simple layout of the study site and sensor configuration, the methodology can be easily modified and extended for applications in other approach layouts with an affordable deployment cost. In the future, the algorithms will be improved to enhance its ability to measure intersection performance at locations with more complicated conditions, such as locations with significant sink and source traffic or intersections with shared movement lanes and permitted or protected left-turn signals. This study will be beneficial for transportation researchers and practitioners, such as traffic engineers in most levels of transportation agencies. Motorists will also be benefited with the real-time intersection performance information.

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