

Analysis of Queue Estimation Methods Using Wireless Magnetic Sensors

Rene O. Sanchez, Roberto Horowitz, and Pravin Varaiya

Four queue estimation methodologies were studied with wireless magnetic sensors installed on a single-lane loop on-ramp. Queue length estimation based on (a) occupancy measurements at the ramp entrance, (b) vehicle counts at the on-ramp entrance and exit, (c) speed measurements at the ramp entrance, and (d) vehicle reidentification were considered. These queue estimation methods were evaluated with available raw and processed sensor data retrieved from the test site through mobile data communication and downloaded from a server. The accuracy and reliability of the queue estimation methods were studied with ground truth data obtained from video. Discrepancies between inconsistent sensor and ground truth data were identified and further analyzed with raw data coming directly from the vehicle detection system at the on-ramp. Each of the methods analyzed had deficiencies that needed to be taken into account and compensated for if they were to be used for applications that involved ramp metering with accurate queue control. The worst performance of the queue estimation methods was observed when the on-ramp was under congestion (queue extends around or beyond the ramp entrance). On the basis of the observations at the on-ramp test site, it was also possible to point out some of the main factors that affect the performance of the queue estimation methods.

Ramp metering is an effective traffic control strategy for managing freeway congestion (1). It consists of restricting the flow of vehicles into the mainline with the objective of improving freeway efficiency, thereby leading to overall improvement in system performance.

In freeways, ramp metering is usually employed along with queue control. This form of ramp metering regulates traffic conditions at the mainline while taking into account the vehicle queue length formed at the on-ramps. The queue control part of the algorithm regulates the length of the queue so as to maximize the use of storage available at the on-ramps during peak traffic hours while avoiding queues spilling into adjacent arterial streets. To implement queue control, it is necessary to have a reliable and accurate estimate of the queue length (2).

Queue control has been addressed in the literature and used extensively in traffic simulation studies. However, when ramp metering with queue control is implemented in the field, the performance of the queue control algorithm has been undermined by the queue

estimation methods employed, which results in inaccurate regulation of the queue length that underutilizes on-ramp storage space (2).

The work presented in this paper was conducted as part of a ramp-metering field test. This field test was proposed to implement ramp metering with queue control on the Heegenberger Road loop on-ramp to I-880 southbound in the California Department of Transportation (Caltrans) Bay Area District (Figure 1) to study its effect in minimizing queue and mainline density oscillations and enhancing performance. The queue regulation methods used for the field test seek to improve ramp storage utilization with respect to queue override, which is currently used on California freeways to regulate queues.

The four methods that were considered for the field test are queue estimation based on (a) occupancy measured at the entrance of the on-ramp, (b) counts of vehicles leaving and entering the on-ramp, (c) speed data at the entrance of the on-ramp, and (d) vehicle reidentification. The first method corresponds to the queue estimation method used with queue override. It consists of determining whether the queue is at or beyond the queue limit by comparing the occupancy measured at the entrance of the ramp with an occupancy threshold. The second method counts vehicles entering and leaving the on-ramp. The difference between the counts gives the queue length, provided the initial number of vehicles at the ramp when the counting is initiated can be accounted for. This queue estimation method has been explored in detail and has been known to introduce errors because of the inability of the method to correct for offset (3–5). Work has been done to improve the performance of this queue estimation approach by incorporating occupancy measurements from the ramp (4–6). The third method is a queue length estimator based on a simplified model for the driving behavior of a vehicle that is approaching the end of the queue: the vehicle decelerates at a constant rate from its cruising speed until it stops. This method was proposed by Sun and Horowitz and assumes it is possible to accurately calculate queue length from vehicle speed measurements at the entrance of the on-ramp (2). The fourth method estimates the length of the queue using a vehicle reidentification algorithm, as described by Kwong et al. (7). This scheme is based on matching individual vehicle signatures obtained from wireless magnetic sensor arrays placed at the two ends of the on-ramp. It relies on counting vehicles entering and leaving the on-ramp and corrects for errors using the vehicle reidentification algorithm. Vehicle reidentification has been validated on arterial streets and has yielded satisfactory results; nevertheless its performance has not been studied at on-ramps.

This paper is organized as follows: The test site is described first, followed by presentation of the vehicle detection system. The different types of data used in the study are then discussed, followed by an explanation of the ground truth data collection method. Next, the results obtained with the different queue estimation methods are presented and the factors affecting different

R. O. Sanchez and R. Horowitz, Department of Mechanical Engineering, 5138 Etcheverry Hall, and P. Varaiya, Department of Electrical Engineering and Computer Sciences, 271M Cory Hall, University of California, Berkeley, Berkeley, CA 94720-1700. Corresponding author: R. O. Sanchez, r2sanche@me.berkeley.edu.

Transportation Research Record: Journal of the Transportation Research Board, No. 2229, Transportation Research Board of the National Academies, Washington, D.C., 2011, pp. 34–45.
DOI: 10.3141/2229-05

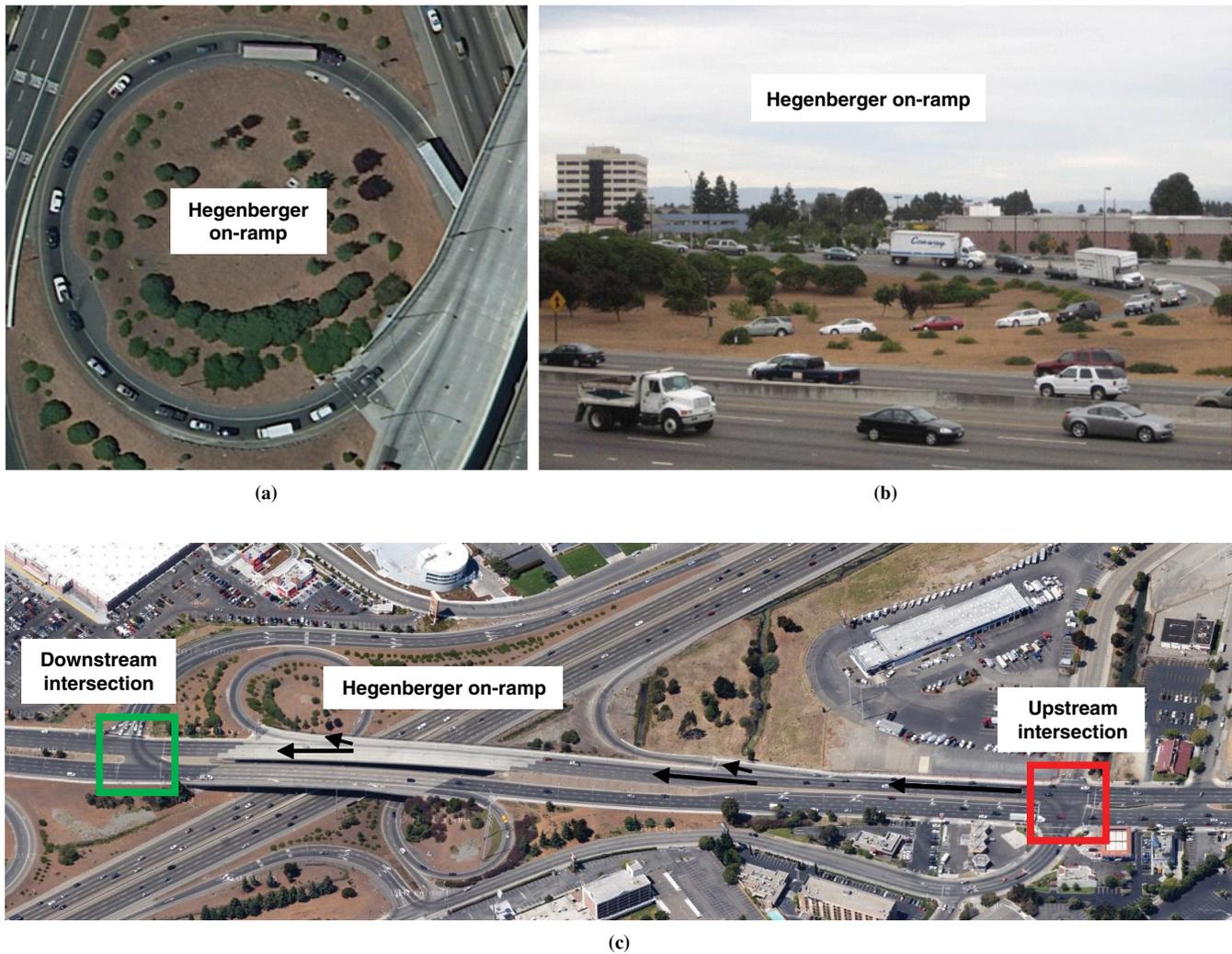


FIGURE 1 Photos showing (a) aerial view of Hegenberger on-ramp with saturated queue, (b) side view of Hegenberger on-ramp with saturated queue, and (c) arterial streets and intersections around Hegenberger on-ramp.

queue estimation methods are discussed. The final section of the paper presents the study's conclusions.

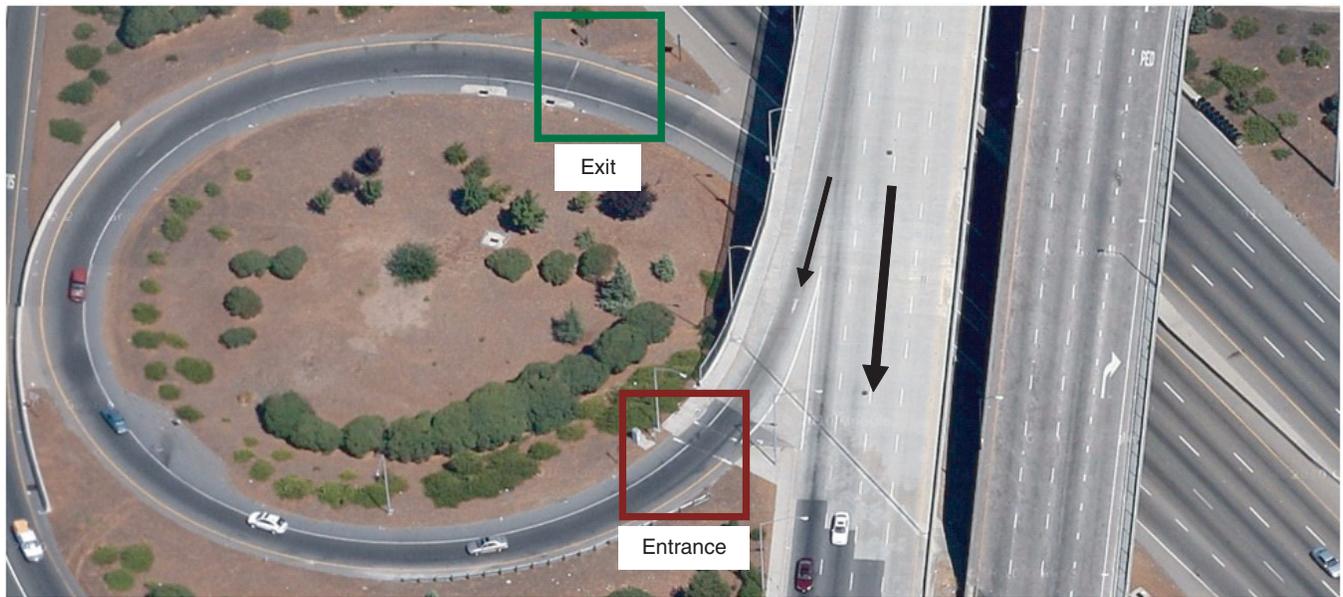
TEST SITE

The Hegenberger on-ramp is suitable for the field test because it is under local control and is subject to heavy demand and long on-ramp queues that frequently go beyond the on-ramp capacity. Furthermore, it is a single-lane ramp, which allows for the testing of the queue estimation methods without having to take into account the dynamics of multiple-lane on-ramps (e.g., lane changing).

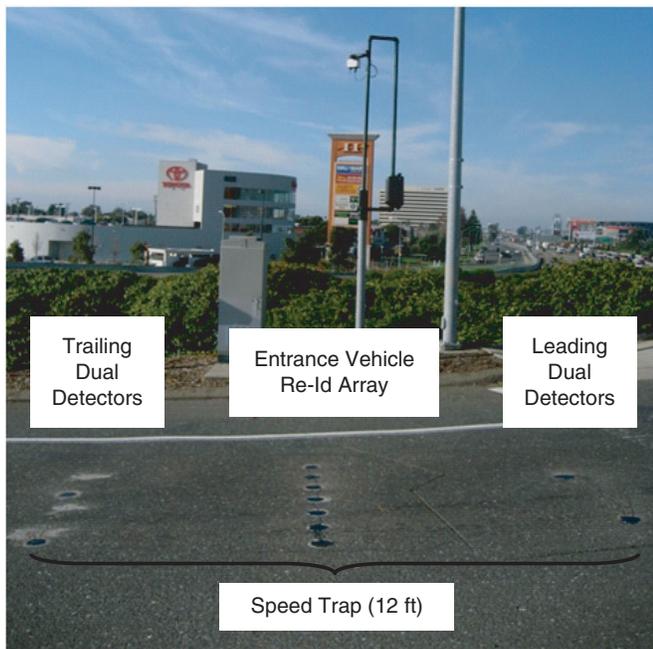
The length of the Hegenberger on-ramp is 616 ft (187.8 m), which corresponds to a capacity ranging from 17 to 25 vehicles. The capacity varies because of vehicle type and intervehicle spacing or headway, which fluctuates throughout the day. For this study, the analysis is concerned with queue estimation performance from the entrance to the exit of the ramp (Figure 2a). When the ramp was saturated and vehicles were beyond the ramp entrance, the ground truth queue lengths presented in this analysis corresponded to the number of vehicles located between the exit and the entrance of the ramp.

VEHICLE DETECTION SYSTEM

The vehicle detection system deployed at the Hegenberger on-ramp was developed by Sensys Networks, Inc. This system consists of an Access Point (AP240-ESG), a repeater (RP240-B), and 18 wireless magnetic sensors (VDS240) installed as shown in Figure 2b and 2c. Two arrays of seven sensors separated by 1 ft and installed at the center of the lane were located at the entrance and at the exit of the on-ramp. These entrance and exit arrays were necessary for the implementation of queue estimation based on vehicle reidentification. More details are available in Kwong et al. (7). These arrays are also used for the analysis of the queue estimation methodology using vehicle counts, even though a single detector placed at the center of the lane at each end of the ramp would have been enough. Four sensors are installed at the entrance of the on-ramp and are arranged in a speed-trap configuration. Two sensors were used for leading vehicle detection (SL1 and SL2) and another two for trailing vehicle detection (ST1 and ST2). This configuration increases the lateral detection zone to capture vehicles that may be traveling off the center of the lane. The speed-trap sensors were used to study the queue estimation methodology based on speed and occupancy



(a)



(b)



(c)

FIGURE 2 Photos showing (a) Hegenberger on-ramp entrance (bottom square) and exit (top square), (b) vehicle detection system installation at ramp entrance, and (c) sensor array installation at ramp exit (Re-Id = reidentification).

and to compare the vehicle counting performance of a single sensor and a sensor array. Details on this vehicle detection system are available in Haoui et al. (8) and Cheung et al. (9).

VEHICLE DETECTION SYSTEM DATA

For the analysis presented in the section on queue estimation results, two different types of data were used: processed data and raw data.

Processed Data

The processed data were obtained using the Sensys SNAPS server, which provides connectivity to the equipment installed at the on-ramp. This software computes counts, speed, occupancy, vehicle length, and other statistics over various time intervals as well as real-time individual vehicle speed, length, and headway using raw data from the sensors (8). It is also possible to obtain the queue length data based on vehicle reidentification in the same way.

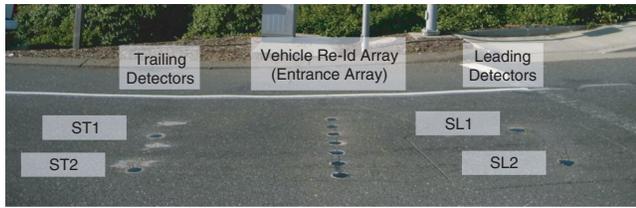


FIGURE 3 Configuration of wireless magnetic sensor at entrance of Hegenberger on-ramp.

The data processing application does not have the capability to OR-gate the leading sensors (SL1 and SL2) or the trailing sensors (ST1 and ST2) (Figure 3). Speed-trap data processing is done independently for the SL1 and ST1 sensors and for the SL2 and ST2 sensors.

Raw Data

The raw data obtained from the sensors were used to analyze different sources of errors. The arrangement of the sensors in the field and the configuration mode of each of the sensors determined the type of raw data [e.g., speed trap (Mode B) raw data or reidentification array (Mode F) raw data]. Data from any of these sensor modes can be used to derive counts and occupancy data. Accurate speed estimation is possible with the speed trap sensors' raw data, and vehicle reidentification is possible with the array sensors generating detailed raw data from which vehicle magnetic signatures are obtained.

Mode B Sensor Raw Data

Each speed trap sensor (Figure 3) generates the following information every time a sensor event occurs:

```
<sensor_id> <unix epoch time> <event>
```

An event value of 0 is the transition from detect to undetect, and a value of 1 is the transition from undetect to detect. Each of the sensors in the speed trap can be used independently to obtain vehicle counts and occupancy.

Mode F Sensor Raw Data

The entrance and exit array raw data are generated every time a vehicle goes on top of the arrays. The data generated by the arrays and used for this analysis contain the following information:

```
<array_id> <undetected time> <duration over sensor>  
                <queue(real time)>
```

Undetected time corresponds to the instance in which the vehicle is no longer detected by any of the sensors in the array. Duration over sensor indicates how much time at least one of the sensors of the array was active because of vehicle presence. Queue(real time) is the queue length calculated with the vehicle reidentification method in real time.

GROUND TRUTH DATA COLLECTION

Vehicles at the on-ramp were videotaped to obtain ground truth data to validate the queue estimation methods. Video was recorded on 3 different days: April 13, May 5, and May 11, 2010. Observations at those three times were important for the conclusions drawn for this analysis; however, the ground truth data presented in the next section of this paper correspond to the day of May 11, 2010, from 4:07 p.m. (16.1 h) to 5:35 p.m. (17.6 h), when ramp metering was active. The data collected on this day are adequate for the analysis presented in the queue estimation results because different queue lengths (zero, intermediate sized, as well as capacity) were observed during the recording time. This allows for the analysis of the queue estimation methods under saturated and unsaturated on-ramp conditions.

Three independent cameras were used to obtain the ground truth data. The first camera recorded vehicles leaving the on-ramp and passing the exit sensor array (Figure 4a). The second camera recorded vehicles entering the on-ramp and passing through the speed trap and the entrance sensor array (Figure 4b). The third camera was used to capture queue dynamics during the ground truth data-collection period (Figure 4c). The three cameras were synchronized with a common clock so that data extracted from different videos could be compared with the vehicle detection system data.

Ground truth queue length was obtained with Cameras 1 and 2. From the video recorded with these cameras, it was possible to extract the time at which the frontal part of all the vehicles entering and leaving the ramp was aligned with the entrance and exit sensor arrays, respectively. Ground truth queue length was calculated by adding and subtracting unity to the queue length every time a vehicle was registered entering or leaving the on-ramp, respectively.

Ground truth data for queue estimation based on vehicle speed were obtained with the second video camera. The time instances of vehicle alignment with leading dual sensors (Figure 3, SL1 and SL2) and trailing dual sensors (Figure 3, ST1 and ST2) were extracted. The ground truth speed was calculated by dividing the distance between the leading and trailing sensors [12 ft (3.7m)] over the difference between the two time stamps extracted from the video for each vehicle. Camera 2 is a cassette video camera with a recording rate of 30 frames per second, which affects the resolution of the speed ground truth data. The largest discrepancies between ground truth data and the vehicle detection system data were expected at greater speed because of quantization.

QUEUE ESTIMATION RESULTS

Occupancy-Based Queue Estimation Method

Occupancy calculated with Mode B speed-trap sensors (sensor SL1 and sensor ST1) over a 30-s calculation interval is shown in Figure 5a. Before 17 h, occupancy magnitude correlates with the ground truth queue length. High occupancies are observed when queue lengths are large and vice versa. However, under on-ramp saturation conditions, after 17.2 h, very low occupancies are observed, even though the queue length was around or beyond the on-ramp entrance. This phenomenon, a so-called zero-speed, zero-occupancy (ZSZO) situation (6), makes queue estimation based on short calculation interval occupancy unreliable.

Figure 5b through 5d shows the scatter plots of queue length versus occupancy for multiple calculation intervals. In these scatter plots, it is evident that occupancy measured at the entrance of the

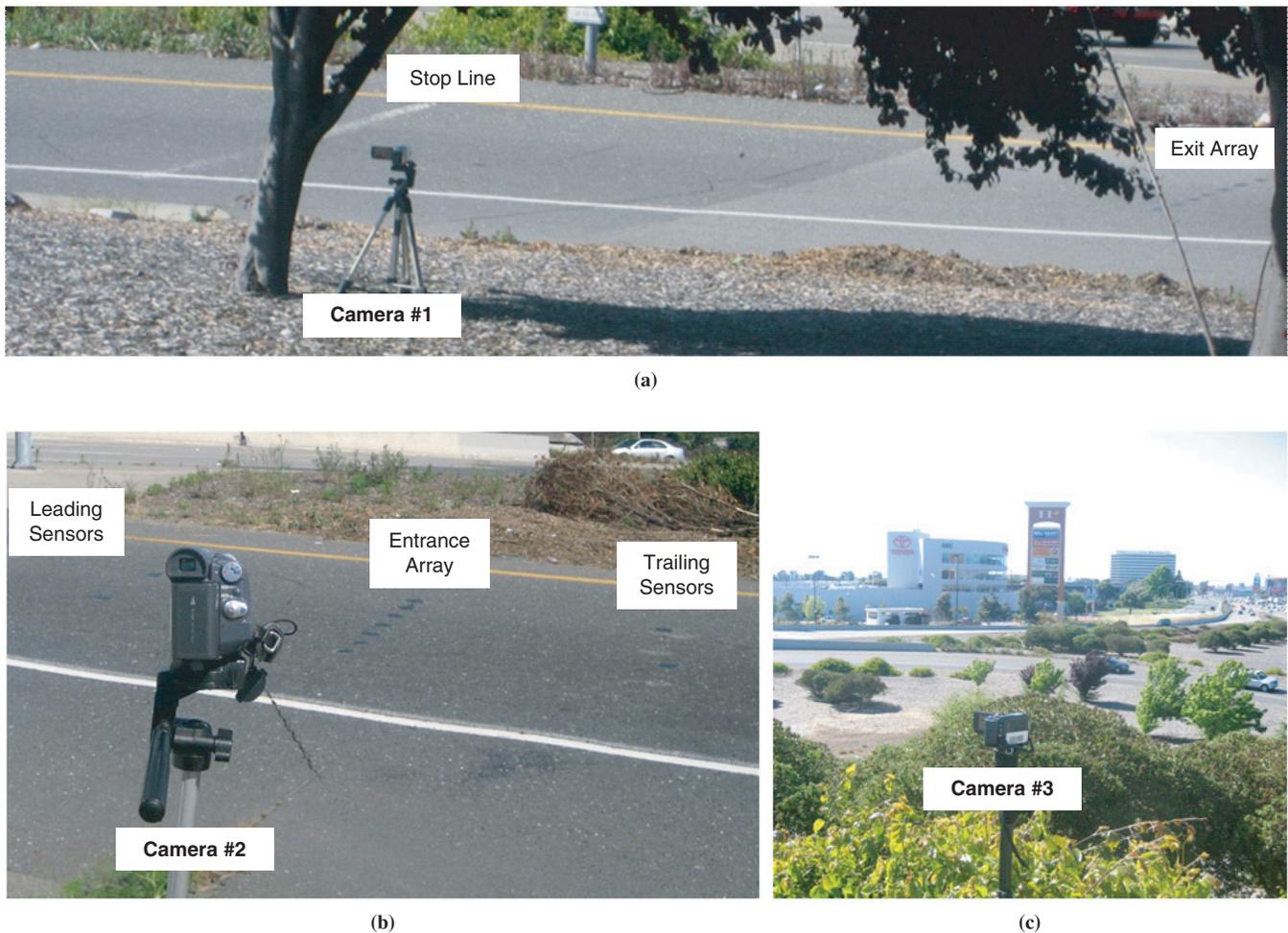


FIGURE 4 (a) Video camera recording vehicles leaving on-ramp, (b) cassette video camera recording vehicles entering on-ramp, and (c) video camera to capture vehicle behavior and queue dynamics.

ramp may only be used to predict whether the on-ramp is either saturated or unsaturated using an occupancy threshold as a reference. The scatter plots show fewer data points present in the upper left corner of the plot as the calculation interval increases. This shows that the accuracy (or applicability) of the occupancy threshold method increases with larger calculation intervals (i.e., fewer chances of the ZSZO phenomenon occurring). However, increasing the calculation interval introduces a delay in detecting queue saturation (see Figure 5a between 17.1 h and 17.2 h), which is an undesirable queue estimation characteristic for accurate queue control.

Queue Estimation Method Based on Vehicle Counts

Array Vehicle Counts

A total of 543 vehicles entered the on-ramp and 522 left the on-ramp during the ground truth data recording period. The raw data coming from the sensor arrays registered that 527 vehicles entered and 520 left the on-ramp during the same period. It would seem that the accuracy of the counting method is adequate, with only 3% error for entering vehicles and less than 1% error for exiting vehicles. This conclusion would be erroneous. When the queue estimation is calculated as a function of time and compared with the ground truth, it is clear that vehicle under- and overcounting exists.

Figure 6a shows large discrepancies between the estimated and ground truth queue lengths. At 17 h, the estimated queue reaches a value of about -10, which suggests considerable offset due to miscounting, even before ramp saturation. When the ramp is saturated, which occurs after 17.1 h, the error between both queue lengths is more pronounced. When the raw data events are analyzed (Figure 6b), it is evident that there are some vehicles that are not detected, while others are counted multiple times (e.g., trucks). It should be noted that the entrance array has twice as many undetected vehicles as the exit array, from which 11 were undetected due to merging. During congestion, cars tend to travel slower and closer together as they move through the entrance array, which sometimes results in multiple cars being registered as a single vehicle. The exit array does not present any case in which multiple vehicles are merged into a single detection event, since there is significant spacing between vehicles as they exit the ramp because the exit array is located after the ramp-metering light.

Entrance Vehicle Count Comparison

Mode B sensors were not installed at the exit of the on-ramp. They were only installed at the entrance of the ramp as part of the speed-trap sensor arrangement (SL1, SL2, ST1, and ST2). As a result, it is not possible to calculate queue length using only Mode B sensors. Nevertheless, it is possible to investigate the reliability of Mode B

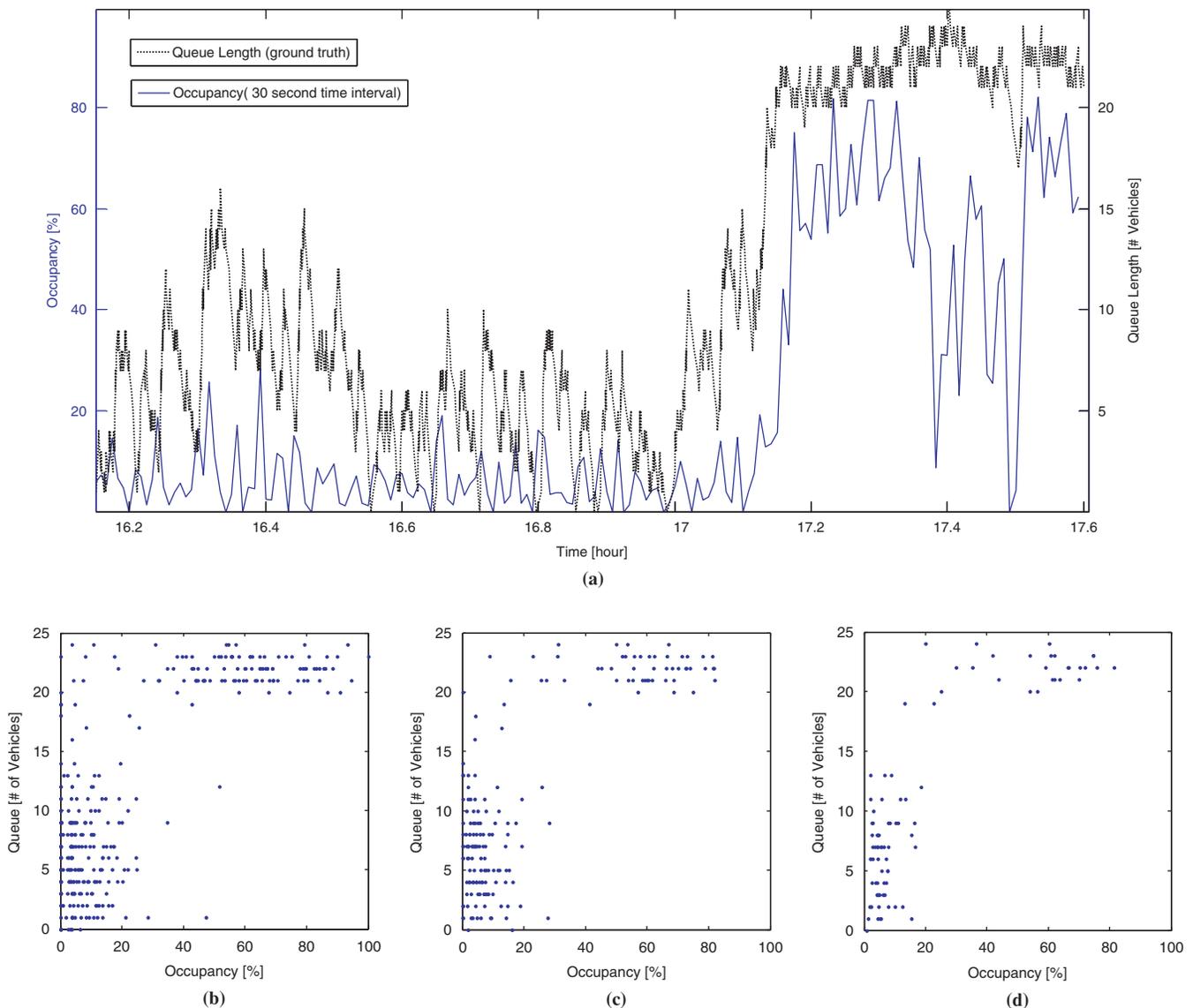


FIGURE 5 (a) Occupancy and queue length graphed as a function of time of day, and scatter plots of queue length versus occupancy for (b) 15-s, (c) 30-s, and (d) 60-s intervals.

sensors for vehicle counting by comparing vehicle counts gathered using the speed-trap sensors with the entrance array and the ground truth vehicle counts.

The comparison of the entrance vehicle counts based on speed-trap sensors, the entrance array, and ground truth is shown in Figure 7a. If cars traveled through the middle of the lane, a similar count would be expected from all the speed-trap sensors. However, it was observed that vehicles tended to travel on the right side of the lane, which is reflected in Figure 7, as sensors SL2 and ST2, which are located on the left side of the lane, registered significantly fewer vehicle counts over the complete time interval. The discrepancies in vehicle counts for sensors SL1 and ST1 and the ground truth vehicle counts becomes evident only after 17.1 h, which corresponds to the time when the ramp goes into saturation mode. It seems that congestion affects the counting performance of both Mode B and Mode F sensors.

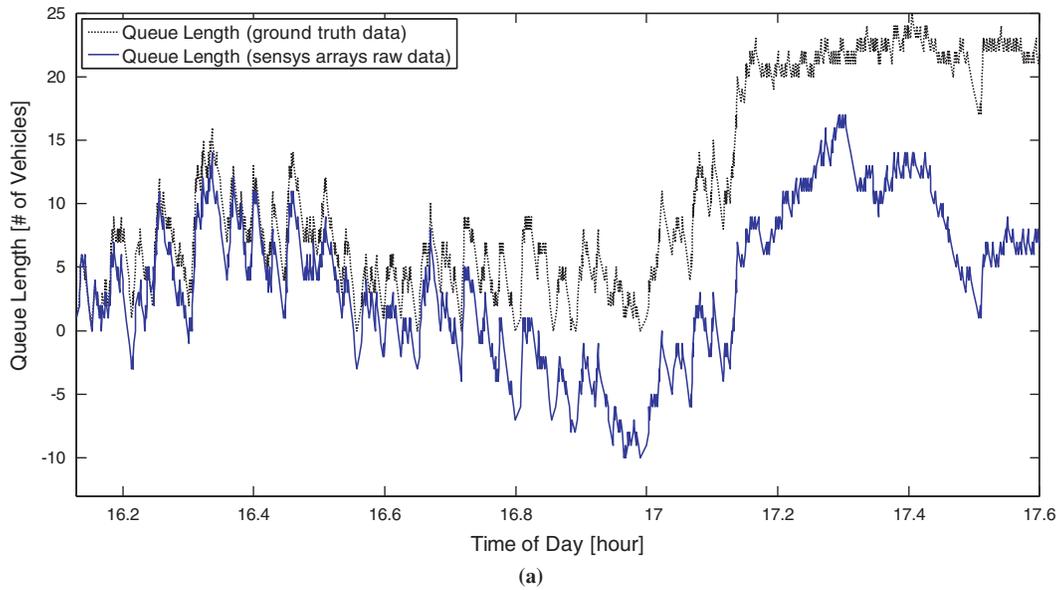
As with the sensor array data, single sensors sometimes register multiple detections for the same vehicle as well as a single detection event for multiple vehicles. Nevertheless, the total count for sensors SL1 and ST1 exceeded the ground truth data, which is the opposite

of the total entrance array vehicle count. This suggests that Mode B sensors may be more likely to generate multiple detections for the same vehicle than Mode F sensors.

For the most part, leading and trailing detectors on the same side of the lane were expected to have very similar vehicle counts; however, trailing sensors register higher total vehicle counts than the leading sensors. This suggests that vehicle counting performance for Mode B sensors depends on the lateral as well as the longitudinal location of the sensor in the ramp lane.

Queue Based on Speed

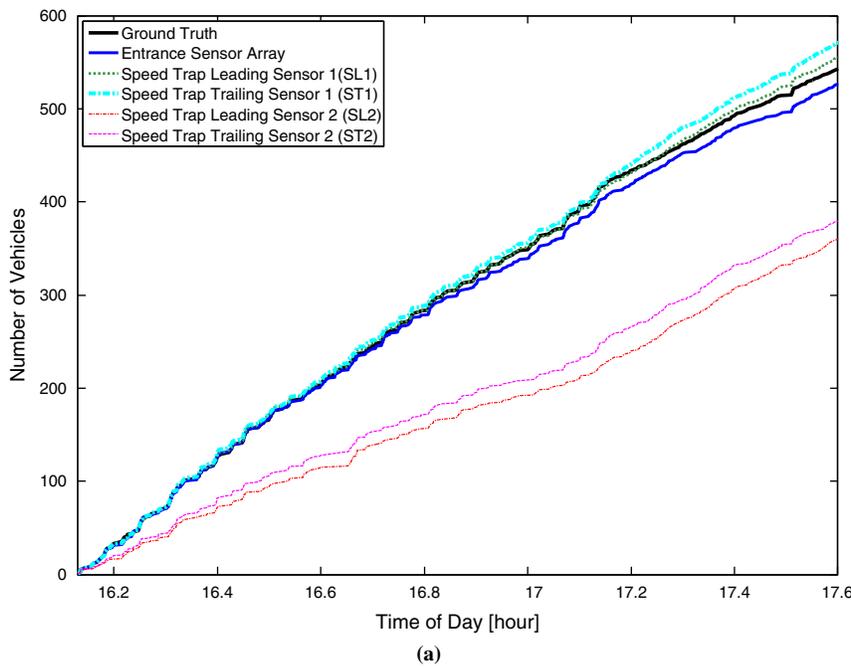
Before analyzing the queue estimation method based on vehicle speed measured at the entrance of the ramp, it was necessary to make sure that speed determined with the speed trap was accurate. Figure 8a shows the comparison between the speed trap and the ground truth speed data sets. Even though both data sets correlate well, it was not possible to calculate a speed for all the vehicles



	<i>ENTRANCE</i>	<i>EXIT</i>
TOTAL VEHICLES (Ground Truth)	543	522
Trucks	21	20
Motorcycles	1	1
TOTAL VEHICLES (Arrays)	527	520
Repeated Detection	21	15
due to Trucks	9	5
Undetected Vehicles	40	19
due to merging into one detection event	11	0

(b)

FIGURE 6 (a) Graph of queue length based on ground truth data and arrays raw data and (b) table showing total vehicle counts for ground truth and arrays raw data between 16.13 h and 17.6 h.



	Total Vehicle Counts
Entrance GT	543
Entrance Array	527
SL1	557
ST1	573
SL2	362
ST2	381

(b)

FIGURE 7 (a) Graph of entrance vehicle counts based on ground truth, entrance array and SL1, SL2, ST1, and ST2 sensors, and (b) table showing total entrance vehicle counts between 16.13 h and 17.6 h.

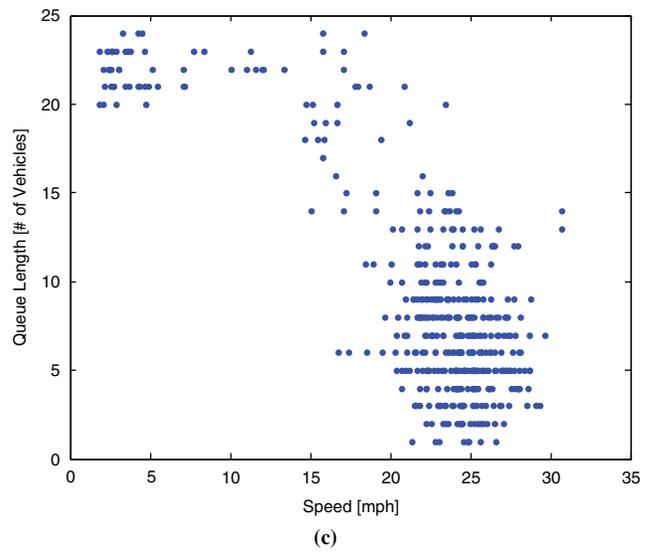
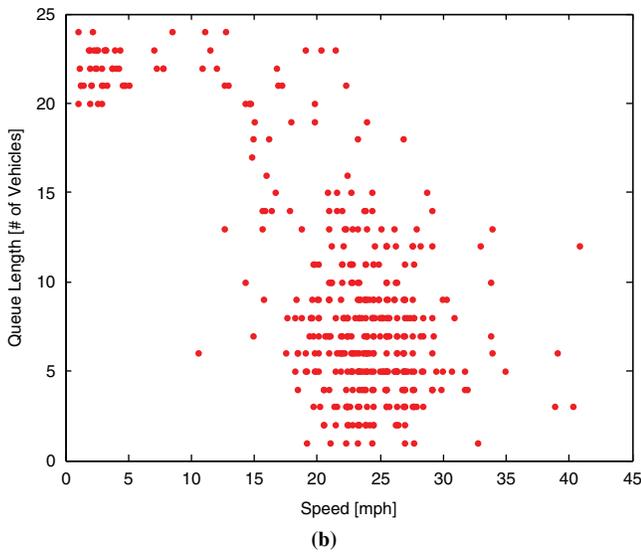
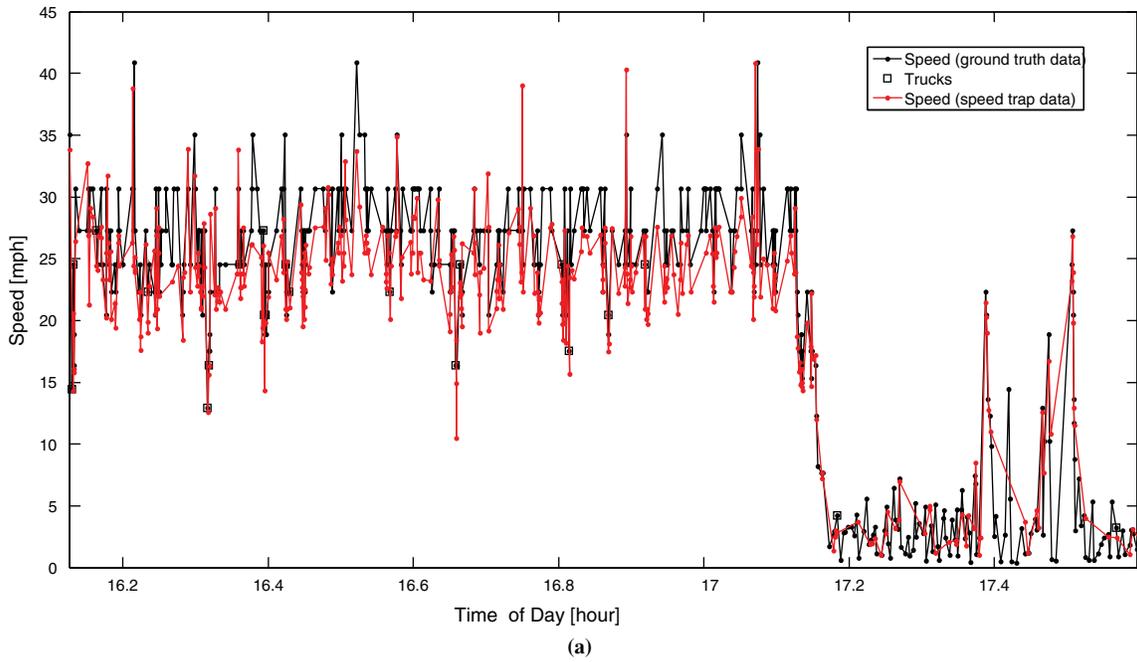


FIGURE 8 (a) Speed-trap measurements and ground truth speed graphed as a function of time of day, (b) scatter plot of queue lengths versus speed at entrance of on-ramp, and (c) scatter plot of queue lengths versus three trailing point moving average of speed.

that entered the on-ramp. The ground truth data set has 543 data points, while the speed-trap data set only has 425 data points, which means that it was not possible to determine the speed of 22% of the vehicles that entered the on-ramp during the ground truth recording time. During on-ramp saturation, there were a larger number of consecutive vehicles for which speed was not calculated. Figure 8a shows clear examples of this problem at around 17.25 h and 17.4 h. Inability to determine the speed of every entering vehicle affects the applicability of this method for queue estimation, as several minutes could pass before a vehicle speed could be calculated again to update the queue estimate.

Speed measurements correlate well with the on-ramp mode. When the queue is unsaturated, the speeds are larger, usually above 20 mph, and when the queue is large, speed tends to drop accordingly. How-

ever, there are multiple factors that result in speed drop at the entrance of the ramp that are unrelated to the queue dynamics. This is the case for large trucks entering the on-ramp, which, independent of the queue length, usually slow down. Figure 8a shows drops of speed at unsaturated queue conditions before 17.1 h for most of the instances when trucks entered the ramp. Another factor that affects the speed of vehicles in a similar way is the presence of pedestrians crossing the street and blocking the entrance of the ramp.

Figure 8b is a scatter plot of queue length versus speed that shows that a wide range of entrance speeds corresponds to a given queue length value. Taking a moving average of the speed data, as done in Figure 8c, decreases the range of speed that corresponds to a given queue length, but it does not allow the finding of a relationship between queue length and speed that could be used for precise queue

control. It is not possible, based on these results, to obtain a relationship between queue length and speed as was obtained by Sun and Horowitz using traffic simulation results (2). Nevertheless, using speed at the entrance of the ramp seems to be a good approach to determining whether the queue is saturated, unsaturated, or transitioning from one mode to the other in an almost instantaneous way, which is an improvement over using occupancy measurements at the entrance of the ramp.

Queue Based on Vehicle Reidentification

There were two queue estimates based on the vehicle reidentification method. The first one was provided in real time and the second one was generated offline.

Figure 9a shows a comparison between the queue estimates calculated using vehicle reidentification in real-time and the ground truth queue length. During on-ramp uncongested conditions, both

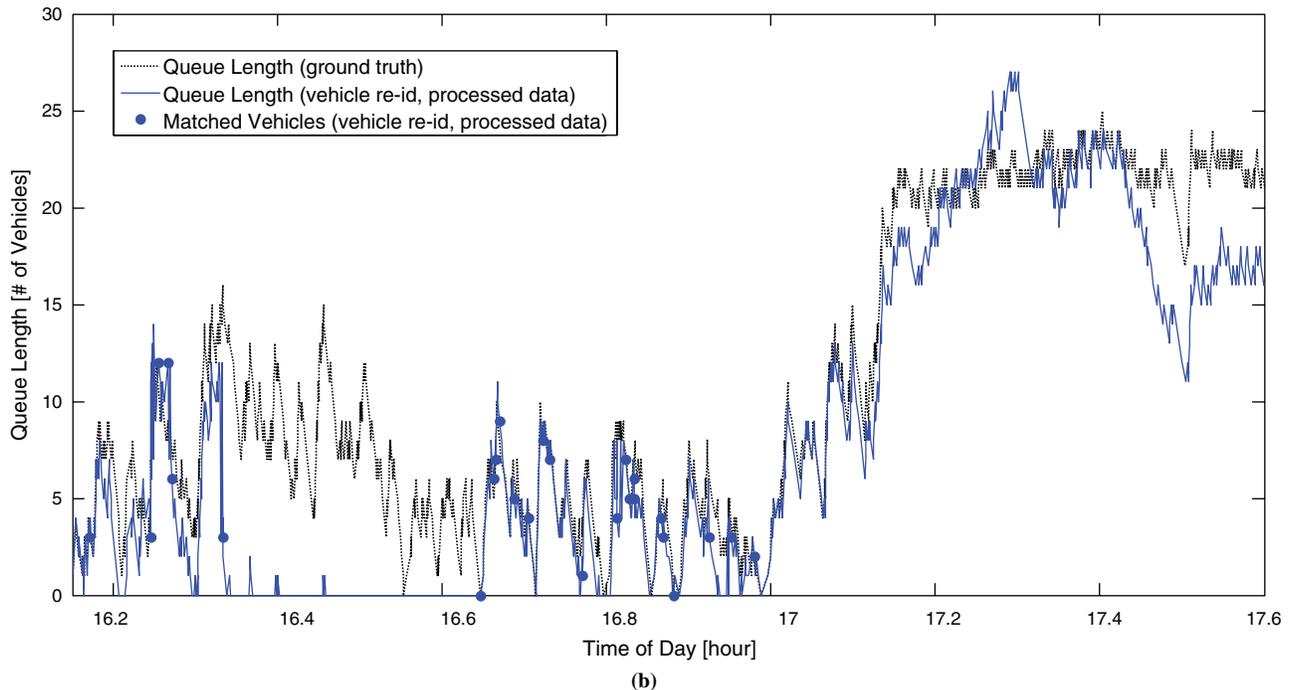
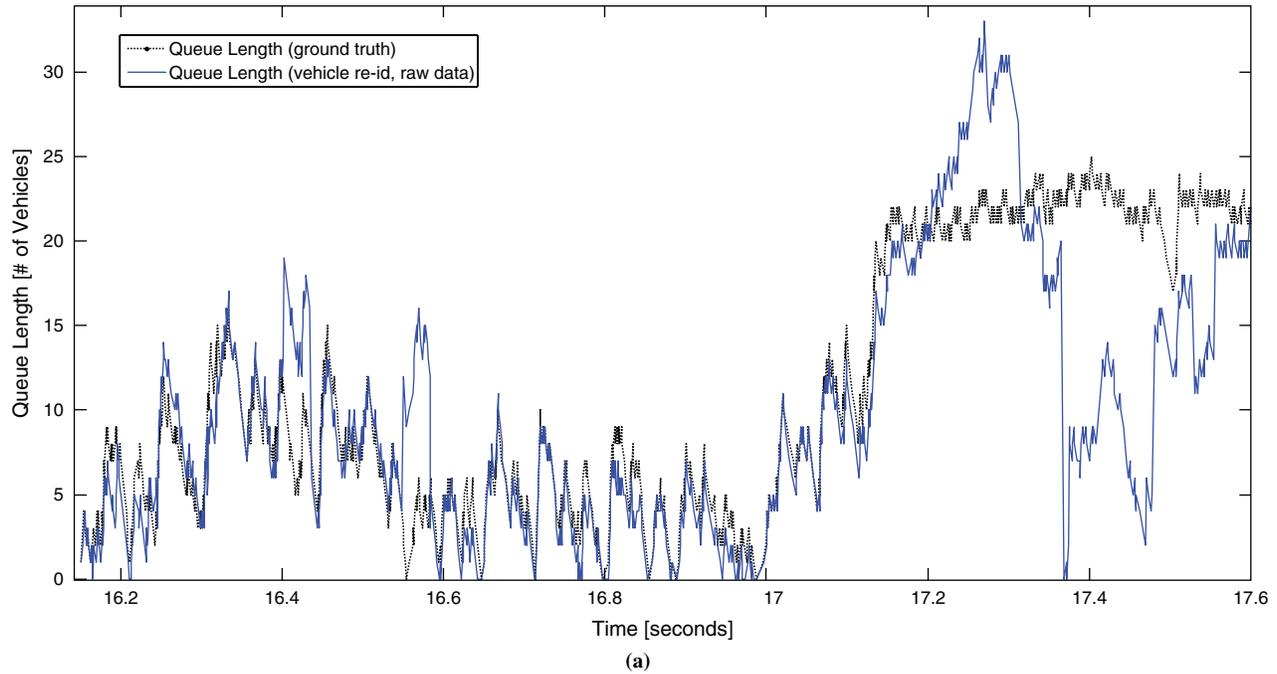


FIGURE 9 (a) Queue length based on real-time vehicle reidentification versus time of day and (b) queue length based on offline vehicle reidentification algorithm versus time of day.

correlated properly, and even when some notorious errors appeared (e.g., at about 16.43 h), the method was able to compensate for the offsets. However, when on-ramp saturation occurred, the performance of the queue estimator dropped and eventually collapsed at about 17.2 h. During congestion, vehicle counting is more inaccurate, as shown earlier, and it becomes very difficult to make appropriate corrections when a vehicle is reidentified because this method relies on vehicle counting to correct for offsets. Despite its underperformance during saturation, this method seems to do better than the queue estimation method, which is based only on counting cars (see Figure 6a).

Figure 9b shows a comparison between the queue estimates based on vehicle reidentification (offline) and the ground truth queue length. For this approach, the performance seems to be better during on-ramp saturation conditions. However, there is a long period of time, between 16.3 h and 16.6 h, during which the queue length estimates were much smaller than the ground truth values.

Figure 9b shows the instances at which vehicles were reidentified (matched). Of the 543 vehicles that entered the on-ramp, only 27 were matched. The matches occurred only during unsaturated on-ramp conditions, which suggests that saturation affects not only vehicle counting, but also the vehicle reidentification matching rate. The matching rate obtained accounted for about 5% of the vehicles, which is significantly lower than the 70% that has been reported for arterials (7).

The vehicle reidentification queue estimation method was implemented on the Hegenberger on-ramp as it has been implemented on arterial streets. The assumption that this method would perform similarly on arterial streets and loop on-ramps seems to be incorrect. Loop on-ramps have characteristics that affect the performance of this method and need to be taken into account. To make this method reliable for queue estimation and regulation, it would be necessary to work on a vehicle reidentification algorithm that takes into account on-ramp-specific factors such as ramp curvature, slope, vehicle headway, location of sensors, and so forth.

As a consequence of the results obtained in this analysis, an improved vehicle reidentification algorithm was formulated and tested. With the modified reidentification algorithm, the reidentification matching rate during saturated conditions on the ramp was significantly improved. A higher matching rate allows for a better and rapid correction of errors, which results in a better queue estimate. The new results will be presented in a subsequent paper.

SOURCES OF ERROR

Even though the number of motorcycles using the on-ramp is very low in comparison to the total number of vehicles, they can introduce important queue estimation errors over time. Motorcycles are more likely to be undetected due to their smaller size and because they tend to miss the vehicle detection station at the exit of the ramp. Figure 10a shows a motorcycle entering the on-ramp, bypassing the queue, and finally missing the exit sensor array.

There have been multiple observations of cars bypassing the queue. This affects the queue estimation methods, because vehicles bypassing the queue tend to miss the detection sensors at the exit of the on-ramp. They usually travel off-center of the lane, as shown in Figure 10b.

Trucks are consistently using the on-ramp, even though they account for a small percentage of the vehicles going through it. When they appear, they can affect the queue dynamics considerably because

they are longer, slower, and have to maneuver to make the turn properly. Figure 10c shows an example of a large truck maneuvering at the entrance of the on-ramp. It was observed with the raw sensor array data and speed-trap sensor raw data that trucks like this one tend to introduce counting errors of one or two vehicles.

Loop on-ramps have wide lanes that allow drivers to maneuver as they go through. The result of the extra lateral space is that vehicles travel highly off center. Figure 10d shows multiple instances when vehicles were at different positions with respect to the center of the lane. Sometimes vehicles are off center and completely miss the vehicle detection station. This phenomenon is an important source of error in queue estimation methods that rely on counting vehicles.

As was shown in the section on queue estimation results, queue estimation methods have their worst performance during saturated on-ramp conditions. One of the reasons for this phenomenon is that two adjacent cars close to each other are likely to stop on top of or very close to the detection zone of the sensors. This creates undercounting problems because two cars close to each other may be registered as one. Figure 10e shows examples of adjacent cars resting on top of the sensor arrangements at the entrance of the on-ramp. This results in errors for queue estimation methods that rely on vehicle counting. It may also occur that vehicles are completely stopped at the on-ramp and none of them are within the sensor detection zone. When waiting time is large in comparison to the occupancy calculation interval, occupancy measurements do not reflect on-ramp queue conditions (the ZSZO phenomenon). This situation was observed in Figure 5a at about 17.4 h.

The sources of error mentioned here also apply to vehicle detection systems based on inductive loops, and some of them have been addressed by Vigos and Papageorgiou (6).

CONCLUSIONS

Four queue estimation methodologies were analyzed using wireless magnetic sensors. The methods for estimating the queue showed the worst performance under saturated on-ramp conditions.

The occupancy queue estimation method may be used to determine whether the ramp is either empty or full, but it cannot be used to estimate the queue length accurately. This approach is highly dependent on the time interval over which occupancy is calculated and under on-ramp saturation conditions may yield misleading results because of vehicle tendency to miss the sensor detection zone while at rest.

Estimating queue length on the basis of counting entering and exiting vehicles is not an acceptable method because of its inability to correct for errors like detector miscounts and offsets resulting from initial conditions.

The speed-based queue estimation method seems to be capable of instantaneously determining the mode of the ramp, whether unsaturated, saturated, or in transition. The results obtained for this queue estimation approach do not match those obtained on the basis of traffic simulations.

Finally, queue estimation based on vehicle reidentification seems to perform better than the other methods, but it underperforms during saturated on-ramp conditions. Furthermore, the vehicle reidentification match rate was extremely low, which affects the ability of the method to correct for errors regularly. To make this method reliable for queue estimation and regulation, it would be necessary to work on a vehicle reidentification algorithm that takes into account on-ramp-specific factors.



(a)



(b)



(c)



(d)



(e)

FIGURE 10 (a) Motorcycle bypassing queue, (b) vehicle bypassing queue, (c) large truck entering on-ramp, (d) vehicles off-center with respect to lane, and (e) adjacent vehicles simultaneously stopped on top of leading and trailing speed-trap sensors.

ACKNOWLEDGMENT

This work was supported by the California Partners for Advanced Transit and Highways.

REFERENCES

1. Papageorgiou, M., and A. Kotsialos. Freeway Ramp Metering: An Overview. *IEEE Transaction on Intelligent Transportation Systems*, Vol. 3, No. 4, 2002, pp. 271–281.
2. Sun, X., and R. Horowitz. Set of New Traffic-Responsive Ramp-Metering Algorithms and Microscopic Simulation Results. In *Transportation Research Record: Journal of the Transportation Research Board, No. 1959*, Transportation Research Board of the National Academies, Washington, D.C., 2006, pp. 9–18.
3. Wu, J., X. Jin, A. J. Horowitz, and D. Gong. Experiment to Improve Estimation of Vehicle Queue Length at Metered On-Ramps. In *Transportation Research Record: Journal of the Transportation Research Board, No. 2099*, Transportation Research Board of the National Academies, Washington, D.C., 2009, pp. 30–38.
4. Wu, J., X. Jin, and A. J. Horowitz. Methodologies for Estimating Vehicle Queue Length at Metered On-Ramps. In *Transportation Research Record: Journal of the Transportation Research Board, No. 2047*, Transportation Research Board of the National Academies, Washington, D.C., 2008, pp. 75–82.
5. Vigos, G., M. Papageorgiou, and Y. Wang. Real-time Estimation of Vehicle-Count Within Signalized Links. *Transportation Research Part C*, Vol. 16, No. 1, 2008, pp. 18–35.
6. Vigos, G., and M. Papageorgiou. Relating Time Occupancy Measurements to Space-Occupancy, Density, and Link Vehicle-Count. *Transportation Research Part C*, Vol. 16, No. 1, 2008, pp. 1–17.
7. Kwong, K., R. Kavalier, R. Rajagopal, and P. Varaiya. Arterial Travel Time Estimation Based on Vehicle Re-Identification Using Wireless Magnetic Sensors. *Transportation Research Part C*, Vol. 17, No. 6, 2009, pp. 586–606.
8. Haoui, A., R. Kavalier, and P. Varaiya. Wireless Magnetic Sensors for Traffic Surveillance. *Transportation Research Part C*, Vol. 16, No. 3, 2008, pp. 294–306.
9. Cheung, S. Y., S. Coleri, B. Dunder, S. Ganesh, C.-W. Tan, and P. Varaiya. Traffic Measurement and Vehicle Classification with Single Magnetic Sensor. In *Transportation Research Record: Journal of the Transportation Research Board, No. 1917*, Transportation Research Board of the National Academies, Washington, D.C., 2005, pp. 173–181.

The Freeway Operations Committee peer-reviewed this paper.