Real-Time Traffic Queue Length Estimation at the Freeway Off-ramp Using Dual-Zone Detectors

Xianfeng Yang, Yao Cheng, Gang-Len Chang
Department of Civil & Environmental Engineering
University of Maryland, College Park

ABSTRACT

Congestion at the downstream of a freeway off-ramp often propagates the traffic queue to the mainline, and thus reduces the freeway capacity at the interchange area. Hence, an accurate queue estimation model can help the traffic engineers to select proper control strategy to mitigate queue spillback at off-ramps. In responds to such a need, this study presents a queue estimation system using dual-zone detectors, where each detector can provide two detection zones. Particularly, the short detection zones are used to count traffic flow rates and the information from long detection zone can indicate the presence of traffic queues. With respect to different congestion levels, the off-ramp queue may be fully discharged during the green time or not. Therefore, this study has developed two queue estimation models for each condition. Based on the field data from the freeway interchange in Zhubei, Taiwan, this study has conducted extensive simulation experiments, and demonstrated the effectiveness of the proposed system on off-ramp queue estimations.

INTRODUCTION

Since most drivers do not tend to segregate themselves by destination well in advance of an off-ramp, but rather make most of their lane-changing decisions at the last moment. The exit queue of an off-ramp might spread itself laterally upstream of an off-ramp, thereby restricting the efficiency of the mainline flows. Hence, congested conditions at downstream intersections can lead to a long traffic queue at the off-ramp, and the queue spillback may propagate to its upstream and block freeway travel lanes. To mitigate freeway congestion caused by the excessive off-ramp queue, a reliable and accurate queue estimation model is essential for off-ramp controls.

In practice, two types of detectors are widely used to capture traffic information: video sensors and loop detectors. Through image interpretations and digital analysis, video sensors can verify the arriving vehicles and consequently capture the queue information. Due to some impact factors such as weather condition, visibility obstacles, and the reliability of image processing, the obtained queue information may not accurately reflect the real traffic conditions. Video sensors are usually installed near intersections for queue identifications. However, for off-ramp queue detections, video sensors may be incapable to cover the entire ramp due to their limited detection scope. In contrast, loop detectors are more reliable compared with video sensors. In review of the literature, practical approaches usually use one or more loop detectors at the upstream or downstream of links for queue estimations. Following the similar principle, the objective of this study is to develop a reliable queue estimation model based on loop detector measurements.

The development of technology has promoted various types of wireless loop detectors, such as Radar, Microwave and Infrared detectors. Dual-loop radar detector is possibly one of the most widely used detectors in the dynamic traffic control systems. Within the pre-defined detection zones, the detector is able to verify the presence of arriving vehicles and provide the flow rate and vehicle speed. Based on the experience of our field implementations, the presence data is the most accurate information provided by radar detectors. Hence, the queue estimation model developed in this study will only use the presence data for calculations. Also, the length of detection zone (distance between two loops) can affect the function of detectors. For instance, short detection zone can be more efficiently to count the number of vehicles while observing 100% occupancy measurements can indicate stopped vehicle over the long detection zone. To take advantage of the both functions, a dual-zone detector is used in this study for providing both short and long detection zones.

This paper is organized as follows: in the next section, a literature review for existing queue estimation techniques at signalized links is provided; then the implementation of detectors along with the presence data analysis are provided in the following section; in response to different traffic conditions, section 4 presents two queue estimation models; using a network in Zhubei, Taiwan for our study site, the proposed models are tested in section 5; key findings and conclusions are summarized in section 6.

LITERATURE REVIEWS

Queue estimation is quite critical for signal optimization since it is one of the most crucial performance measurements in an intersection (Newell, 1965, Webster, 1958, Balke et al., 2005, Mirchandani and Zou, 2007, Lu and Yang, 2014). A lot of researches focus on average or maximum queue length estimation in a signal cycle or during a period of time. Loop detectors are often used when researching queue length estimation and various methods have been reported. The input-output method counts the accumulative arrival at the rear of the queue and accumulative discharge at the front (Sharma et al., 2007; Vigos et al., 2008). However, the major limitation of the input-output method is basically caused by the fact that it cannot handle long queues exceeding the rear detector.

Skabardonis and Geroliminis (2008) estimated intersection queue length with aggregated 30-sec loop detector data based on the shockwave theory. Their methods examine the flow and occupancy data every 30 seconds to estimate the rear end of the queue. It can theoretically handle a long queue length even if it exceeds the location of the rear detector but the 30-sec aggregation smoothies the variation the traffic pattern and makes the method less sensitive to the change of traffic state. Similarly, Smaglik et al., (2007) and Liu et al. (2009) also uses event-based data, which means that the traffic state change can be identified by investigating the real-time data and therefore queue length can be estimated.

Vehicle trajectory data was made possible by probe vehicle technology. Cheng et al., (2011) proposed a method based on sampled vehicle trajectories as the only input. The concept of critical point is introduced to represent the changing vehicle dynamics. This method is also one of the shockwave methods and is evaluated by a recently collected data set from a GPS logger. Mobile sensors are also used to estimate real-time queue length. Ban et al., (2011) examines the discontinuities and non-smoothness in travel time data from mobile sensors, which indicates signal timing or queue length changes. The concept of Queue Rear No-delay Arrival Time is then introduced after the maximum and minimum queue length in a cycle has been estimated.

Despite the research progress on real-time queue estimation at signalized intersections, the unique characteristic of off-ramp queue may require a new model for estimation. For instance, the long distance between upstream and downstream of off-ramp may cause extremely long queues. Also, the occurrence of spillover at downstream link can directly impact the queue discharging process. By investigating the relations between time occupancy and indirectly measureable density, Qian et.al (2012) developed a queue estimation model over signalized off-ramps. Their numerical example demonstrates satisfactory estimation accuracy in the simulation tests. However, the proposed method has shown relatively unsuccessful results in capturing short queues. Also, only total number of vehicles within the off-ramp is estimated in this study.

DATA DETECTION AND ANALYSIS

As aforementioned, the distance between two loops will determine the function of detectors. To take advantage of both short and long loop detectors, dual-zone detectors are implemented at both upstream and downstream of off-ramp, as shown in Figure 1.

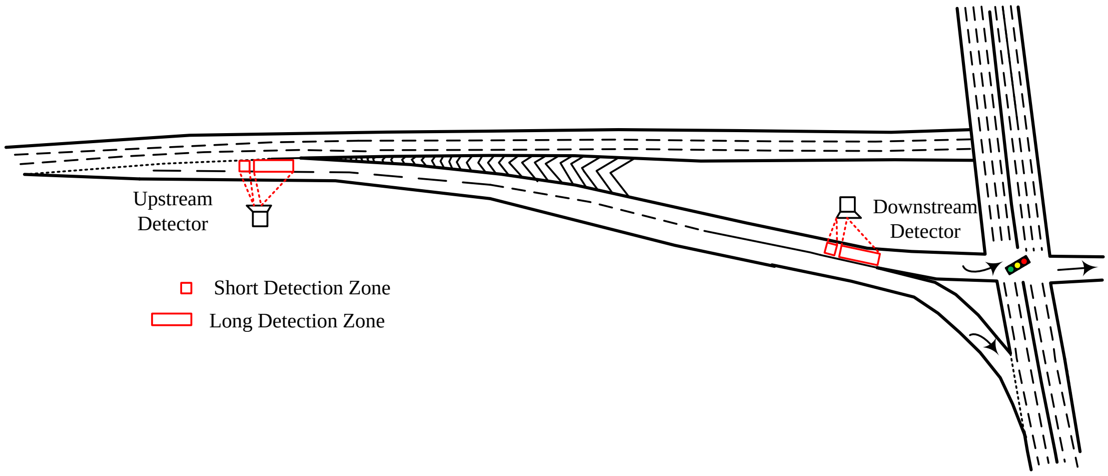

Figure 1 Location of dual-zone detectors on the target off-ramp

Since the presence data is much more accurate and reliable than the other data provided by the detectors, this study only use presence data for calculations. In practice, a “0-1” format data with short interval (e.g. 0.1 second) may be obtained from the detectors, as shown in Figure 2. For the convenience of discussion, the following analysis and calculation will assume a “0-1” format data are available.

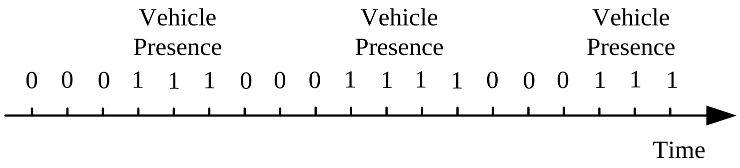

Figure 2. An illustrative example for the presence data format

Based on the obtained data, the emerging of multiple continuously “1” or “0” can indicate the traffic conditions over the detection area. As shown in Figure 3(A), the presence of “0” from short detection zone can be used to record the number of passing vehicles within the target time period. Similarly, for long detection zones, multiple “1” can reflect the formation of queue and the presence of “0” will indicate the clearance of queue.

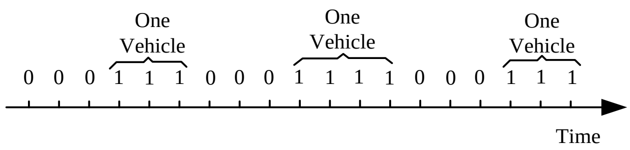

Figure 3(A) The recording of number of passing vehicles by the short detection zone

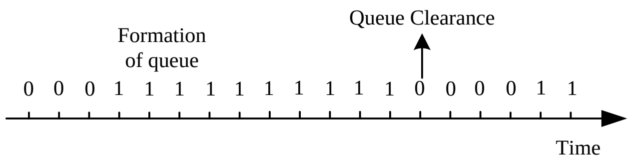

Figure 3(B) The detection of queue formation and clearance by the long detection zone

Obviously, some detection errors may exist in practice using the deification methods introduced above. As shown in Figure 4(A), when using the short detection zone to record number of passing vehicles, if the loop distance is longer than the headway between two adjacent vehicles, it may be identified as one large size vehicle. Hence, to ensure the estimation accuracy, the loop distance of short detection zone should be shorter than the minimum vehicle headway. Figure 4(B) shows the detection errors under two possible conditions. If the loop distance is short than the stopping vehicle headway, the detector may not occasionally identify the formation of queue. Also, when the loop distance is longer than the headway between two moving vehicles, the model may mistakenly identify a queue.

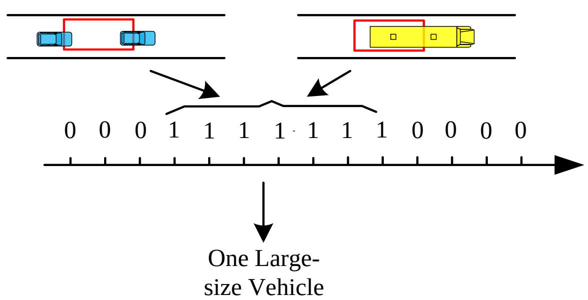

Figure 4(A) Identification errors caused by short detection zone

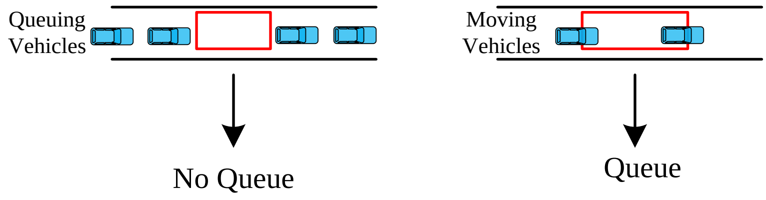

Figure 4(B) Identification errors caused by long detection zone

To overcome the potential errors caused by various traffic conditions, this study develops a set of rules for vehicle identifications:

–Within the short detection zone: the loop distance should be shorter than the minimum vehicle headway;

–Within the long detection zone: 1) the loop distance should be longer than the maximum headway of stopping vehicles; 2) only more than *n* continuously "1" can indicate the formation of queue, where n is a pre-set parameter.

QUEUE ESTIMATIONS

Since detectors are installed at both upstream and downstream of the target off-ramp, one simple way to estimate the queue length is using the flow rates provided by the detectors and recursively computing the number of vehicles between two detectors. However, due to the unexpected detection errors, the recursive computation method may accumulate the estimation errors cycle by cycle. Hence, to ensure the reliability and efficiency of our estimation model, two critical criterions are considered: 1) the estimation error by every signal cycles cannot be accumulated; 2) the computation process should be efficient.

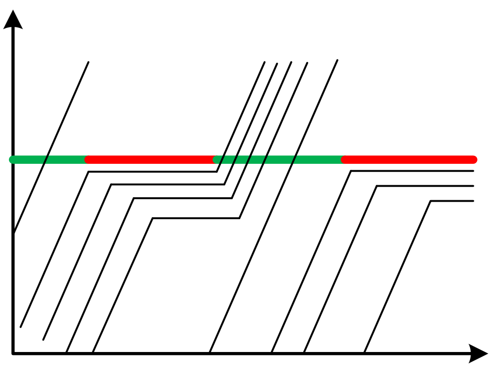

Figure 5(A) Queuing vehicles can be fully discharged during the green phase

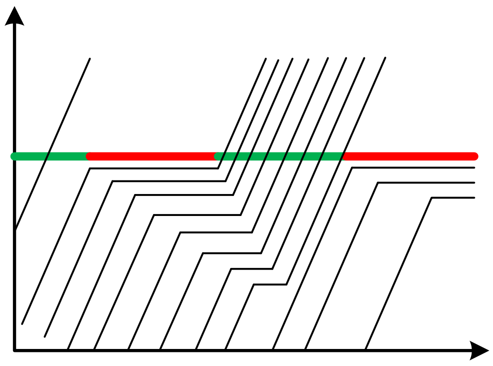

Figure 5(B) Queuing vehicles cannot be fully discharged during the green phase

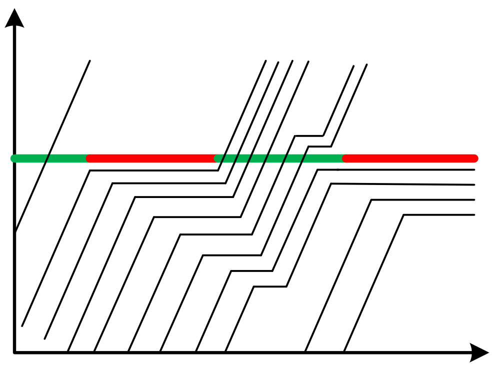

Figure 5(C) Queue spillover at downstream link may affect the discharging process

With respect to different congestion levels, four scenarios may be encountered during the queue estimation process. 1) When the inflow exceeds the discharging capacity at the downstream of off-ramp, the queue may be built up quickly and spillbacks to the freeway mainline. 2) As shown in Figure 5(A), during the green time, the traffic queue could be fully discharged. 3) The traffic queue is not cleared after the green phase and some residual queuing vehicles are remained on the off-ramp (see Figure 5(B)). 4) As shown in Figure 5(C), queue spillover at the downstream link may affect the queue discharging process and the effective green time would be less than the given green time.

By analyzing the queue evolutions at the off-ramp, queue length may be changed periodically by each signal cycles. Assuming one signal cycle starts from green phase, our proposed model will require the detector data at the end of each signal cycle for analysis.

Figure 6 shows the flowchart of the entire queue length estimation process. For the first scenario that queue already spillbacks to the freeway mainline, this model uses the data from long detection zone at off-ramp upstream for identification. Based on the data analysis method introduced above, if the upstream detector data detects the queue, a queue spillback warning will be provided.

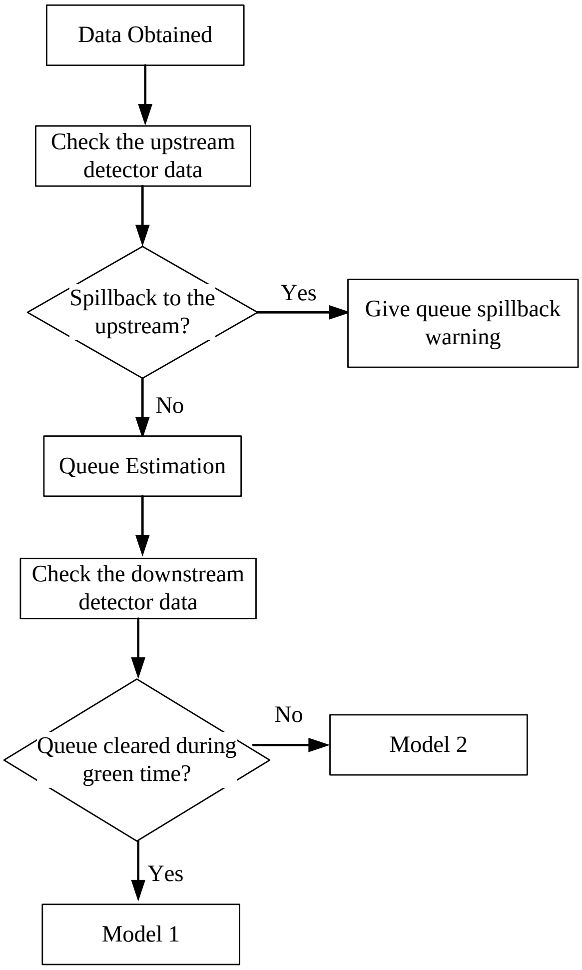

Figure 6 Flowchart of the entire queue estimation process

If the off-ramp queue doesn't spillback to the upstream detection zone, further queue estimation is required. According to the classification of different scenarios in Figure 5, the proposed model will then examine the downstream detector. If the data from long detection zone indicates the clearance of queue during green time, Model 1 will be used for queue estimation; otherwise Model 2 should be implemented.

Model 1

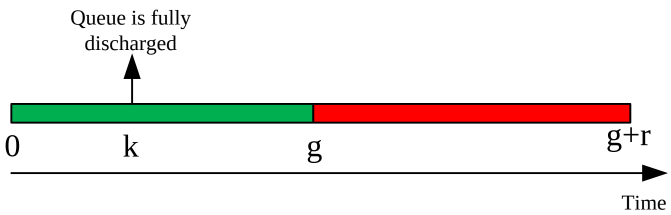

Figure 7 Time slots within the target signal cycle

For the convenience of discussion, it is assumed that the time slots start from "0" to "g+r" within the target signal cycle, as shown in Figure 7. At time slot "k", the downstream detector data indicate the clearance of queue. Also assuming a fixed travel speed on the off-ramp, then the travel time between upstream and downstream detector is given by:

$$t = \frac{L}{v} \tag{1}$$

Where L denotes the distance between two detectors and v is the average travel speed.

Since queue is fully discharged, at time “k”, the number of moving vehicles between two detectors is equaled to the number of vehicles passed the upstream detector during time period [k-t, k]:

$$N_k = q_u(k-t, k) \tag{2}$$

Where $q_u(m,n)$ is the detected number of queues by the upstream detector during time [m, n].

Then, at time “g”, the total number of vehicles between two detectors is given by:

$$N_g = N_k + q_u(k,g) - q_d(k,g) \tag{3}$$

Where $q_d(m,n)$ is the detected number of queues by the downstream detector during time period [m, n].

During the red phase, no queuing vehicle is discharged. Hence, at the end of cycle, the total number of vehicles between two detectors is:

$$N_{g+r} = N_g + q_u(g, g+r) - q_d(g, g+r) \tag{4}$$

Therefore, the queue length at the end of cycle could be approximately computed as:

$$Q_{g+r} = N_{g+r} + N_c \tag{5}$$

Where N_c is a constant, which indicates the number of vehicles between downstream detector and stop line.

Model 2

If residual queue still exists at the end of green time, two cases may be encountered:

1) The residual queue doesn’t reach the downstream detector;
2) The residual queue has researched the downstream detector.

For the first case, the downstream detector data will be examined first. As shown in Figure 8, it is assumed that traffic queue has reached the downstream detector at time “k”.

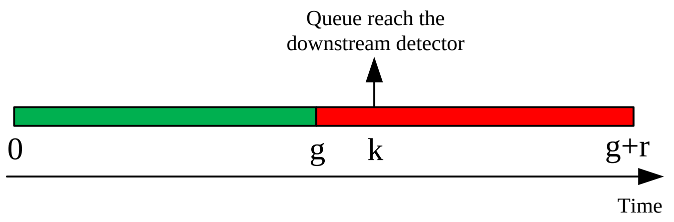

Figure 8 Time slots within the target signal cycle

Then, at the end of red time, the total number of vehicles between two detectors is given by:

$$N_{g+r} = q_u(k-t, g+r) \tag{6}$$

Similarly, the queue length at the end of cycle could be computed by:

$$Q_{g+r} = N_{g+r} + N_c \tag{7}$$

If the residual queue has exceeded the location of downstream detector, the data from the long detection zone will always be "1" during the red time. The queue length at the end of cycle will be approximated by:

$$Q_{g+r} = Q_{g+r} + q_u(0, g+r) - q_d(0, g+r) \tag{8}$$

Where Q_{g+r} is the estimated queue length at the previous signal cycle.

NUMERICAL EXAMPLES

To evaluate the proposed queue estimation model, one freeway segment in Zhubei, Taiwan along with its off-ramp is selected as the study site. Since the current pre-timed signal timings are designed to coordinate the through traffic on the arterial, the NB off-ramp flows often form a long queue and spill back to the freeway mainline during the peak hours. As shown in Figure 7, to estimate the queue evolution, two dual-zone detectors are installed at both upstream and downstream of the off-ramp.

Hence, the Transportation Department of Taiwan has sponsored a national project to mitigate off-ramp queue spillback at this location. Therefore, an accurate queue estimation model is essential for the entire signal control system. To evaluate the effectiveness of our proposed model, the data collection team in National Chiao Tung University (NCTU) has completed a field survey from 16:30PM to 21:30 PM on April 24-25, 2013. The collected data includes:

1) Freeway mainline flow rate;
2) Off-ramp flow rate;
3) The signal timings at nearby intersections;
4) Queue length evolution at critical links.

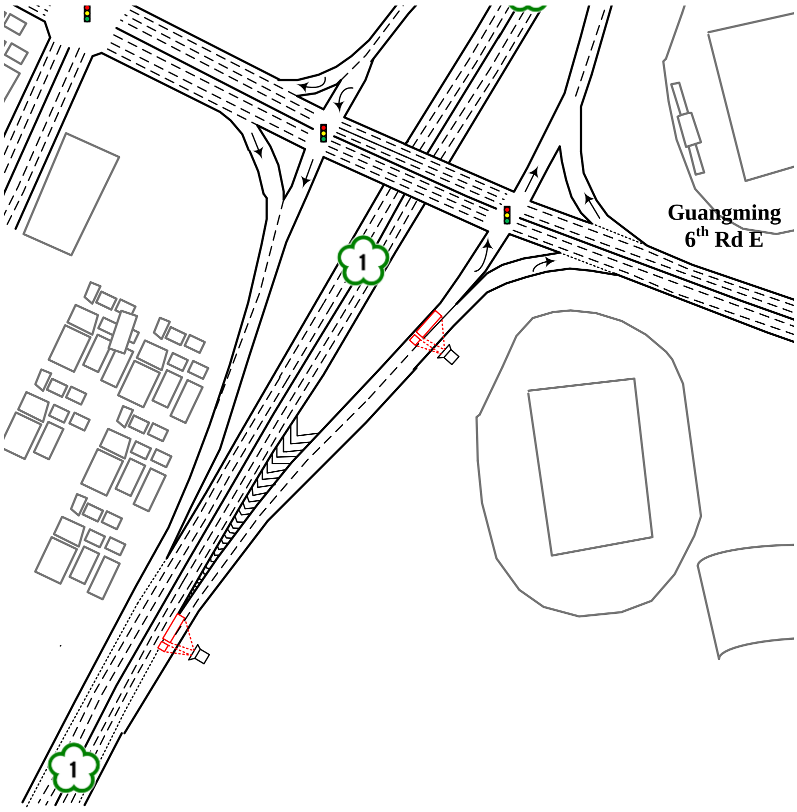

Figure 9 The overview of the study site

Since the detectors are still under calibration at the study sites, this study has produced a simulation network with VISSIM 5.20 for the model evaluations. Recognizing that a simulation system is useful only if it can faithfully reflect the behavior of its target driving populations, this study has performed the calibration by minimizing the difference between simulated and field-collected queues as well as flow rates. The calibration results for VISSIM simulation are listed is Table 1.

Table 1(A). Percentage difference between simulation and field volume data

Intersection No.	Approach			
	WB	NB	EB	SB
1	1%	0.6%	2%	N/A
2	0.9%	N/A	2%	0.2%
3	2%	3%	0.6%	1%

Table 1(B). Adjusted VISSIM parameters

Parameters	Value
Average stand still distance (Urban)	3.22 ft
Maximum deceleration (Lane Change)	-14.99 ft/s^2
Accepted deceleration (Lane Change)	-6.00 ft/s^2
Maximum deceleration for cooperative braking	-14.99 ft/s^2

Based on the presence data obtained from VISSIM, the proposed estimation model is implemented and the estimation results are compared with the actual queue lengths. Also note that the actual queue lengths at the target off-ramp are obtained by our observations of VISSIM animations. The study period is from 17:00-19:30 and the results comparisons are presented in Figure 10.

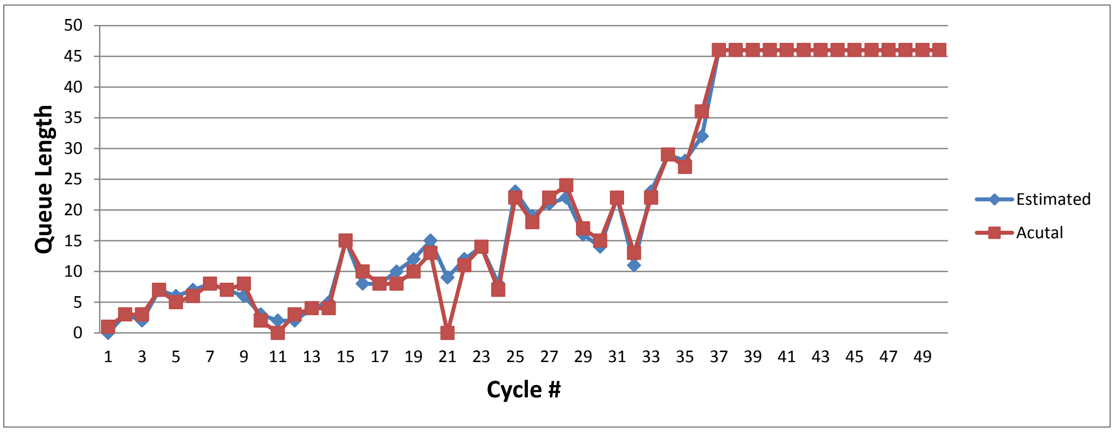

Figure 10(A) The comparison between estimated queue and actual queue

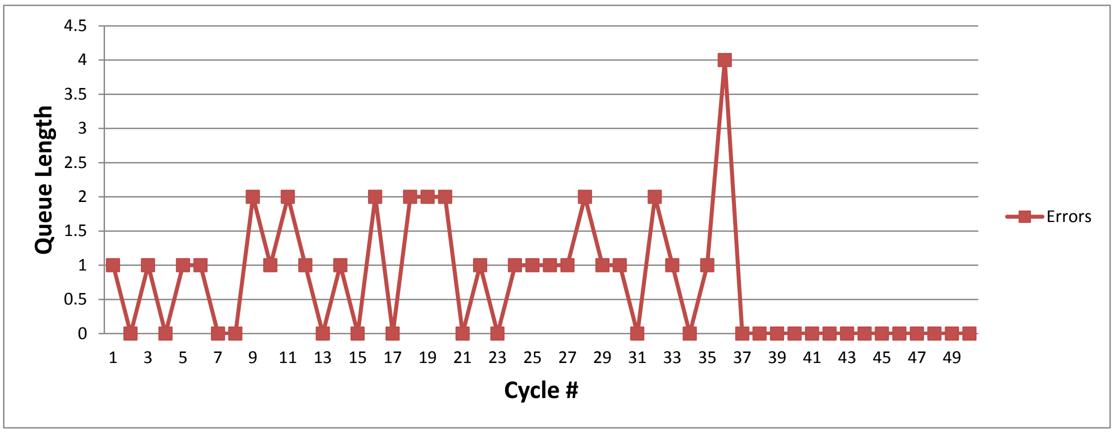

Figure 10(B) The absolute estimation errors

As shown in Figure 10, the entire study period includes 50 signal cycles, where the cycle length of the first 25 cycles and last 25 cycles are 150 seconds and 180 seconds, respectively. Also, the queue length at off-ramp is increasing with time. Figure 10 (A) presents the results comparison between estimated queue and actual queue. Obviously, the proposed model can actually estimate the off-ramp queue during both under-saturated and over-saturated conditions, which demonstrates the reliability and effectiveness of the proposed model. After the 38th cycle (18:45), the traffic queue has exceeded the location of upstream detector and the proposed model reported the queue spillback warning.

By examining the results shown in Figure 10 (B), the absolute estimation errors of queue range from 0 vehicles to 4 vehicles, which are within the acceptable range. Also, with the analysis of the estimation process and the simulation animations, the estimation errors are mainly caused by several factors: 1) the pre-determined travel speed on the off-ramp may bring some noise to the estimation model due to the variation of vehicles' traveling speeds; 2) the long detection zone of downstream detection may not accurately detected the reaching of queue by identifying the moving vehicles with short headways as queuing vehicles; 3) lane changing behaviors between upstream and downstream detectors can also bring estimation errors.

CONCLUSIONS

This study presented a queue estimation system using dual-zone detectors, where each detector can provide two detection zones. Particularly, the short detection zones are used to count traffic flow rates and the information from long detection zone can indicate the presence of traffic queues. With respect to different congestion levels, the off-ramp queue may be fully discharged during the green time or not. Therefore, this study has developed two queue estimation models for each condition. Based on the field data from the freeway interchange in Zhubei, Taiwan, this study has conducted extensive simulation experiments, and demonstrated the effectiveness of the proposed system on off-ramp queue estimations.

REFERENCES

Yang Cheng, Xiao Qin, Jing Jin, Bin Ran, and Jason Anderson, 2011. Cycle-by-Cycle Queue Length Estimation for Signalized Intersections Using Sampled Trajectory Data, Transportation Research Record 2257, 87-94

Mirchandani, P.B., Zou, N., 2007. Queuing models for analysis of traffic adaptive signal control. IEEE Transactions on Intelligent Transportation Systems (1).

Balke, K., Charara, H., Parker, R., 2005. Development of a Traffic Signal Performance Measurement System (TSPMS). Texas Transportation Institute, Report 0-4422-2.

Sharma, A., Bullock, D.M., Bonneson, J., 2007. Input-output and hybrid techniques for real-time prediction of delay and maximum queue length at a signalized intersection. Transportation Research Record 2035, 88–96.

Vigos, G., Papageorgiou, M., Wang, Y., 2008. Real-time estimation of vehicle-count within signalized links. Transportation Research Part C 16 (1), 18–35.

Liu, X., Wu, X., Ma, W., Hu, H., 2009. Real time queue length estimation for congested signalized intersections. Transportation Research Part C 17, 412–417.

Lu, Y. and Yang, X., "Estimating Dynamic Queue Distribution in a Signalized Network Through a Probability Generating Model", *IEEE Transaction on ITS*, vol. 15 (1), pp. 334-344, 2014.

Webster, F., 1958. Traffic signal settings. Road Research Technical Paper 39. Road Research Laboratory, Her Majesty’s Stationery Office, London.

Newell, G.F., 1965. Approximation methods for queues with application to the fixed-cycle traffic light. SIAM Review 7.

Skabardonis, A., Geroliminis, N., 2008. Real-time Monitoring and Control on Signalized

Arterials. Journal of Intelligent Transportation Systems. 12 (2), 64–74.

Smaglik, E.J., Sharma, A., Bullock, D.M., Sturdevant, J.R., Duncan, G., 2007. Event-based data collection for generating actuated controller performance measures. Transportation Research Record 2035, 97–106.

Liu, X., Wu, X., Ma, W., Hu, H., 2009. Real time queue length estimation for congested signalized intersections. Transportation Research Part C 17, 412–417.

Ban, Xuegang, Hao, Peng, Sun, Zhanbo 2009 Real time queue length estimation for signalized intersections using travel times from mobile sensors, . Transportation Research Part C 19 1133-1156