A Kalman filter based Queue Estimation Algorithm using Time Occupancies for Motorway On-ramps

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92nd Annual Meeting of the Transportation Research Board,
Washington D.C., January 2013

Submission date: August 1 2012

Word count 4515 plus 1 table and 8 figures, total 6765

ABSTRACT

The primary objective of this study is to develop a robust queue estimation algorithm for motorway on-ramps. Real-time queue information is the most vital input for a dynamic queue management that can treat long queues on metered on-ramps more sophistically. The proposed algorithm is developed based on the Kalman filter framework. The fundamental conservation model is used to estimate the system state (queue size) with the flow-in and flow-out measurements. This projection results are updated with the measurement equation using the time occupancies from mid-link and link-entrance loop detectors. This study also proposes a novel single point correction method. This method resets the estimated system state to eliminate the counting errors that accumulate over time. In the performance evaluation, the proposed algorithm demonstrated accurate and reliable performances and consistently outperformed the benchmarked Single Occupancy Kalman filter (SOKF) method. The improvements over SOKF are 62% and 63% in average in terms of the estimation accuracy (MAE) and reliability (RMSE), respectively. The benefit of the innovative concepts of the algorithm is well justified by the improved estimation performance in the congested ramp traffic conditions where long queues may significantly compromise the benchmark algorithm's performance.

INTRODUCTION

Ramp metering is an access control for motorways in which a traffic signal located on on-ramps regulates the rate of vehicles entering the motorway. Ramp metering is an effective traffic management tool to efficiently exploit the existing motorway capacity. Preventing flow breakdowns in merging areas can effectively increase the vehicle throughput. On-ramp traffic also takes advantage of ramp metering, because the congestion on the mainline eventually reduces the opportunity of on-ramp traffic to use the motorway.

Although ramp metering is becoming an increasingly popular and is now considered as a proven traffic management strategy, some limitations and drawbacks are well documented in the literature. The most significant limitation of the existing ramp metering method is its adverse impacts on the on-ramp and surface street traffic. The nature of ramp metering and the way in which control algorithms operate, restrict the entry of ramp traffic to the motorway mainline and thus creates traffic queues. Long ramp queues may cause queue spillover onto the adjacent surface streets and interfere with the traffic streams. In practice, a queue management must be implemented alongside ramp metering. Upon a detection of queue spillover, the queue management overrides the normal metering control allowing the queued vehicles to bypass the metering to prevent queue spillover and potential street blockages.

A commonly used on-ramp queue management is the so-called “queue flush” method. This method is enabled by placing a detector close to the upstream end of the ramp. If the measured detector occupancy exceeds a threshold, it considers that the queue has reached the detector location and then increases the metering rate to the maximum setting to mitigate the queue. Although this simple method can effectively reduce queue spillover, queue flush adversely affects the mainline traffic stream by suddenly increasing the metering rate and diminishes the ramp metering benefit as a result (1, 2).

Research Objectives

The primary objective of this research is to develop a robust queue estimation algorithm for motorway on-ramps. Real-time queue information is the most vital input for a dynamic queue management on metered on-ramps. Accurate and reliable queue information enables an adaptive management of the ramp queue size and thus minimises queue flush and its adverse impacts while increasing the benefit of ramp metering for the mainline stream. Spiliopoulou and Manolis (2010) reported that accurate queue information could reduce the on-ramp queue spillover by 45.7% compared with a simple queue flush control (3).

The proposed algorithm is developed based on the Kalman filter framework. The fundamental traffic flow conservation is used to estimate the system state (i.e., queue sizes) with the flow-in and flow-out measurements. This estimation inevitably produces a noise due to the counting error. Therefore the estimation results are updated with the Kalman Filter measurement that uses loop detector time occupancies. This study also proposes a novel single point correction.

This method resets the system state when a significant change in the mid-link time occupancy is observed to eliminate the accumulated counting errors.

Abundant literatures describe queue estimation techniques, but only few propose appropriate solutions for motorway on-ramps. Those existing techniques are reviewed in the next section. The new algorithm is presented in the following section with a brief introduction to the Kalman Filter. The algorithm is evaluated in the microsimulation environments against a benchmark algorithm. The simulation results are discussed in the last section.

EXISTING TECHNIQUES FOR RAMP QUEUE ESTIMATION

Given the motorway on-ramp as the applying object and the conventional loop detector as the information source, recent queue estimation studies can be categorised into two types. The first approach uses the flow conservation model with flow-in and flow-out counts. This method assumes the traffic flow conservation rule and estimates the number of vehicles in a given roadway segment by calculating the difference of flow-in and flow-out counts measured by two detectors placed at the entrance and exit of the link. Although this approach is easy to understand and implement, a critical drawback is the detector counting error that accumulates over time. Even with a reasonable level of error rate, the accumulative errors may render the estimation results useless. Liu et al. reported that 31% of metered ramps have biased loop detectors in counting number of vehicles according to their study in Minnesota (3). The conservation model could be applied to 60% of ramps because of the counting noise of loop detectors.

A second approach uses advanced techniques to correct the estimation results of the first approach. Liu et al. proposed two methods: a regression model and a Kalman filter for the ramps with erroneous link-entrance and link-exit detectors (4). For the Kalman filter measurement, a linear regression model was developed using the occupancy and count measurements of the link-entrance and link-exit detectors as variables. A study by Vigos et al. also employs the Kalman filter to improve the accuracy of the flow-in and flow-out approach by continuously adjusting the system state using the time occupancy measurements from an extra loop detector placed in the middle of the link (5). This method translates time occupancies into space occupancies using the basic relationship between these two measurements in signalised links as demonstrated by Papageorgiou and Vigos (6). The time occupancy measurement is an unbiased estimation and does not accumulate over time. Therefore, the mid-link occupancy can be used to generate a correction (or measurement) term in the Kalman filter framework. This method can produce reliable queue estimations while the queue end is fluctuating around the mid-block detector. However, for long queues where the queue end locates upstream of the mid-link detector, the mid-link occupancy will be constantly high and thus it is no longer an unbiased estimation and the generated correction term is no longer an accurate correction term.

ALGORITHM DEVELOPMENT

The Kalman Filter is a set of mathematical equations that provides an efficient tool to estimate the state of a system, in a way that minimises the mean of the squared error (7). The filter is very powerful in estimating past, present, and future states even when the precise information of the modelled system is unknown. The Kalman Filter theory has two basic sets of equations including a system state equation and a system measurement equation. The system state equation represents the nature of the system states, and is usually written as the following discrete form:

$$x(t) = A \cdot x(t-1) + B \cdot u(t-1) + w(t-1) \quad [1]$$

Where,

x is system state vector;
A is input matrix;
u is control input vector;
B is control matrix;
w is process noise; and,
t represents the time instance

The system measurement equation describes the relationship between system states and measurements. Acknowledging that measurements inevitably contain noise, the measurement equation is expressed as follows:

$$z(t) = H \cdot x(t) + v(t) \quad [2]$$

Where,

z is measurement vector;
H is output matrix; and,
v is measurement noise.

System Estimation and Measurement

A typical metered motorway on-ramp is illustrated in Figure 1. The figure also illustrates the detector requirements for the proposed algorithm. The algorithm estimates the ramp queue size or the number of vehicles between the link-exit detectors and the link-entrance detectors. It assumes three detector sets including link exit detectors, mid-link detectors, and link entrance detectors. The link exit and link entrance detectors provide flow measurements. Occupancy measurements are also required from the mid-link and link entrance detectors.

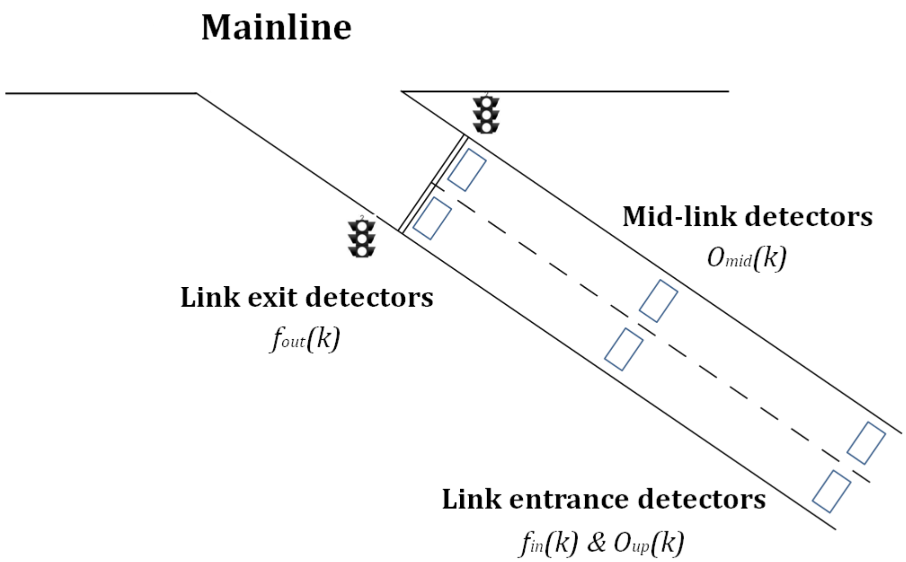

FIGURE 1 Metered motorway on-ramp and detector requirements.

The new algorithm is developed based on the Kalman filter framework. Two linear relationships are assumed to formulate the system state equation and the system measurement equation. The system state equation is formulated using the flow-in and flow-out count differences over time based on the flow conservation law, which can be expressed as follows:

$$NV(t) = NV(t-1) + [f_{in}(t) - f_{out}(t)] \quad [3]$$

Where,

NV is the system state in terms of the number of vehicles on the ramp;
f_{in} is the traffic flow-in measured by the ramp entrance detectors; and,
f_{out} is the traffic flow-out measured by the ramp exit detectors.

The system measurement equation is developed based on the linear relationship between the space occupancy and the number of vehicles or *NV*, which can be estimated using the following equation:

$$NV_{mea}(t) = \frac{O_S(t) \cdot L_{ramp} \cdot N_{lanes}}{L_{vehicle} \cdot 100} = NV(t) \quad [4]$$

Where,

O_s is the space occupancy;
$L_{vehicle}$ is the average vehicle length;
N_{lanes} is the number of lanes in the on-ramp; and,
L_{ramp} is the ramp length.

Space occupancy "O_s" is an instantaneous (at a certain time instance) space extended quantity that reflects the portion of link length covered by vehicles. It is impossible to directly measure the space occupancy using loop detector measurements; alternatively, time occupancies can be converted to approximate space occupancies. The time occupancy is a bias-free estimate of the space occupancy in a sufficiently small space-time window assuming the effective vehicle length equals the physical vehicle length (6). The Kalman Filter measurement equation proposed by Vigos et al. uses the time occupancy from the mid-link detector to update the system state (5). However, this method has a limitation in congestion conditions when the queue size is constantly long and the time occupancy measurements from the mid-link detector do not represent the actual queue size on the entire ramp.

This study also builds on the relationship between time occupancies and space occupancies; however, it includes the time occupancy from the link-entrance detector in the measurement equation to overcome the aforementioned limitation. The time occupancy measurements from the mid-link and the link entrance detectors are processed to approximate the link space occupancy using the following equation:

$$\hat{O}_s(t) = \begin{cases} O_{mid}(t), & O_{mid}(t) < O_{con} \\ \frac{\left(O_{con}+O_{up}(t)\right)}{2}, & otherwise \end{cases} \qquad [5]$$

Where,

O_{mid} is the time occupancy measurement from the mid-link detector;
O_{up} is the time occupancy measurement from the ramp entrance detector;
O_{con} is the congestion occupancy; and,
$\hat{O}_s$ is the estimated space occupancy.

The above equation implies that the space occupancy is directly approximated using only the mid-link time occupancy for short queues. For long queues, the algorithm assumes a linear increase in the space occupancy with the increase in the link-entrance time occupancy at the rate of $\frac{\left(O_{con}+O_{up}(t)\right)}{2}$. The value of O_{con} was set at 70% based preliminary simulation tests.

Kalman Filter Estimator

The process noise, *w*, is sourced from the loop detector counting errors, and is assumed to be an unbiased error with the mean value of zero. On the other hand, the measurement noise, *v*, is caused in converting the time occupancy into the space occupancy. As the two linear relationships are independent from each other, the two noises are assumed to be independent of each other, and normally distributed with constant variances as expressed follows:

$$p(w) \sim N(0, Q) \text{ and } p(v) \sim N(0, R) \quad [6]$$

Where,

Q is the constant process noise variance; and,
R is the constant measurement noise variance.

In the standard Kalman Filter process, a prediction process and a correction (estimation) process are employed. The errors involved in each process are referred to as a priori errors and a posterior error, respectively, and their definitions are as follows:

$$e^-(t) \equiv x(t) - \hat{x}^-(t) \quad [7]$$

$$e(t) \equiv x(t) - \hat{x}(t) \quad [8]$$

Where,

$e^-(t)$ is the priori error;
$\hat{x}^-(t)$ is the prediction;
$e(t)$ is the posterior error; and,
$\hat{x}(t)$ is the estimation (correction).

Accordingly, the two error covariances are given as follows:

$$P^-(t) = E[e^-(t) \cdot e^{-T}(t)] \quad [9]$$

$$P(t) = E[e(t) \cdot e^T(t)] \quad [10]$$

The correction equation is given by:

$$\hat{x}(t) = \hat{x}^-(t) + K(t)[z(t) - H\hat{x}^-(t)] \quad [11]$$

Where,

K is the Kalman gain matrix.

The correction process is to use measurement to correct prediction. The Kalman Filter method attempts to select a K matrix to minimize the estimation error. One widely used solution for determining the K matrix is given as follows (8):

$$K(t) = P^-(t) \cdot H^T(HP^-(t)H^T + R)^{-1} \quad [12]$$

The purpose of the Kalman Filter is to minimise a posterior estimation error covariance by selecting an appropriate Kalman gain matrix. In other words, it uses actual measurements to correct the system state prediction and then obtains a better estimation of the system state. There are two steps at each interval. The first step is a time update, the results from which are used as the prediction. For time update, the prediction is calculated by a system equation and the prediction error covariance is updated:

$$\hat{x}^{-}(t) = A \cdot \hat{x}(t-1) + B \cdot u(t-1) \quad [13]$$

$$P^{-}(t) = AP(t-1)A^{T} + Q \quad [14]$$

Note that the Kalman Filter is applied to a single dimensional problem in this study where A=1, B=1, and H=1. The next step is the measurement update. For measurement update, the K matrix is firstly updated and then, the estimation is calculated. Finally, the estimation error covariance is updated as follows:

$$P(t) = [I - K(t)H] \cdot P^{-}(t) \quad [15]$$

According to Welch and Bishop (8), the estimation error covariance, $P(t)$, and the Kalman gain matrix, $K(t)$ stabilise quickly and then remain constant once the filter is converged, if the variances of the two noises (i.e., Q and R) are constant. In this study, the process noise variance, Q, and the measurement noise variance, R, are assumed to be constant. Therefore, the value of $P(t)$ and $K(t)$ can be pre-computed by defining $P^{-}(t) \equiv P(t)$ and equation [12] can be re-written as follows given H=1.

$$P(t) = \frac{RK}{1-K} \quad [16]$$

Since $P^{-}(t) \equiv P(t)$ and A=1:

$$P(t+1) = P(t) + Q \quad [17]$$

$$P(t+1) = \frac{RK}{1-K} + Q \quad [18]$$

Since the noise is assumed to be unbiased, the estimation error covariance will converge to zero (i.e., $P(t+1) \rightarrow 0$). Consequently, equation [18] can be re-written as:

$$K = \frac{Q}{Q-R} \quad [19]$$

The noise ratio, denoted as $\mu = \frac{Q}{R}$, yields,

$$K = \frac{\mu}{\mu-1} \quad [20]$$

The value of K depends on the noise ratio, μ, rather than the explicit values of Q and R. If $\mu \rightarrow 0$ (i.e. zero system noise and a significant measurement noise), equation [20] yields $K=0$, which indicates no need of correction; on the other hand, $\mu \rightarrow \infty$ yields $K=1$, which means that only the measurement is reliable.

In this study, the system noise should be smaller than the measurement noise. This is because the estimation method (i.e., flow-in and flow-out difference) is more accurate and reliable than the measurement method (i.e., converting time occupancies into space occupancies). Therefore, a small Kalman gain makes a little effect of the measurement correction on the system state. A previous study suggested the Kalman gain in the range of (0.05, 0.25) based on the actual error rate of the loop detector [4]. The Kalman gain is set at 0.05 in this study based on iterative tests of the gain value between 0.05 and 0.25 with increments of 0.05.

Finally, the basic formulation of the queue estimation algorithm can be built as follows:

$$NV_{sys}(t) = NV_{est}(t-1) + [f_{in}(t) - f_{out}(t)] \qquad [21]$$

$$NV_{mea}(t) = \frac{\hat{O}_{spc}(t) \cdot L_{ramp} \cdot N_{lanes}}{L_{vehicle} \cdot 100} \qquad [22]$$

$$NV_{est}(t) = NV_{sys}(t) + K \cdot [NV_{mea}(t) - NV_{sys}(t)] \qquad [23]$$

Where,

NV_{sys} is the *NV* calculated using the system equation;
NV_{mea} is the *NV* calculated using the measurement equation;
K is the Kalman gain;
NV_{est} is the *NV* estimation, the result of the Kalman Filter process.

The correction equation [23] can be re-arranged as follows:

$$NV_{est}(t) = (1-K) \cdot NV_{sys}(t) + K \cdot NV_{mea}(t) \qquad [24]$$

In equation [24], the estimate is a smoothed value of NV_{sys} and NV_{mea}. Thus, the selection of the Kalman gain must consider the relative size of the system noise and the measurement noise. Since the system noise NV_{sys} is much smaller than the measurement noise, NV_{mea}, K must be a small number to make NV_{sys} as the dominant term in the smoothing.

Single Point Correction

The idea behind of the single point detection is that with an extra detector at the mid-link position, it can be observed when the queue end passes the detector in either forward or backward direction. For instance, a significant increase in the observed occupancy may indicate that the queue end has passed the detector location backward. On the other hand, a rapid reduction in the occupancy value implies that a forward moving queue (i.e., dissipating queue) has passed the detector position. Figure 2 shows the occupancy measurements from a mid-link detector in comparison to the actual number of vehicles using microsimulation date.

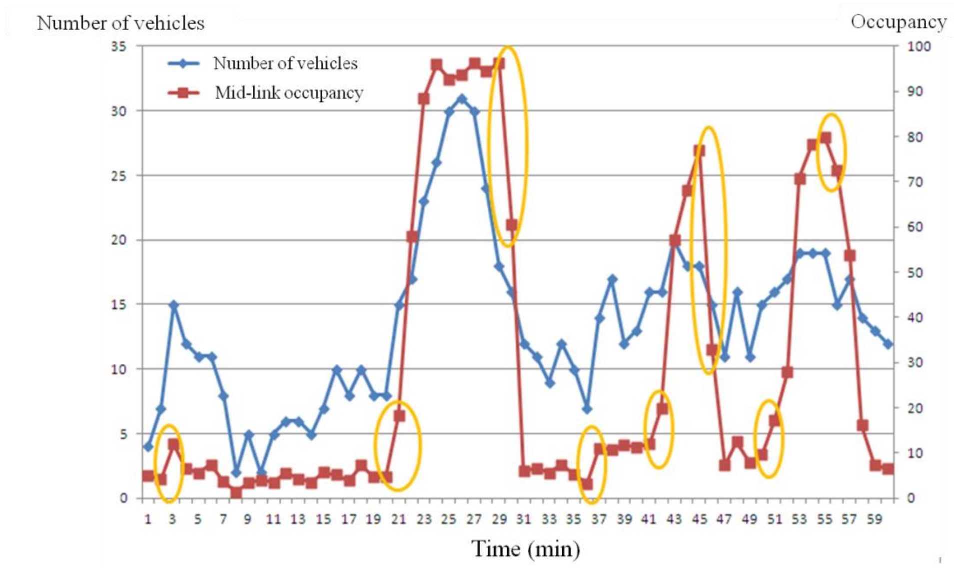

Figure 2 Mid-link time occupancies and number of vehicles.

The yellow circles indicate the occurrence of a significant increase or decrease of the mid-block occupancy value. It is clear in the graph that the detector occupancy changes sharply when the number of vehicles increases or decreases over the half of the ramp storage (around 15 vehicles). This phenomenon can be used to reset the estimated number of vehicles. The single correction point is defined as the instances when the occupancy measurements from the mid-link detector drop or spike in a short-time period. A single correction point is defined as follows:

$$\Delta O_{mid} = |O_{mid}(t) - O_{mid}(t-1)| \; > \; \gamma \qquad [25]$$

Where,

ΔO_{mid} is the observed occupancy increment
$O_{mid}(t)$ is the time occupancy measurement from the mid-link detector in the t^{th} interval
γ is the single point correction threshold

This study defines the single point correction threshold γ at 35% based on preliminary simulation tests. Therefore, an increment or decrement of the time occupancy greater than 35% will activate the single point correction. Once the single point correction is activated, the estimated number of vehicles in this interval, $NV_{est}(k)$, is set at half of the maximum queue size, $0.5 \cdot NV_{max}$. This process can effectively eliminate the previously accumulated counting errors.

Algorithm Flow

With the single point correction term, the proposed queue estimation algorithm is displayed in Figure 3.

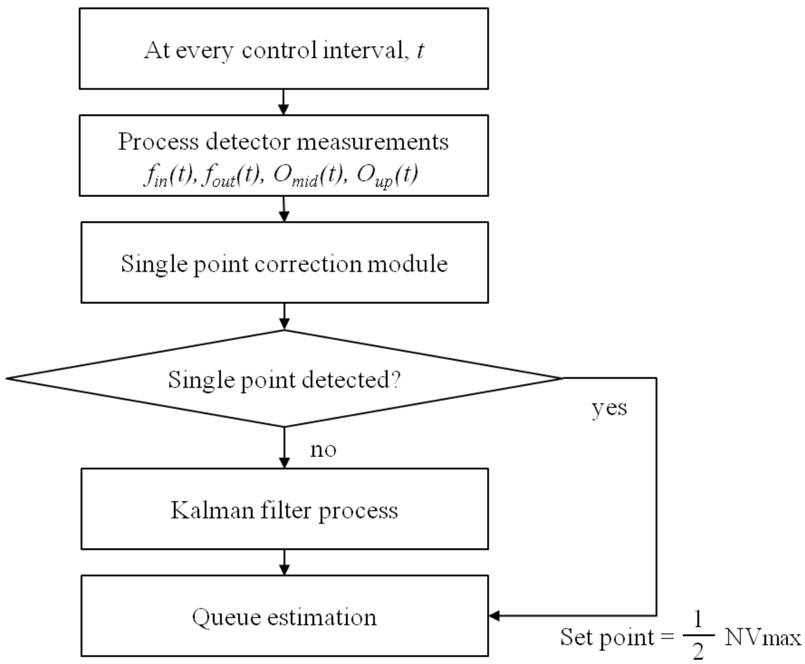

Figure 3 Queue estimation algorithm flow.

The single point correction requires occupancy measurements from the mid-link detector. Detection of a single point will yield the estimated queue size at the set point of $\frac{1}{2}NV_{max}$ without the Kalman filter processing. The queue estimation algorithm takes the input of traffic count measurements from the link-exit and link entrance detectors for the system state equation. The occupancy from the mid-link and the link entrance detectors are used for the system state estimation.

ALGORITHM EVALUATION

Simulation Testbed and Scenario

The estimation accuracy and reliability of the new queue estimation algorithm were evaluated using the Aimsun microsimulation model. The evaluation was conducted on three on-ramps including the Birdwood Road northbound ramp, Marquis Street southbound ramp, and Logan Road northbound ramp, on the Pacific Motorway. The Pacific Motorway is a 100 km long motorway between Brisbane and the Queensland-New South Wales border. It is the major commuting route for commuters from south suburbs to the Brisbane CBD. Recurring congestion occurs to the northbound in the morning peak-hours and to the southbound in the afternoon peak-hours. Figure 4 shows the road geometry of these ramps including the position of the existing ramp signals. The motorway is three lanes and the on-ramps are two lanes as shown in the figures.

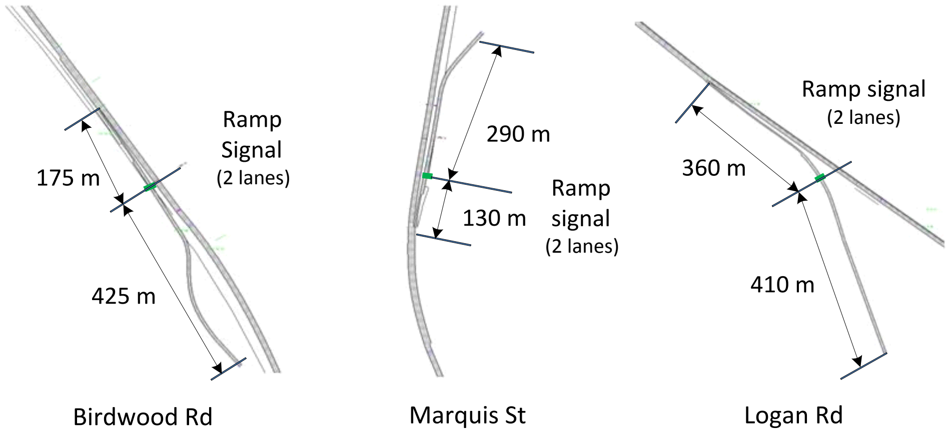

Figure 4 Road geometry of the selected on-ramps for the algorithm evaluation.

The ramp and mainline traffic volumes were drawn from the actual loop detectors data on the 25th of May in 2010. The simulation period is 5 hours starting from 5 to 10 am for the Birdwood Road ramp and the Logan Road ramp to mimic the traffic conditions in the morning peak-hours. The afternoon peak period was modeled for the Marquis Street ramp from 2 to 7 pm. Figure 5 presents the traffic demand profiles of the selected ramps during the simulation period. The time-step of the simulation was 0.5 seconds or 2 steps per second.

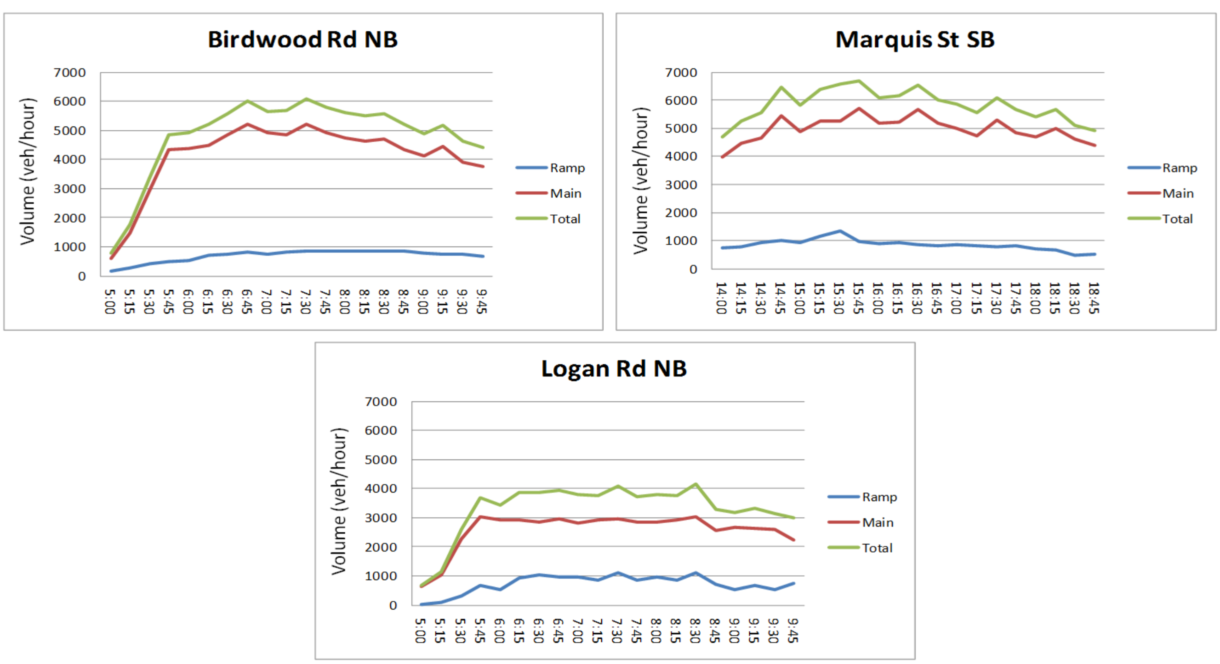

Figure 5 Traffic flow profiles (15 minutes period).

The proposed algorithm was implemented using the Application Programming Interface (API) functions provided by AIMSUN. The algorithm receives the time occupancies and traffic count data from the simulation model to estimate the space occupancy and queue size based on the proposed method. The processed results were compared against the actual queue and space occupancies observed from the simulation model.

Ramp Metering Control

To evaluate the algorithm under realistic conditions, the ALINEA ramp metering strategy was implemented on the simulation models to reproduce the traffic flow characteristics under a ramp metering control. ALINEA is a local-level traffic adaptive metering control that uses time occupancies as the feedback variable (9). The control objective is to maintain the merging area occupancy at the desired level by controlling the ramp flow. In addition, a simple queue flush strategy was modeled and operated with the metering control. The queue flush activates when the occupancy from the link-entrance detector is greater than a threshold value of 40%. The queue flush extends the metering rate to the maximum setting at 900 veh/hour/lane for a pre-determined intervals to clear off the queue.

Modeling the loop detector counting error

In the simulation environment, all the detector measurements have no noise and are perfectly accurate. In order to test the proposed algorithm in realistic environments, a random noise in the counting error ranged between -10% and 10% was artificially added. This artificial error is applied to each 1 minute aggregated count measurements.

Performance Measure

The primary measure of the algorithm performance is the comparison of the actual queue lengths with the estimated values. The study uses three measures of performance for the model calibration and validation: mean absolute error (MAE), root-mean-square error (RMSE), and mean percentage error (MPE). MAE is a measure of the estimation accuracy. A small MAE value indicates more accurate estimation. RMSE is a measure of estimation stability in number of vehicles. A smaller RMSE value indicates a higher degree of estimation reliability. MPE indicates the degree estimation errors in a relative way to the actual queue length.

$$MAE = \frac{1}{n}\sum_n \left|Observation - Estimation\right| \quad [26]$$

$$RMSE = \sqrt{\frac{1}{n}\sum_n (Observation - Estimation)^2} \quad [27]$$

$$MPE = \frac{MAE}{\frac{1}{n}\sum_n Observation} \times 100\% \quad [28]$$

Benchmark algorithm
A benchmark algorithm was modeled and evaluated for comparison with the performance of the proposed queue estimation algorithm. This method mimics the queue estimation method utilising only the mid-link time occupancy (4). The benchmark algorithm does not use the link entrance occupancy data. A potential drawback is therefore the estimation reliability in long queue conditions. The benchmark algorithm is referred to the Single Occupancy based Kalman Filter (SOKF) method in the rest of this paper.

Simulation Results and Discussions
The simulation results are presented and discussed in this section. The queue estimation performance is presented in comparison to the SOFK method with and without singular point correction. Total 20 simulation replications were performed to collect the results for each test scenario. Table 1 provides the summary of the simulation results. Note that the percentage in the bracket represents the relative changes from the benchmark algorithm.

Table 1 Queue Estimation Algorithm Evaluation Results

Strategy	Performance measure	Test on-ramps			Average
		Birdwood Rd	Marquis St	Logan Rd	
Benchmark algorithm	MAE	18.45	16.95	13.08	14.49
	MPE	38.79%	30.86%	27.74%	32.46%
	RMSE	26.90	22.09	19.58	19.63
Proposed algorithm without singular point correction	MAE	6.75 (-63.4%)	5.96 (-64.8%)	6.25 (-52.2%)	6.32 (-56.4%)
	MPE	13.83% (-64.3%)	10.63% (-65.6%)	13.17% (-52.5%)	12.54% (-61.4%)
	RMSE	9.63 (-64.2%)	7.61 (-65.6%)	8.81 (-55.0%)	8.68 (-55.8%)
Proposed algorithm with singular point correction	MAE	6.06 (-67.2%)	5.13 (-69.7%)	6.13 (-53.1%)	5.70 (-60.7%)
	MPE	12.81% (-67.0%)	9.32% -69.8%)	14.01% (-49.5%)	12.05% (-62.9%)
	RMSE	8.98 (-66.6%)	6.62 (-70.0%)	8.95 (-54.3%)	7.53 (-61.6%)

Overall, the new algorithm demonstrated reliable queue estimation performances at all the test sites outperforming the benchmark algorithm. The observed improvements over SOKF are 60.7%, 62.9%, and 61.6% on average in terms of MAE, MPE, and RMSE, respectively, with singular point correction enabled. Without singular point correction, the improvements slightly decline to 56.4%, 61.4%, and 55.8% in terms of MAE, MPE, and RMSE, respectively.

Singular point correction played a supplementary role to further improve the queue estimation as expected. In high volume ramps, the ramp queue is likely to stay beyond the mid-block detector position for most of the simulation period. As a result, the impact of singular point correction is insignificant, for example, 7 activations over the 5 hour period on the Birdwood Road on-ramp.

Birdwood Road ramp

This ramp has heavy mainline and ramp volumes during the peak-hours. The ramp is heavily congested from 7:30 to 9:30 am and long queues and queue spillover are frequently observed as a result. The proposed algorithm produced the averaged MAE, MPE, and RMSE at 6.06 (veh), 12.81%, and 8.98 (veh), respectively, which are 67.2%, 67.0%, and 66.6% improvements over the benchmark algorithm.

Figure 6 displays the estimated queue sizes by the SOKF method and the proposed algorithm with singular point correction in comparison to the actual queue size. The graphs were drawn from one simulation replication as an example. It is clear in the graph that the SOKF method continuously overestimates the queue length especially in the peak-hours from 7:30 to 9:30 am when long queues are present. The proposed algorithm captures the changes in the queue length reasonably well and the actual queue size does not affect the estimation accuracy. Note that similar results are found from other replications too.

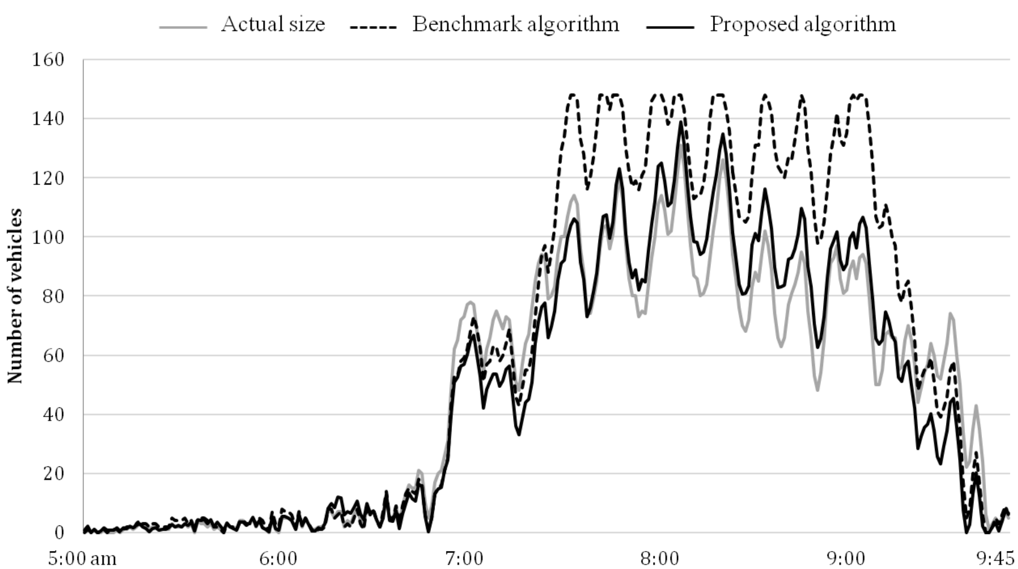

Figure 6 Queue estimation results example (Birdwood Road ramp).

Marquis Street Ramp

The ramp traffic volume on the Marquis Street ramp is one of the heaviest in the Brisbane area. As a result, the afternoon peak congestion begins at around 3:00 pm and lasts until the end of the simulation period at 7:00 pm. The queue size is constantly long on this ramp except the first one hour.

In Figure 7, both queue estimation algorithms perform reasonably well until 4:00 pm and then produce overestimations for the next 20 minutes approximately until 4:20 pm. During this period, the ramp queue size significant fluctuates in the range of 80 and 100 vehicles caused by the queue flush operations. After 4:30 pm, the SOKF method constantly overestimates the queue size whereas the estimates by the proposed algorithm follow the actual queue size quite closely. The actual queue size in this time period fluctuates at around the mid-link position where the single point correction activates and supplements the Kalman Filter process.

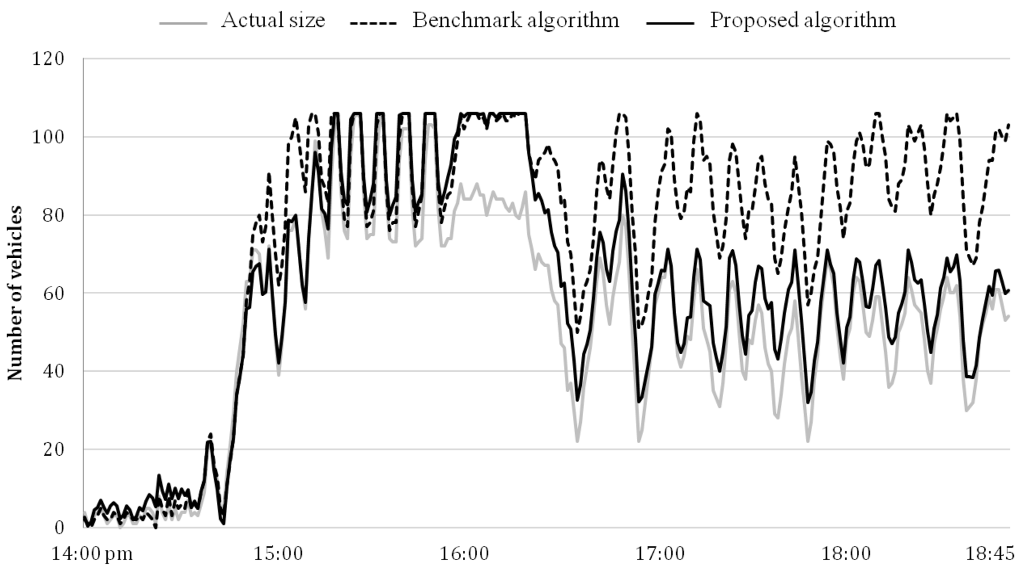

Figure 7 Queue estimation result example (Marquis Street ramp).

Logan Road Ramp

The simulation results of the Logan Road are similar to the other two ramps. However, the performance difference between the SOKF method and the proposed algorithm is relatively insignificant compared with the other two ramps. The mainline traffic volume is much lower at this location. Although the ramp traffic volume is still significantly high, the moderate traffic condition on the mainline allows less restrictive ramp metering and thus prevents long queues on the ramp.

Relatively moderate traffic conditions and queue sizes impacts on the estimation performance as evidently shown in Figure 8. The estimation accuracy of the SOKF method is much improved from those of the other two ramps, although overestimations are still observed between 7:10 and 7:40 am and between 8:40 and 9:00 am when long queues are present. On the other hand, the proposed algorithm captures the actual queue size reasonably well during the entire simulation period. The benefit of the innovative concepts of the proposed algorithm is well justified by the improved estimation performance in the high ramp traffic demand conditions where long queues significantly affected the benchmark algorithm's performance.

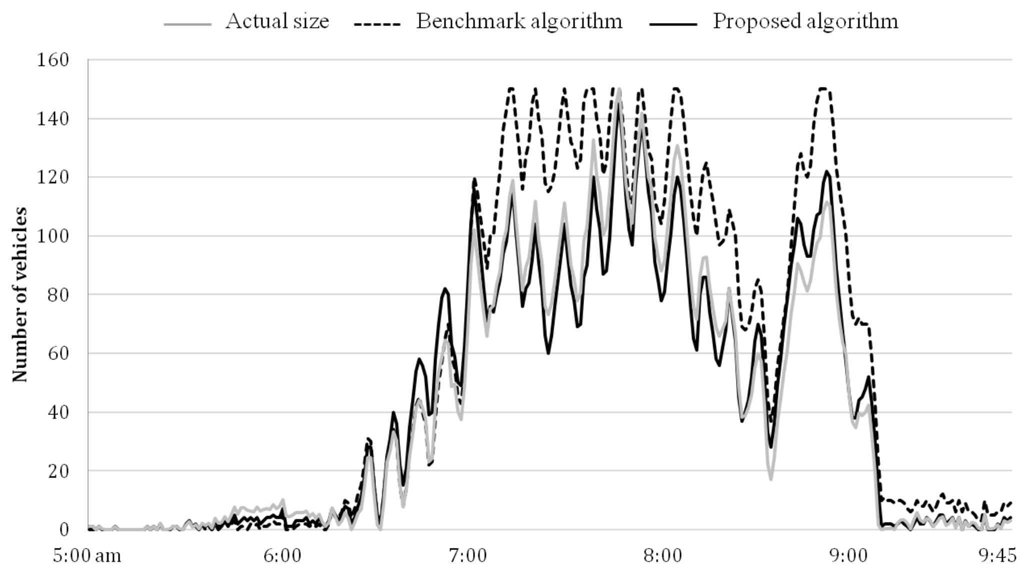

Figure 8 Queue estimation result example (Logan Road ramp).

CONCLUDING REMARKS

The proposed queue estimation algorithm introduces two innovative concepts. Firstly, it continuously corrects the system state estimation using the time occupancy measurements from the mid-link and link entrance detectors. Having the additional occupancy term in the state measurement equation is to overcome the limitation of the existing method that the space occupancy estimation could be significantly compromised under heavy ramp traffic conditions. Additionally, a novel single point correction method is proposed to improve the queue estimation reliability. Although, the single point correction may occur occasionally depending on the ramp volumes, it can potentially eliminate significant counting errors that accumulate over time and substantially improve the queue estimation.

In the performance evaluation, the proposed algorithm demonstrated accurate and reliable estimation performances constantly outperforming the benchmarked Single Occupancy Kalman Filter (SOKF) method. The observed improvements over the SOKF method are 62% and 63% in average in terms of the estimation accuracy (MAE) and reliability (RMSE), respectively. The singular point correction feature played a supplementary role to further improve the queue estimation. The benefit of the innovative concepts of the algorithm is well justified by the improved estimation performance during the peak-hours when long queues are present. The proposed algorithm captured the actual queue size reasonably well in the peak-hours when long the performance of the benchmark algorithm significantly compromised.

The proposed algorithm requires additional validation tests using actual detector measurements and queue size information. Proper calibration of the algorithm parameters is also necessary using field data for the space occupancy estimation equation and the single point correction threshold.

ACKNOWLEDGEMENT

This research was supported by the members of the Smart Transport Research Centre under the Managed Motorways project. The authors wish to acknowledge the support and contribution of the centre partners.

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