Experiment to Improve Estimation of Vehicle Queue Length at Metered On-Ramps

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ABSTRACT

Two types of on-ramp queue estimation algorithms are discussed, a Kalman filter and a conservation model. A volume balancing ratio is introduced to both models in order to account for unavoidable detector miscounting behavior. Estimation results are compared with field observed queue data. The volume balancing ratio improves both models. While the conservation model may provide more accurate prediction with balanced volumes, the Kalman filter tends to provide better estimation when the volume balancing ratio deviates from 1. Although the Kalman filter provides generally a better prediction, the conservation model is simpler to implement. Attempts to improve the Kalman filter further are also explored.
INTRODUCTION

Ramp meters are traffic signals on freeway entrance ramps to control the rate of vehicles entering the freeway so that demand stays below capacity and platoons of vehicles experience smoother merging. By regulating ramp access to the mainline, freeway recurrent congestion can be prevented, mitigated, or reduced. Appropriate use of ramp meters is able to produce positive benefits. Those benefits include increased freeway throughput, reduced travel times, improved safety, and reduced fuel consumption and emissions. However, inappropriate use of ramp meters can produce negative impacts. Queues that back up onto adjacent arterial streets from entrance ramps can adversely affect the surface roadway network. Drivers may occasionally divert from freeways to adjacent arterial streets to avoid queues at ramp meters. Local emissions near ramps may increase due to stop-and-go conditions and vehicles idling within a queue.

The ability to accurately monitor vehicle queue lengths at a metered on-ramp and adjust the metering rate correspondingly could allow control of the on-ramp delay in real time and improve ramp metering performance at the system level. However, carefully performed simulations and empirical studies of vehicle queues at metered on-ramps are rare. The direct impact of not knowing queue lengths on real world operations is an inability to respond effectively to changing traffic demand. This lack of knowledge could affect the decision to activate a queue override even if a severe spillback has happened, or it could lead to vehicles being prematurely flushed onto freeway mainline when there is hardly any queue on the ramp.

In order to collect on-ramp queue information useful for freeway traffic operations, traffic professionals have been researching two categories of methods, physically directly measuring queues through detection technologies or estimating queues through various models based on detector data. For example, video image detection is one method to directly monitor queues and deliver vehicle queue length. However, some on-ramps can be very long and curvy, so one video image detector cannot cover the entire on-ramp. In such cases, multiple video image detectors need to be installed at a substantially higher cost. Alternatively, a single video image detector can cover part of the on-ramp, with the rest of the queue length estimated from an algorithm or from other detection technologies like loop detectors. Another even higher cost approach is to install many of loop detectors at close spacings along the on-ramp, which helps to improve the accuracy of queue length estimation to a certain degree. According to a simulation study conducted by Vigos et al. (1), when the number of detectors exceeds a certain amount, a larger number of detectors cannot reliably produce better queue length estimates. Because of high costs, these two physical queue measuring methods are not currently feasible for extensive deployments.

Researchers have been studying various algorithms to estimate vehicle queue lengths at metered on-ramps. Vigos et al. (1) developed an algorithm to estimate the number of on-ramp queued vehicles by employing a Kalman filter and using data from queue loop detectors. Time occupancy data collected by loop detectors are translated into space occupancy data, which are directly related to the number of on-ramp vehicles. Wu et al. (2) tested a Kalman filter using manually collected field queue data and demonstrated that this algorithm could produce reasonable estimates. Liu et al. (3) proposed a conservation model to estimate the on-ramp queue sizes that are used as inputs to the Twin Cities’ Stratified Zone Metering (SZM) strategy. By comparing the estimated queue sizes with the recorded surveillance video data, they found
that the proposed conservation model could greatly improve the accuracy of the queue length estimation.

Sun and Horowitz (4) designed an on-ramp vehicle queue length regulator to prevent queue spillback to surface streets from ramp meters. To provide input to the queue length regulator, a queue length estimator was designed, which was based on kinematical theories and used the queue loop detector speed data to estimate the on-ramp vehicle queue length. Because a majority of current on-ramp queue detectors are single inductive loop detectors, it is almost impossible to directly measure speeds of vehicles waiting in the queue. In addition, the speed data from queue loop detectors are not reliable when vehicle queues have reached or are beyond the queue loop detectors. Wu et al. (2) demonstrated a linear occupancy method, which was developed to interpret the assumed linear relationship between the number of queued vehicles and the time occupancy data directly collected by loop detectors. The estimated queue length provides a decent prediction for most of the spikes, where the queue length has a much higher value than adjacent values. However, the estimation results introduce an unrealistic amount of randomness, which causes more fluctuation than actual.

The following sections explore the relationships between queue length and time occupancy and between queue length and volume. Two types of estimation algorithms are discussed, which are a Kalman filter model and a conservation model. Variations on these models are tested. The original models and the slightly modified versions are compared with one another and with the field observed queue data.

**QUEUE ESTIMATION PRECONDITIONS**

**Time Occupancy and Space Occupancy**

An important data stream from a loop detector is time occupancy, which is defined as the percentage of time that a loop detector is occupied by vehicles. Space occupancy is defined as the proportion of space of a roadway that is covered by vehicles. Video image detectors are the only detectors available that are able to directly collect space occupancy data; however, this technology has various disadvantages, including problems with bad weather, inability to see difficult roadway geometries, and high cost. Vehicle queue length at metered on-ramps is directly related to space occupancy. Papageorgiou and Vigos explored the relationships between time occupancy and space occupancy (5). It was found that time occupancy was not identical to space occupancy and it was not simply proportional to space occupancy on signalized links like on-ramps. The relationships were complicated and a set of formulas were proposed to convert measured time occupancy to estimated space occupancy (1). The following equation is one of those proposed. These authors also concluded that the location of the loop detector was important to the occupancy conversion. In addition, if the measurement update interval was short, a higher number of loop detectors could improve the space occupancy or the queue length estimation.

\[
q_{n-1} = \frac{L \times n}{l + D} \times O_{n-1}
\]  

(1)

where
\( q_{n-1} \) = number of on-ramp queued vehicles calculated from detector time occupancy data (veh),
\( L \) = length of the on-ramp (ft),
\( n \) = number of lanes,
\( l \) = average physical vehicle length (ft),
\( D \) = safety distance between vehicles (ft), and
\( O_{n-1} \) = time occupancy collected by loop detectors.

**Queue and Time Occupancy Correlation**

A series of continuously large time occupancies from queue loops may indicate that queues are long. However, time occupancy data themselves cannot clearly imply the length of queues. FIGURE 1 shows a typical scatter diagram with queue loop detector time occupancy as the X axis and on-ramp vehicle queue length as the Y axis. The data are from a metered on-ramp during the morning peak period from 7:00 to 8:30. If queue length has a strong correlation with time occupancy, the data points with higher occupancy and longer queues should be found in the upper right area of the chart, and vice versa. However, this assumption is not always true for this specific metered on-ramp. In fact, for most of the metered on-ramps that were researched for this paper, the relationship between queue length and queue loop detector time occupancy is similar to this diagram. The correlation coefficient between queue length and queue loop time occupancy for this metered on-ramp is 0.63. A correlation coefficient reasonably close to 1 indicates that the correlation between queue length and time occupancy is close to perfectly linear. This scatter diagram suggests that there might be other factors besides time occupancy affecting queue length. Because the correlation between these two variables is far from perfect, queue length estimation algorithms solely based on time occupancy can only be improved to a certain degree.

Equation 1 inappropriately assumes a linear relationship between queue length and time occupancy, which will introduce a certain amount of estimation errors. As described in the following sections, Equation 1 is part of a proposed Kalman filter, which indicates that the estimation of this filter could be further improved by modifying Equation 1.
Queue and Volume Correlation

The volume data from loop detectors are the total number of vehicles that pass over a given point of a roadway during a given time interval. The on-ramp queue length is directly related to density. Based on the general relationship between density and volume, a low volume could be accompanied by either a low density or a high density. FIGURE 2 shows a scatter diagram with vehicle counts entering this same on-ramp as the X axis and on-ramp vehicle queue length as the Y axis. Data from the same metered on-ramp during the same time period as FIGURE 1 are used to plot the diagram. The correlation coefficient of the two variables is 0.18, which implies the relationship is much more complex than linear. Again, most of the metered on-ramps that were researched for this paper presented a similar pattern of relationships. This poor correlation indicates that there is no simple or readily apparent relationship between on-ramp queue length and volume data at any single on-ramp spot.

FIGURE 1 On-ramp vehicle queue length and loop detector occupancy data.
QUEUE ESTIMATION ALGORITHMS

Original Kalman Filter Algorithm

Vigos et al. (1) developed the original Kalman filter on-ramp queue length estimation algorithm, which is presented below as Equation 2. Time occupancy data from queue loop detectors are used as one of the inputs. The other inputs include vehicle counts entering and exiting the on-ramp. Equation 1 is used to translate time occupancy data to space occupancy data. Equation 2 consists of two major components, the time update component and the measurement update component. The time update is responsible for projecting forward the current state and error covariance estimates to obtain the estimate for the next time step. The measurement update is responsible for the feedback, incorporating a new measurement into the estimate to obtain an improved estimate.

\[
Q_n = Q_{n-1} + T(V_{in} - V_{out}) + K(q_{n-1} - Q_{n-1})
\]

where

\[
Q_n = \text{predicted number of on-ramp queued vehicles in the next time period (veh)},
\]
\[ Q_{n} = Q_{n-1} + T(CV_{in} - V_{out}) + K(q_{n-1} - Q_{n-1}) \] (3)

where

- \( C \) = adjustment factor to account for the miscounting of the detectors.

**Conservation Model**

Liu et al. (3) proposed a conservation model to estimate the on-ramp queue sizes that are used as inputs to the Twin Cities’ Stratified Zone Metering strategy. On-ramps were divided into three categories based on sources of detector counting errors. Vehicle counts from passage loops were used as volumes exiting on-ramps and vehicle counts from queue loops were used as volumes entering. FIGURE 3 shows a typical on-ramp loop detector layout. Type I on-ramps are considered as error-free or at worst subject to minor errors. If the ratio of 15-minute total vehicle counts between the passage loops and the queue loops is within 0.98 to 1.02, then it is considered as a minor error. Type II on-ramps have passage loop counting errors and Type III on-ramps have both passage and queue loop counting errors. Different queue estimation algorithms were developed for different categories. Equation 4 is a simplified version used for Type I on-ramps.

\[ Q_{n} = Q_{n-1} + N_{in} - N_{out} \] (4)

where

- \( Q_n \) = predicted number of on-ramp queued vehicles in the next time period (veh),
- \( Q_{n-1} \) = number of on-ramp queued vehicles in the current time period (veh),
\[ N_{in} = \text{vehicle counts entering the on-ramp during a data collection time interval like 20 seconds, which can be from queue loop detectors or entrance reporting loop detectors (veh), and} \]
\[ N_{out} = \text{vehicle counts exiting the on-ramp during a data collection time interval like 20 seconds, which can be from passage loop detectors (veh).} \]

![FIGURE 3 A typical on-ramp loop detector layout.](image)

**Conservation Model with Volume Balancing Ratio**

Equation 4 can only be used for on-ramps that have almost identical entering and exiting volumes over long periods of time. Even for these Type I on-ramps, Liu et al. (3) added an occupancy constraint to improve the estimation. It was subjectively determined that there was a queue spillback when the time occupancy of the queue loop detector was over 25%. Because of detector counting error and occupancy constraints, it may not be practical to transfer this algorithm to locations beyond the Twin Cities. Like Equation 3, an adjustment factor was also introduced to balance the volume in and volume out. This adjustment factor can also be calculated in real time or set to a constant value.

\[ Q_n = Q_{n-1} + CN_{in} - N_{out} \]  

(5)

where

\[ C \quad = \text{adjustment factor to account for the miscounting of the detectors.} \]
COMPARISON OF ESTIMATION ALGORITHMS

Two types of algorithms are presented above, which are the Kalman filter and conservation model. It can be seen that Equations 4 and 5 are special cases of Equations 2 and 3. Equations 2 and 3 use flow rates, and Equations 4 and 5 use counts – the difference being just the length of the counting period. When setting the Kalman filter coefficient to zero, Equations 2 and 3 are identical to Equations 4 and 5. Each type of algorithm has two similar formulas, one with the volume balancing ratio and one without the ratio. If the volumes entering and exiting the on-ramp are equal or very close, like Type I on-ramps from Twin Cities, the two formulas become the same. As a result, the testing and comparison between Equations 2 to 5 reduces to determining whether the volume balancing ratio and the time occupancy input are necessary. Estimated queue data using the above algorithms will be compared to field data to perform the analysis.

Field Data

Data used in this paper were collected as a part of a large project that identified methods for evaluating the effectiveness of ramp meters on Wisconsin freeways (6). The purpose of this larger study was to determine the benefits of ramp meters in the Milwaukee area freeway system, to determine underlying relationships that permit evaluation of new ramp meters or ramp meter systems elsewhere, and to develop a coherent framework for performing evaluation of ramp meter effectiveness on a whole system. Data collected included floating car runs, queue length counts, tube counts, origin-destination studies, questionnaires and archiving of a variety of loop detector data (volumes, speeds and occupancies). Queue length data used in this paper were collected from four locations, US 45 southbound on-ramps at Capitol Drive, Burleigh Street, North Avenue, and Wisconsin Avenue. There was an observer physically presented at each location. The observer manually counted the total number of on-ramp queue vehicles and recorded the number on a data collection sheet every 20 seconds, throughout the 1.5 hour morning and afternoon peak periods. Because the geometry is relatively simple and the ramp length is considered as not long at these four on-ramps, the field queue data is reasonably reliable. Volume and occupancy data used in this study were raw loop detector data recorded every 20 seconds. All data sets were carefully synchronized.

Data for three morning peak periods and two afternoon peak periods at each location are used for the analysis in this paper. As a result, there are 20 sets of completed field data used in the analysis. With the limited amount of data in the same geographic area, this paper is trying to present the concept and comparison of on-ramp vehicle queue length estimation algorithms. However, to establish statistical significance for any method, extensive data from various locations and various time periods is necessary.

Estimation Analysis

TABLE 1 presents correlation coefficients of queue length and average occupancy from queue loops, the volume balancing ratios used in Equations 3 and 5, the Kalman filter coefficients used in Equations 2 and 3, the Kalman filter queue and occupancy bias, and the root mean squared errors (RMSE) of the estimated queues. The Kalman filter coefficients are obtained by using the Excel Solver Add-In to minimize the RMSE, which is a nonlinear function. The volume balancing ratios are calculated by using the total volumes exiting the on-ramps divided by the
total volumes entering over the 1.5 hour peak periods. The exiting volume is calculated as the sum of volumes from all passage loop detectors as shown in FIGURE 3. The entering volume is obtained by summing volumes from all advanced queue loops or entrance reporting loops located at the upstream end of the ramp as shown in FIGURE 3. The occupancy data used in the Kalman filter formulas are from the intermediate queue loops as shown in FIGURE 3, which are normally located in the middle between demand loops and the upstream end of the ramp.

In practice, the volume balancing ratio can be calculated in real time. At least seven parameters should be introduced, the volume balancing ratio calculation time period, the total exiting volume, the total entering volume, the exiting and entering vehicle counts in the calculation start time period and in the current queue estimation time period. If there is a central ramp meter control software application available, these values can be calculated and cached at central. In order to calculate the volume balancing ratio for the next queue estimation time period, the vehicle counts from the calculation start time period should be removed from the total volumes and the vehicle counts from the current queue estimation time period should be added to the total volumes.

In 17 out of the 20 data sets, the Kalman filter with the volume balancing ratio is able to provide the same or better estimation results than the Kalman filter without the ratio. With the volume balancing ratio, the conservation model also outperforms the same model without the ratio in 90% of the data sets. The Burleigh Street on-ramp has volume balancing ratios close to 1, which would be categorized as a Type I on-ramp in the Twin Cities based on the standards from Liu et al. (3). FIGURE 4 shows that the volume balancing ratio minimizes the conservation model estimation errors due to time-accumulation of the detector counting errors. By introducing the volume balancing ratio, both the Kalman filter and the conservation model can be improved considerably, though there are a very few cases for which volume balancing ratios introduce slightly more errors to the estimation results.

It can be seen that when the Kalman filter queue and occupancy bias are very large and the volume balancing ratios are close to 1, the Kalman filter coefficients would be very small or close to zero and the conservation model would predict better. In this situation, the right part of Kalman filter formulas plays nominal roles in the final queue estimation. Introducing time-occupancy in the estimation process may introduce more errors rather than improve the prediction. It should be noted that the zero value Kalman filter coefficients in TABLE 1 are not really zeros. They are shown as zeros because all of their 6 digits to the right of the decimal separator are zeros.

The relationship between the volume balancing ratio and the estimated queue is complicated. Both Burleigh Street and Wisconsin Avenue have volume balancing ratios close to 1. However, the conservation model outperforms the Kalman filter at the Burleigh Street on-ramp and the Kalman filter provides more accurate estimation at the Wisconsin Avenue on-ramp. The Kalman filter queue and occupancy bias at the Wisconsin Avenue on-ramp are much smaller than those values at the Burleigh Street on-ramp. It should be noticed that volume balancing ratios of the same on-ramp may vary in different peak periods. Selecting a queue estimation algorithm solely based on the volume balancing ratio may result in inconsistent queue prediction. It can be noted that when the volume balancing ratio starts to deviate from 1, the Kalman filter tends to provide better estimation than conservation model. In TABLE 1, when the volume balancing ratios are 1.09 or 1.10, the Kalman filter’s estimation is much better than the conservation model’s. The Kalman filter has the self-correction ability, which conservation
model lacks. As expected, the conservation model tends to accumulate many more errors than Kalman filter over a long time period of operation. However, a longer analysis peak period than 1.5 hours would be necessary to completely confirm this observation.

The Kalman filter provides better estimation for more data sets than conservation model. However, TABLE 1 suggests that the Kalman filter coefficient has different values for different on-ramps or different values for different peak periods at the same on-ramp. In order to be used for the real world operations, the Kalman filter coefficient would need calibration for each ramp metering location, and for both the morning and afternoon peak periods. The Kalman filter coefficient cannot be calculated in real time, because the actual on-ramp queue length is not available in the real-time operations. In addition, the Kalman filter requires other inputs such as the length of the on-ramp, number of lanes, average physical vehicle length, and the safety distance between vehicles. The advantage of the conservation model is that there is only one coefficient in the formula, which is the volume balancing ratio and this ratio can be updated in the real-time. Compared with the Kalman filter, the conservation model is easier to implement in different cities or different peak periods.

TABLE 1 shows another very interesting fact that that the March 16 PM peak periods have considerably larger RMSE values than other peak periods. By carefully examining the data, it is revealed that there are much longer initial on-ramp queues in this peak period than those in other peak periods. The initial queue length has a very important effect on both the Kalman filter and the conservation model. The field queue data in this paper included the initial queue. However, it is assumed that there was no initial queue when the queue was estimated using the Kalman filter or the conservation model. Introducing the initial on-ramp queue to the process should improve the quality of the results.
### TABLE 1 Coefficients and Root Mean Squared Errors

<table>
<thead>
<tr>
<th>Location</th>
<th>Time Period</th>
<th>Queue and Occupancy Correlation</th>
<th>Volume Balancing Ratio (C)</th>
<th>Kalman Filter Coefficient (K)</th>
<th>RMSE Kalman Filter</th>
<th>(q-Q) Average Error</th>
</tr>
</thead>
<tbody>
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<td>Burleigh Street</td>
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<td>0.26</td>
<td>0.99</td>
<td>0.000069 0.003864</td>
<td>3.26</td>
<td>3.25 2.93 3.89</td>
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<td></td>
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<td>0.67</td>
<td>1.00</td>
<td>0.000530 0.000530</td>
<td>4.86</td>
<td>4.86 4.26 4.89</td>
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<td>3.66 3.28 4.13</td>
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<td></td>
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<td>0.64</td>
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<td>0.00              0</td>
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<td>13.94 11.27 13.84</td>
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<td>0.63</td>
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<td>0.010245 0.003435</td>
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<td>7.18 9.50 7.04</td>
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<td>5.70</td>
<td>7.54 6.16 7.63</td>
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<td>1.44 2.15 2.17</td>
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<td>0.120548 0.126077</td>
<td>5.23</td>
<td>5.22 5.39 5.47</td>
</tr>
</tbody>
</table>

Note: Kalman Filter coefficients are used to adjust the model predictions based on observed data. The Root Mean Squared Error (RMSE) measures the average magnitude of error in the predictions. The (q-Q) Average Error represents the average deviation of the ratio of queue to occupancy from the expected value.
FIGURE 4 Kalman Filter and Conservation Model queue estimation and field queue data at Burleigh Street On-ramp for March 14 AM Peak Period
EXPERIMENTAL IMPROVEMENTS

Occupancy Input

As mentioned above, the conservation model formulas are special cases of the Kalman filter formulas. The feedback component of the Kalman filter can improve the estimation. Thus, improving the input to the feedback component may improve the final result. TABLE 1 does not indicate an obvious relationship between average occupancy from multiple queue loops and the queue length. Since time occupancy data from detectors only describe the local condition close to the detector, a weighted average of data from multiple detectors across the on-ramp may strengthen the correlation between occupancy and the queue length. As shown in FIGURE 3, occupancy data from demand loops, intermediate queue loops and upstream queue loops indicate the roadway coverage conditions at different locations within the on-ramp. When a queue exists on the ramp, the demand loops should have higher occupancy than the queue loops. This is because vehicles actually stop in front of the stop bar. Adding demand loop occupancy to the process may improve the Kalman filter estimation. Weight coefficients of 0.25, 0.5 and 0.25 are assigned to demand loops, intermediate queue loops and upstream queue loops, respectively.

TABLE 2 presents the RMSE values for the Kalman filter estimated queues with weighted average occupancy as inputs. The results are not conclusive. In half of the 20 data sets, weighted average occupancy inputs improve the Kalman filter estimation slightly. However, in 6 of the 20 data sets, the estimation results are worse. Weights for different loops should be tested and analyzed further with extensive data sets before weighted average occupancy inputs can be implemented in real world operations.

### TABLE 2 Root Mean Squared Errors for Weighted Average Occupancy Input

<table>
<thead>
<tr>
<th>Location</th>
<th>Time Period</th>
<th>RMSE for Kalman Filter With C</th>
</tr>
</thead>
<tbody>
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<td></td>
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<td>Average</td>
</tr>
<tr>
<td>Burleigh Street</td>
<td>March 14 AM</td>
<td>3.26</td>
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<td>3.85</td>
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<td></td>
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<td>Capital Drive</td>
<td>March 14 AM</td>
<td>5.82</td>
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<tr>
<td></td>
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<td>3.48</td>
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<tr>
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**Kalman Filter Coefficient**

The Kalman filter coefficient is the most difficult element in the Kalman filter formulas to determine. The Kalman filter coefficients in this study are obtained by minimizing RMSE. This requires accurate and independent knowledge of the actual queue length, which is not always available in the real world operations. In addition, the Kalman filter coefficient has different values for different on-ramps or different values for different peak periods at the same on-ramp. FIGURE 5 shows the RMSE elasticity of a Kalman filter coefficient. RMSE values change dramatically while the Kalman filter coefficient increases from 0 to the optimum value. However, after the coefficient value exceeds the optimum value, the relationship becomes less elastic. This is because the Kalman filter coefficients are close to 0 in these two data sets. The Kalman filter coefficient values of 0.1 or 0.2 would lead to a sub-optimal estimation, but the RMSE values are still acceptable. In real world operations, using a slightly larger Kalman filter coefficient than the optimum value at these two locations may minimize the average RMSE across different peak periods. A more effective way to obtain a Kalman filter coefficient would be to calculate it in real time based on field conditions; however this idea requires further study.

![Kalman Filter Coefficient and RMSE at Capitol Dr. On-ramp for March 15 AM Peak Period](image-url)
CONCLUSION
Physically directly measuring queues through detection technologies are still prohibitively expensive for extensive deployments. Also, carefully controlled simulation and empirical studies of methodologies for estimating the vehicle queue length at metered on-ramps are very rare. The traffic engineering community does not possess a reliable methodology to predict the on-ramp vehicle queue length.

The relationships between queue and time occupancy and between queue and volume are explored. Two types of estimation algorithms are discussed, which are the Kalman filter and the conservation model. A volume balancing ratio is introduced to both models in order to account for the unavoidable detector miscounting and to balance the volumes entering and exiting on-ramps. The original models and the slightly modified versions are compared with one another. With the volume balancing ratio, both the Kalman filter and conservation model can be improved considerably, though there are a few cases where the volume balancing ratios introduce slightly more errors to the estimation results. The conservation model may provide more accurate prediction with balanced volumes. When the volume balancing ratio starts to deviate from 1, the Kalman filter tends to provide better results than conservation model. However, the relationship between the volume balancing ratio and the estimated queue is complicated. Selecting a queue estimation algorithm solely based on the volume balancing ratio may result in inconsistent queue prediction.

The Kalman filter provides better estimation for more data sets than the conservation model. When the Kalman filter queue and occupancy bias are very large and the volume balancing ratios are close to 1, the conservation model provides better prediction than the Kalman filter. Weighted average occupancy inputs do not consistently improve the Kalman filter estimation. The Kalman filter coefficient is relatively difficult to determine. Also the Kalman filter requires additional inputs such as the length of the on-ramp, number of lanes, average physical vehicle length, and the safety distance between vehicles.
The advantage of conservation model is that there is only one coefficient in the formula, which is the volume balancing ratio and can be updated in real-time operations. Compared with the Kalman filter, the conservation model is easier to implement in different locations or for different peak periods, and it requires no calibration.

It is observed that the initial queue length has a very important effect on both the Kalman filter and the conservation model estimation results. Introducing the initial on-ramp queue to the process will improve the estimation. As expected, the conservation model tends to accumulate many more errors than the Kalman filter over a long time periods of operation.

REFERENCES