A SIMPLE METHODOLOGY TO ESTIMATE QUEUE LENGTHS AT SIGNALIZED INTERSECTIONS USING DETECTOR DATA

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ABSTRACT

This paper presents a simple methodology to estimate queue length on an approach to a signalized intersection. This method has a minimal set of data requirements specifically flow, occupancy, cycle length, and detector setback in contrast to prevailing methods that rely on estimating vehicle trajectories using detailed data defined on a per signal cycle basis. The key element of the algorithm is the estimation of two baseline occupancies that correspond to the relative position of the queue with respect to the detector location. The results of the algorithm have been evaluated using traffic simulation and also compared to field observations. The comparison of the queue estimates suggest that the detector location would be ideal to estimate queues, if under prevailing conditions the tail of the queue is routinely longer than the detector setback. For detectors with appropriate setback, queue estimates match well in both comparisons. This algorithm was developed as part of the Midtown in Motion project and is currently operational in the field, in New York City as one of the elements of the active traffic management.

Word Count: 178
BACKGROUND
Over the last few years New York City Department of Transportation (NYCDOT) has been upgrading the ITS infrastructure with Advanced Solid State Controllers (ASTC), microwave sensors, Electronic Toll Collection (ETC) readers, and a communication network that is both wired and wireless to build a network of these devices that can be managed and controlled from the Traffic Management Center (TMC). NYCDOT commissioned Midtown in Motion (MIM) to improve mobility and relieve congestion by a combination of measures including active traffic management (ATM) in Midtown Manhattan.

MIM includes a hierarchical control system with strategic and tactical control components. The strategic control was focused on the controlling the approach segments to the zone based on travel time data. The tactical component was focused on a local (intersection) level using microwave sensor data.

The zone of interest was between 57St and 42St from 2\textsuperscript{nd} Avenue to 6\textsuperscript{th} Avenue. This 110 square block area urban grid network is oversaturated routinely. Developing signal control for such conditions is focused primarily on queue control to avoid breakdown within networks from gridlock conditions.

In order to address this need, a rule based control algorithm was developed with an embedded methodology to estimate queue lengths using microwave sensor data. This paper presents this algorithm and the comparison of results using simulation and real world observations.

LITERATURE REVIEW
There have been many techniques to estimate queue lengths. The research has been ongoing for over 50 years with early research focusing on input-output balancing method, shockwave theory and newer techniques using vehicle trajectories from GPS data.

Research presented in (1), (2) and (3) are good overviews of the different techniques to estimate queue lengths at signalized intersections. The method presented in (1) derives time-dependent queue length by examining the changes in an advance detector’s occupancy profile within a cycle. It uses both time-stamped signal phase changes and vehicle-detector actuations collected from traffic signal systems. The method relies on high-resolution of data with accuracy, which might not be practical in real time control where the quality of data is compromised with other factors.

The method presented in (2) is able to provide cycle-by-cycle queue length estimation for signalized intersections with sampled vehicle trajectories as the only input. Using the estimate of critical points related to queue formation and dissipation, the authors propose an improved queue length estimation method based on shock waves. However, the accuracy or reliability of this method is dependent on the assumption that the sampled vehicle trajectories accurately reflect the queuing conditions.

The paper (3) compares input-output method by using an advanced detector with hybrid method by using both an advanced detector and a stop line detector for queue estimation. Both methods need arrival profile which is estimated based on the detections obtained from the advanced detector and departure profile estimated by considering the phase state only or that with stop line detections and delay estimation. The paper recommends input output method as a first choice for the queue estimation because the hybrid technique is more costly compared to input output technique and the input noise of the stop bar count detector degrades the overall performance of the hybrid technique.
SCOOTS (4) and MOTION (5) are two common systems used across Europe, the latter is a variant of the former. Both methods use the dispersion flow theory to estimate and arrival and departure profiles. These are in turn used as part of input-output balancing at the stop line to calculate queue length. These approaches works reasonably well in an undersaturated traffic environment. However, it is challenging to accurately represent input-output flow conditions in an oversaturated traffic environment.

The relationship between queues and traffic control decisions (signal settings) especially for oversaturated conditions are discussed in (6), (7) and (8). The key element as addressed in these research articles is that managing queues is critical to oversaturated control (prevailing condition in an urban area such as Midtown Manhattan during peak periods) with an acute need to estimate queues for effective control. The queue estimation method presented in (6) uses the input-output balancing with every second advance detector’s occupancy profile. As discussed above, the approach like this is not practical considering the real time environment.

The methods presented in (9), (10), (11) and (12) focus on queue estimation for freeways and on-ramps.

Most of the techniques discussed above rely on an estimate of the vehicle trajectory using detailed data of the signal state and detector information at short frequencies such as one second. It is input-intensive and may not be practical in real time control when the quality of data is compromised with other factors.

This paper presents a method which uses only flow and occupancy at an advanced detector for queue estimation. As long as flow and occupancy aggregated over an integer number of cycle lengths are reliable, the estimation of queue based on these are accurate enough to apply to any queue control based polices. The shock wave theory is implicitly used in deriving an occupancy threshold discussed in detail later. The following section presents this methodology.

**METHODOLOGY**

Occupancy is defined as the percentage of time in which a detector is occupied by a vehicle. It can be expressed as follows.

\[ \text{Occ} = \frac{\sum_{i=1}^{n} t_i}{T} \]  

(1)

Where, \( T \) = the time interval,
\( n \) = number of vehicles passing through a detector during the \( T \).
\( t_i \) = time to take for vehicle \( i \) to cross a detector (passage time) i.e. Elapsed time from the moment the front end of vehicle \( i \) arrives at the trailing edge of the detector till the moment the rear end of vehicle \( i \) departs from the leading edge of the detector.

\( t_i \) can be expressed as

\[ t_i = \frac{L_v + L_d}{v_i} \]  

(2)

Where \( L_v \) = the vehicle length of vehicle \( i \)
\( L_d \) = the length of detector (longitudinal)
\( v_i \) = mean speed of vehicle \( i \) when crossing a detector.
Occupancy is the measure of flowing condition; higher occupancy indicates congested flow condition while the lower occupancy indicates free flowing condition. Equations (1) and (2) reinforce the fact that occupancy and queue lengths are inversely related to vehicle speeds.

Based on this simple principle, the methodology that translates an occupancy measure into a queue measure is developed. The initial thoughts leading to the algorithm are as follows:

- The range of occupancies at a detector can be divided into three regimes based on queuing conditions (see Figure 1) using two thresholds ($Occ_1$ and $Occ_2$)
  1) Queue Length $\approx 0$, free flowing condition (occupancy $\leq Occ_1$)
  2) Queue length $< $ Detector location ($Occ_1 < $ occupancy $< Occ_2$)
  3) Queue length $> $ Detector location (occupancy $\geq Occ_2$)

These thresholds can be formulated as follows:

$$Occ_1 = \frac{\left(\frac{L_d + L_v}{v_f}\right) \times flow_{obs}}{3600} \tag{3}$$

Where, $Occ_1 = $ Occupancy threshold 1 corresponding to free-flowing condition

$v_f = $ Free flow speed (feet per second)

$L_d = $ Length of detection zone (feet)

$L_v = $ Length of vehicle (feet)

$flow_{obs} = $ Flow (pcphpl) derived from detector data as passenger cars per hour per lane

Here $v_f$ is the free-flow speed. As seen, the term $\left(\frac{L_d + L_v}{v_f}\right)$ is elapsed time for a vehicle to cross the detector and $(flow_{obs}/3600)$ is the reciprocal of discharge headway. Therefore, $Occ_1$ is the occupancy when a vehicle crosses the detector with free flow speed.

Similarly, it is postulated that there is a speed “$v_2$” at which the queue reaches near the detector location, and using the same equation (3), $Occ_2$ can be formulated.

$$Occ_2 = \frac{\left(\frac{L_d + L_v}{v_2}\right) \times flow_{obs}}{3600} \tag{4}$$

Where, $Occ_2 = $ Occupancy threshold 2 corresponding to queue reaching a detector

$v_2 = $ Mean speed when the queue reaches near the detector (feet per second)

The estimate of $v_2$ can be obtained from field observations or through an iterative approach of comparing the observed queue and the estimated queue. Since $v_2$ is the mean speed
of vehicles of which some are free flowing and others are affected by stopping shockwave, \( v_2 \) is lower than free flow speed, \( v_f \).

Also, \( v_2 \) is dependent on the detector location. As detector setback increases, the portion of vehicles supposedly resulting in queue length equal to detector setback also increases. In short, \( v_2 \) reduces as detector setback increases.

Figure 2 presents the flow and occupancy measured in the field along with \( Occ_1 \) and \( Occ_2 \). Based on observations of prevailing traffic conditions \( v_f \) and \( v_2 \) are estimated to be 30 mph and 15 mph, respectively. The points below the \( Occ_1 \) line reflects free flowing condition. The points between \( Occ_1 \) and \( Occ_2 \) lines reflect short queuing condition where queue is less than detector setback. The points above \( Occ_2 \) line reflect significant queuing condition where queue extends beyond the detector.

![Flow and Occupancy](image)

**FIGURE 2 Flow, Occupancy and Occupancy Thresholds**

Using the occupancies estimated in Equations (3) and (4) queue length can be calculated as follows:

1) Regime 1: No Queue, (occupancy \( \leq \) \( Occ_1 \))

\[
Q = 0
\]

2) Regime 2: Queue does not reach detector (\( Occ_1 < \) occupancy \( < \) \( Occ_2 \))

\[
Q = \frac{Occ_{obs} - Occ_1}{Occ_2 - Occ_1} \cdot D_s \tag{5}
\]
3) Regime 3: Queue extends beyond detector (occupancy \(\geq \text{Occ}_2\))

\[
Q = D_s + \frac{f_q \ast (\text{Occ}_{\text{obs}} - \text{Occ}_2) \ast C \ast L_q}{h}
\] (6)

Where, \(Q\) = Estimated queue length (feet)
\(\text{Occ}_{\text{obs}}\) = Occupancy as reported by detector
\(D_s\) = Detector set back (feet)
\(C\) = Signal cycle length (seconds)
\(f_q\) = Queue growth adjustment factor
\(L_q\) = Average vehicle spacing (feet) in queue
\(h\) = Discharge headway (sec/vehicle) at the detector calculated as 3600/\(\text{flow}_{\text{obs}}\) where \(\text{flow}_{\text{obs}}\) is defined in Equation (3)

Equation (5) is a linear interpolation between the occupancy thresholds. Equation (6) has two terms. The first term is the detector setback and the second term is the queue beyond the detector from the detector location. The term \((\text{Occ}_{\text{obs}}-\text{Occ}_2)\ast C\) is the time during which the queue grows from the detector. The division by \(h\) converts this queuing time into a number of queued vehicles. The multiplication of \(L_q\) converts the number of queued vehicles to feet. Also, there is a difference in the arrival and discharge rates, due to queuing conditions. The flow measured at the detector is the discharge flow; however the rate of increase in the queue length is related to the arrival flow. Hence, a factor \(f_q\) is used to adjust for this difference. Also, this factor varies depending on the detector location. This factor is greater than or equal to 1 based on the assumption that arrival rate is higher than discharge rate in queuing condition. As a detector gets closer to upstream intersection, this factor gets closer to 1 indicating that arrival rate is close to discharge rate.

This methodology estimates queue lengths on a cyclic basis and for intervals shorter than the cycle length \(C\) Equation 6 would not be applicable. This is the inherent lower bound for the frequency of queue estimation.

The following section presents two case studies. The first case study includes comparing queue estimates to those generated by a simulation model. The second case study discusses a comparison of queue estimates to those observed in the field.

**CASE STUDY 1 – USE OF DATA FROM SIMULATION MODEL**

Traffic simulation presents a good platform to evaluate this methodology. A microscopic simulation model provides queue measures, and a set of concurrent flow/occupancy measurements which are input to the algorithm. Also, it allows for a range of inputs to facilitate evaluation of the algorithm for different traffic conditions. For this case study, the Aimsun microscopic simulation model was used (12). An urban arterial segment as shown in Figure 3 was defined.
The following inputs were used to evaluate the methodology:

- Detectors were placed at 100, 200, and 300 feet from the stop line on the westbound link between the two intersections.
- Two different sets of traffic movements were defined with varying turn percentages for the subject link (Case A – left turns allowed, and Case B – no left turns allowed).
- The traffic demand was defined in 15-min increments with a varying input profile for a 2-hour duration as shown in Figure 3.
- The signals were set to 90s cycle lengths with a 50-40 split for main street/cross street respectively.
- 5% heavy vehicles were used as part of the demand.
- Model output included queue lengths for the subject link, and flow/occupancy at each detector.

The traffic conditions from the above assumptions results in a period of under saturated and over saturated conditions during the simulation. This allows the testing of the algorithm under both conditions.

For each run, using the simulated flow and occupancy a queue length for the link was estimated using the proposed method. This was repeated for each of the three detectors, separately and compared to the simulation model output over a 270-second interval (3 signal cycles). As discussed earlier, the queue estimation algorithm can be applied at intervals smaller than 3 signal cycles. Because the control policy using this queue estimation as implemented in the project used a frequency of 3 signal cycles (270s), the queue estimation results were evaluated using simulation for the same interval.

Figures 4 and 5 present the comparisons of queue lengths over time for each lane for both cases. The RMSE (Root Mean Square Error) was used as a metric to evaluate accuracy. The RMSE values are shown in the figures and also summarized in Table 1.
FIGURE 4 Comparison of Queue Estimates – Case A – With Left Turns


**FIGURE 5** Comparison of Queue Estimates – Case B – Without Left Turns

**TABLE 1 - Model Output vs Queue Estimate**

<table>
<thead>
<tr>
<th>Detector Location</th>
<th>Using Lane 1 Data</th>
<th>Using Lane 2 Data</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Ds=100</td>
<td>Ds=200</td>
</tr>
<tr>
<td>Case A RMSE (feet)</td>
<td>46.2</td>
<td>47.5</td>
</tr>
<tr>
<td>Case B RMSE (feet)</td>
<td>32.0</td>
<td>48.3</td>
</tr>
</tbody>
</table>
Based on the data in Figure 4, Figure 5, and Table 1, the following observations can be made:

- Queue lengths from the model output for the case with left turns (Case A) are longer compared to the case without left turns (Case B), as expected. There is a difference of 100 feet in the maximum queue length.

- All three detectors matched the simulation output (queue profile) reasonably well in both cases.

- Towards the end of the simulation in the intervals where traffic is transitioning from over-saturated to under-saturated conditions (intervals 22 & 23), the queue estimates have the highest difference from the simulation model outputs. This can be attributed to having higher departure rates compared to arrival rates, in those intervals, which causes an exception as the methodology is based on the opposite premise (arrival rates ≥ departure rates).

- The highest RMSE of 70 feet corresponds to an error of 3-4 vehicles in queue (17 feet avg. vehicle with 3 feet spacing).

- The detector placed at 100 feet from the stop line provides the best queue estimates in comparison to those placed at 200 and 300 feet considering all intervals, and range of queue lengths.

- In the first few intervals (1 through 10) it appears the queues using the detectors at 200 feet or 300 feet, are generally underestimated. This is expected given that when the queue is shorter compared to the detector location, the linear interpolation in Equation (5) will result in underestimation of the queue length.

- In the intervals (10 through 20) when demand exceeds capacity and the link is oversaturated, queue estimated using all three detectors match simulation model outputs well.

The set of parameters used for the queue computations are shown in Table 2. These were determined through an iterative process to find a “best fit” in Figures 4 and 5.

**TABLE 1 Queue Estimation Parameters**

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$L_d$ (feet)</td>
<td>10</td>
</tr>
<tr>
<td>$L_v$ (feet)</td>
<td>13</td>
</tr>
<tr>
<td>$L_q$ (feet)</td>
<td>17</td>
</tr>
<tr>
<td>Free Flow Speed (mph)</td>
<td>35</td>
</tr>
<tr>
<td>$f_q$</td>
<td></td>
</tr>
<tr>
<td>Detector Location</td>
<td></td>
</tr>
<tr>
<td>Ds=100</td>
<td>1.25</td>
</tr>
<tr>
<td>Ds=200</td>
<td>1.15</td>
</tr>
<tr>
<td>Ds=300</td>
<td>1</td>
</tr>
<tr>
<td>Case A, Lane 1</td>
<td></td>
</tr>
<tr>
<td>$v_2$ (mph)</td>
<td>12</td>
</tr>
<tr>
<td>Case A, Lane 2</td>
<td>15</td>
</tr>
<tr>
<td>$v_2$ (mph)</td>
<td>10</td>
</tr>
<tr>
<td>Case B, Lane 1</td>
<td></td>
</tr>
<tr>
<td>$v_2$ (mph)</td>
<td>15</td>
</tr>
<tr>
<td>Case B, Lane 2</td>
<td>15</td>
</tr>
</tbody>
</table>

**CASE STUDY 2 – USE OF FIELD DATA**

NYCDOT currently has cameras installed at various locations within the MIM study area. The location at 3rd Avenue and 57 Street was selected because this has both the video feed and a microwave sensor on the block. Figure 6 shows a snapshot of the view and the location of the
detector. The flow and occupancy data was processed to estimate queue lengths and compared to the observations made from video.

This location is the upstream block leading to the Ed Koch/59 Street/Queensboro Bridge from 3rd Avenue. The two right lanes are generally oversaturated because they lead directly to the bridge. Hence the center lane was selected for the queue observations and validation of the methodology.

The queue observations from the video were made for the block along the center lane (third lane from the left). Figure 7 presents the comparison of the queue estimates by lane with the observed queue from the video. A value of $v_2 = 15$ mph and $f_q = 1.25$ were used for the estimation. The other parameters as defined in equation (6) were used from Table 2. The time varying nature of the queues is captured well as seen in Figure 7. The RMSE is 24.5 feet. This is acceptable given the inherent variability with observing queues (manually using video).
CONCLUSIONS

Different methodologies exist to estimate queue lengths using a variety of data. However, most of those require high resolution of detector data and detail information on signal timing data and estimated vehicle trajectories. This paper suggests a methodology requiring lesser amount of data with a relatively simple effort for calibrating the parameters. The methodology was evaluated using simulation, and field data. The results of the comparison are promising. Also, the analysis leads to suggest that the detector location would be ideal to estimate queues, if under prevailing conditions the tail of the queue is routinely longer than the detector setback.

NEXT STEPS

The sensitivity of the algorithm to the calibration parameters needs to be explored using larger data sets. This will be done as part the ongoing system refinement for the MIM project in New York City. Also, the effectiveness of the algorithm needs to be further examined for lanes with shared use. The linear interpolation presented in Equation (5) can be further examined to improve the queue estimates.

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REFERENCES


