On the Performance of Adaptive Traffic Signal Control

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ABSTRACT

In this paper, we present a study in understanding sensing error’s impact on traffic signal control performance. Adaptive traffic signal control systems depend on information from traffic sensors to interpret the state of traffic. Signal timings are adjusted at real time according to the state of traffic. Queue length is an important element of the state of traffic, and errors in estimating queue length influences control decision and hence the performance. This paper presents the first attempt to quantify the effects of sensing error on control performance in the field of traffic control. A novel technique to estimate queue length using data from single loop detector is presented, and estimations are compared with parallel observations. The results show that moderate overestimation of queue length may significantly improve control performance. The benefit from overestimation suggests including arriving traffic in system state, and using look-ahead algorithms to calculate signal timings.

Categories and Subject Descriptors
1.2.1 [Simulation and modeling]: model validation and analysis

General Terms

Keywords
Traffic Signal, Sensor Error, Queue Estimation.

1. INTRODUCTION

In this paper we present a simple model based traffic signal controller that switches cycle time and splits based on the perceived queue lengths on the approaches. In reality queue lengths are hard to determine. We develop a novel Bayesian technique based on a single upstream loop detector in order to obtain a probabilistic estimate of the queue length. Our objective is to understand the impact of estimation error on control performance.

2. TRAFFIC SIGNAL CONTROL SYSTEMS

Conventional traffic signal control systems calculate fixed cycle time and green time splits for conflicting signal groups. While satisfying the overall demand structure at the signalized intersection, fixed-time systems inadequately accommodate systematic or random variations in traffic demand. Adaptive control systems, on the other hand, adjust to changes in traffic demand by calculating signal timings in real time.

The state-of-the-art for adaptive signal control usually involves state-space representation of the control system and sequential decision-making in real time. The control objectives are commonly set to optimize some measures of generalized control performance over a time period, whilst accommodating both systematic and random variations. The quantities to be calculated are the sequences of signal changes to be invoked and the associated timings.

Central to the state-space presentation are the techniques that use sensing information to construct the system state. The state of a traffic signal control system is defined in [1] as a composite of two elements: the state of traffic and the state of controller. The state of traffic at a junction can be specified by the number of vehicles queuing in each of the links and the arrivals of vehicles in the near future. The former of these is influenced by the signal controls applied. The state of the controller can be specified by the signals that are green, any changes that are currently underway, the times at which they will be completed and the times of expiry of any minimum or maximum permitted durations.

Since the state of the controller is easily accessible, the main challenge in constructing the system state is to achieve accurate estimation of queue length. The difficulty in this is that loop detectors are usually the only source of traffic information, and the norm is that only one loop detector may be available for a traffic lane. The loop detector can be installed upstream of the stopline or at the stopline. For the upstream detector, if the queue spills beyond the location of the detector, no more arriving vehicle can be detected until the queue length is less than the distance between the stopline and the detector position. This poses a difficult problem for updating the traffic state.

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Literature addressing queue length estimation in real time with the possibility of spilling back is limited. A deterministic model using shockwave theories [2, 3] was proposed by Liu et al. [4]. An important assumption for this approach is that the progression of shockwaves in traffic flow can be detected by high-resolution detectors.

In this study, we present a novel technique called the Q_tracker that uses vehicle counts and vehicle speed from a single loop detector to estimate queue length.

3. THE Q_TRACKER

The Q_tracker is a technique that estimates queue length in real time. It provides the probability distribution of queue length at a given time. The mean value of the distribution is used to construct the traffic state. A traffic controller implements the control policy according to the traffic state and the controller state.

3.1 Queue Length Estimation

For queue length estimation, the measurement obtained from inductive loop detector is denoted by \( o_i \) at each time instant \( t \). In this work, \( o_i \) is the velocity measured by the loop detector. Given the measurements over time, the posterior distribution of queue length \( q_t \) can be iteratively updated at each time instant \( t \). Using Bayes’ rule, we have

\[
p(q_{t+1} | o_{t+1}) \propto p(q_{t+1} | o_t) p(o_{t+1} | q_{t+1}) = p(o_{t+1} | q_{t+1}) \sum_{q_t} p(q_{t+1} | q_t) p(q_t | o_t),
\]

where \( o_t = \{ o_i | i = 1, 2, ..., t \} \) is the history of measurements up to time instant \( t \).

The transition probabilities of the queue length are assumed as the following:

\[
p(q_{t+1} | q_t) = \begin{cases} 
\alpha, & \text{if } q_{t+1} = q_t \pm 1 \\
1 - 2\alpha, & \text{if } q_{t+1} = q_t, 0 < q_t < q_{\text{max}} \\
1 - \alpha, & \text{if } q_{t+1} = q_t, q_t \in \{0, q_{\text{max}}\} \\
0, & \text{otherwise}
\end{cases},
\]

where \( q_{\text{max}} \) is the maximum number of vehicles in the queue, and parameter \( \alpha \) the transition probability factor. Considering vehicle inflow \( f^m \) and outflow \( f^o \), the actual transition probability \( p(q_{t+1} | q_t) \) is then shifted by \( f^m - f^o \) toward the original point for \( q_{t+1} \). Since \( f^m \) and \( f^o \) usually are not integers, linear interpolation is employed during the shift of the transition probability.

The queue length from the stop line to the loop detector is denoted by \( q_{\ell} \). In the case where \( q_t < q_{\ell} \), the observation likelihood \( p(o_t | q_t) \) is approximated by a Gaussian distribution \( N(o_t; \mu, \sigma^2) \). For a vehicle passing through the loop detector with constant deceleration, we have \( \mu^2 = q_{\ell} - q_t \), where \( \mu \) denotes the mean velocity. Hence we have

\[
\mu = \alpha \sqrt{q_{\ell} - q_t},
\]

where parameter \( \alpha \) adjusts the mean velocity. Similarly, it is assumed that \( \sigma^2 = q_{\ell} - q_t \). Additionally, there exist two factors influencing the velocity distribution. The first factor \( \beta_1 \) concerns that even when the queue length is beyond the loop detector, vehicles in the queue may keep moving. The second factor \( \beta_2 \) concerns the bias in measuring vehicle velocity. This is because mean vehicle length rather than actual vehicle length is used for velocity estimation. Regarding these two factors, we have

\[
\sigma^2 = \beta_1(q_{t+1} - q_t) + \beta_2.
\]

We further define the posterior distribution of the velocity as

\[
p(o_t | q_t) = \begin{cases} 
N(o_t; \alpha \sqrt{q_{t+1} - q_t}, \beta_1(q_{t+1} - q_t) + \beta_2), & \text{if } q_t < q_{\ell} \\
N(o_t; 0, \beta_2), & \text{if } q_t \geq q_{\ell}
\end{cases},
\]

where \( 0 \leq o_t \leq v_{\text{max}} \), and \( \int_0^{v_{\text{max}}} p(o | q_t) \, do = 1 \).

3.2 Vehicle Velocity Measurement

The mean vehicle velocity estimated from the loop detector signal is used as the observation or measurement at each time instant. A method for estimating mean velocity from the loop detector signal over time is presented in this work. To estimate the vehicle velocity, the relationship between vehicle count \( C_t \), time occupancy \( O_t \), vehicle velocity \( v_{ij} \), and vehicle length \( l \) can be described as:

\[
O_t = \frac{1}{T} \sum_{i=1}^{T} \int_{v_i}^{v_{\text{max}}} f_{\text{loop}}(v_i) \, dv_i,
\]

where \( l_{\text{loop}} \) is the length of the loop detector, and \( T \) is the duration of the measurement. For the update process of the queue length tracking, it is assumed that velocity \( v_{\text{mean}} \) is constant within interval \( T \) and the mean vehicle length \( l_{\text{mean}} \) is computed from historical data. Hence we have

\[
O_t = \frac{C(l_{\text{max}} + l_{\text{loop}})}{v_{\text{mean}} \cdot T}.
\]

The measured mean velocity can be written as

\[
o_t = v_{\text{mean}} = \frac{C(l_{\text{max}} + l_{\text{loop}})}{O_t \cdot T}.
\]

3.3 Inflow and Outflow

Inflow rate is defined as the average number of vehicles that have passed through a loop detector during a period of time. Inflow rate estimation is related to vehicle count as well as the detection of long queue. Vehicle count is the number of vehicles that have passed through a loop detector on a road and it can be obtained by counting the number of falling edges of the loop signal. If the length of a queue is longer than \( q_{\ell} \), then the queue is beyond the loop detector and is considered to be a long queue. When a long queue occurs, the estimate of inflow rate is updated by using the historical information, e.g. the inflow rate calculated one or two days ago. Kalman filter has been employed to improve the robustness of the inflow rate estimation.

The outflow rate estimation is to estimate the flow rate at which vehicles enter an intersection from an approach. When the traffic light is red, the outflow rate becomes zero. Otherwise the outflow rate is simply approximated by a constant value in this work.
4. TRAFFIC SIGNAL CONTROL POLICY

A simple heuristic control policy is employed for this study. This policy is derived from exploiting the apparent optimality of saturation flow algorithm [5], in which the signal changes only when the favored queue is exhausted. The saturation flow algorithm was further studied in [6], where it was treated as the basis policy and was compared to two other comparison policies. One of the comparison policies considers switching traffic signal before the favored queue is empty. The other allows extending green after the favored queue is exhausted. Dynamic programming [7] was used to show that there were domains in the state space where the basis policy was optimal, and that there were other domains in which the comparison policies were optimal. Recent studies in adaptive traffic signal controlling using advanced dynamic programming techniques [8, 9] suggested that considering information of arriving traffic as an extra dimension of state space improves performance of the basis policy. In this study, we simply use detected vehicle headway as an indicator of the arriving traffic. The basis policy is often impractical in reality since it may extend green for too long. Regarding this, we add a few conventional constraints to traffic signal timings, including minimum green, maximum red, and maximum cycle length. An inter-green period is further added to ensure safety at the intersection. The control policy can be summarized as the following.

Decision (a). Switching signal if all the following conditions are satisfied: 1) favored queues are exhausted, 2) vehicle headways of the concerned approaches exceed critical value, and 3) minimum green is exhausted. Decision (a) is overridden if decision (b) is applicable.

Decision (b). Switching signal if maximum red is exhausted or if maximum cycle time is exhausted.

5. NUMERICAL EXPERIMENT

In numerical experiments Q_tracker and actual observation of queue length are in turn employed to present the traffic state. Depending on the traffic state, the control policy supervises switching of the traffic signals. Performance results thus obtained are analyzed to show the impact of sensing error in control performance. We use the PARAMICS simulation software [10] for numerical experiments. A specific plug-in was supplied so that actual queue length can be observed parallel to the simulation. The configuration of the traffic intersection in PARAMICS is provided in Section 5.1. The definition of queue for the PARAMICS plug-in is introduced in Section 5.2. Analysis of numerical results is included in Section 5.3.

5.1 PARAMICS Model

We present a very simple PARAMICS network for this study. It contains one signalized intersection, consisting of two perpendicular roads. Each road is a two-way road with a single lane in each direction and a speed limit of 60 km/h. The intersection has four signal groups that can be independently controlled by the user. Each of the four signal groups controls one of the four approaches. The intersection does not allow right or left turns, therefore vehicles can only proceed straight ahead. This model is graphically shown in Figure 1.

Each of the four approaches to the intersection is 1100 metres long. The first 100 metres at the far ends of the network are zones or vehicle source areas. Vehicles loaded are only from a single vehicle type defined as a car of length 4.40 metres and mass of 1370 kg and the traffic volume loaded into the network can be configured by the user. The volumes of traffic demand are summarized in Table 1.

There are advance and stop line loop detectors in each approach. Only the advanced loop detector is used for estimating queue length. Each loop is 4.5 metres long. The advance loop detectors upstream edges are located 80 metres before the stop line. The stop line detectors' downstream edge coincides with the stop line position.

<table>
<thead>
<tr>
<th>Origins of traffic</th>
<th>West</th>
<th>East</th>
<th>South</th>
<th>North</th>
<th>Sum</th>
</tr>
</thead>
<tbody>
<tr>
<td>West</td>
<td>600</td>
<td></td>
<td>600</td>
<td></td>
<td>600</td>
</tr>
<tr>
<td>East</td>
<td>600</td>
<td></td>
<td>400</td>
<td></td>
<td>400</td>
</tr>
<tr>
<td>South</td>
<td></td>
<td>400</td>
<td></td>
<td></td>
<td>400</td>
</tr>
<tr>
<td>North</td>
<td></td>
<td></td>
<td>400</td>
<td></td>
<td>400</td>
</tr>
<tr>
<td>Sum</td>
<td>600</td>
<td>600</td>
<td>400</td>
<td>400</td>
<td>2000</td>
</tr>
</tbody>
</table>

5.2 Definition of Queue

For the purposes of this paper, we require a definition of the queue length of vehicles for each individual lane of the intersection approaches. The queue length is the length between the lane stop line and the last stationary vehicle on that lane. A stationary vehicle is defined by two hysteresis thresholds of 5 km/h and 15 km/h. A vehicle joins a queue if its velocity falls below 5km/h, and leaves the queue if its velocity goes above 15 km/h. Flow conservation applies to the formulations of the queue. This definition of queue is written as a plug-in to the PARAMICS model, and runs parallel to the simulation process.

5.3 Results and Analysis

We first look at the accuracy of the Q_tracker in estimating queue length by comparing with the observation obtained from the PARAMICS plug-in, and then discuss the results in control performance.

5.3.1 Accuracy in estimation

The results presented here were obtained from a single run of simulation, with one hour of simulated time and a time step of 1.0s. We illustrate the estimated queue and the observed queue in the East and North approaches in Figure 2(a) and 2(b).
respectively. The $Q_{\text{_tracker}}$ estimation is marked by the dark (black) line and the observations by the lighter (orange) line. The dynamics of the queues are broadly similar, but the $Q_{\text{_tracker}}$ seems to be consistently overestimating the queue length. Overestimation results in longer time to exhaust the queue, and thus provides longer green time for the favored signal group, according to the control policy we stipulated. A visual comparison between $Q_{\text{_tracker}}$ and observation is shown in Figure 3.

Common methods for measuring estimation accuracy in time series are mean absolute percentage error (MAPE), which is calculated as

$$\text{MAPE} = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{\text{Observation} - \text{Estimation}}{\text{Observation}} \right| \times 100\%,$$

and mean absolute error (MAE), which is calculated as

$$\text{MAE} = \frac{1}{n} \sum_{i=1}^{n} |\text{Observation} - \text{Estimation}|.$$

The MAPE method is more informative than the MAE, but has drawback in case with observations of zero value, which is true in our case (an empty queue is common). We therefore use the MAE, and the results are shown in Table 2. The error in estimation is greater for approaches with heavier demand. Given the consistent overestimation, the results suggest that, by using $Q_{\text{_tracker}}$, approaches with heavier demand will usually be given more green time than in the case of using observation.

### Table 2. Mean absolute error (in vehicles) as an indicator of accuracy in queue length estimation; $Q_{\text{_tracker}}$ as the estimation tool and PARAMICS plug-in as the source of observation

<table>
<thead>
<tr>
<th></th>
<th>West</th>
<th>East</th>
<th>South</th>
<th>North</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>2.45</td>
<td>3.09</td>
<td>1.69</td>
<td>2.08</td>
</tr>
</tbody>
</table>

5.3.2 Performance in control

We obtained 10 paired results for the comparison in control performance. Each paired run of simulation is fed with independent seed with 1 hour simulated time and a time step of 1.0s. The measure for control performance is vehicle delay, which is indicated by the average vehicle seconds per seconds. Results are summarized in Table 3.

Despite the error in estimating queue length, the controller using $Q_{\text{tracker}}$ seems better in performance. Using the hypothesis of equal mean, and by using the paired $t$-test, we found that $t = -17.84$ while the two tail $t$-critical $= 2.26$, thus rejecting the hypothesis. The controller using $Q_{\text{tracker}}$ performs significantly better than using observation — reducing average vehicle delay by 23%.

This combination of persisting bias in estimation and better performance presents an interesting scenario. An explanation for this is that delay is more sensitive to cycle time shortening than extension. Using Webster’s [11] delay formula, we can find that the rate of delay increases rapidly for values of the cycle time smaller than the optimum, but less rapidly for values larger than the optimum. This means that it is better to err on the safe side by stretching the cycle length a little longer than the computed optimum, so does the controller equipped with $Q_{\text{tracker}}$ and the basis policy.

The numerical results also suggest that considering arriving traffic as an extra dimension in state space is necessary and improves control performance as this may lead to an appropriate extension or shortening in green time. This requires the system to look ahead from the current state, and achieve optimality in the immediate term as well as in long-term. Dynamic programming techniques are ideal to address such problems. Reinforcement learning techniques may also be incorporated to progressively improve control policies.

### Table 3. Control performance comparison between using $Q_{\text{_tracker}}$ and using observation

<table>
<thead>
<tr>
<th>Run</th>
<th>$Q_{\text{tracker}}$</th>
<th>Observation</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>18.20</td>
<td>23.73</td>
</tr>
<tr>
<td>2</td>
<td>17.75</td>
<td>22.94</td>
</tr>
<tr>
<td>3</td>
<td>17.89</td>
<td>25.06</td>
</tr>
<tr>
<td>4</td>
<td>19.34</td>
<td>24.17</td>
</tr>
<tr>
<td>5</td>
<td>18.61</td>
<td>26.16</td>
</tr>
<tr>
<td>6</td>
<td>18.18</td>
<td>24.09</td>
</tr>
<tr>
<td>7</td>
<td>19.59</td>
<td>24.88</td>
</tr>
<tr>
<td>8</td>
<td>20.25</td>
<td>24.48</td>
</tr>
<tr>
<td>9</td>
<td>18.66</td>
<td>24.34</td>
</tr>
<tr>
<td>10</td>
<td>19.54</td>
<td>24.87</td>
</tr>
</tbody>
</table>
3(a) Estimated distribution of queue from Q_tracker at a particular time; there are 10.3 vehicles (mean value) in the queue in the West approach, and 8.8 vehicles (mean value) in the East approach.

3(b) Observed queue length in PARAMICS model; 7 vehicles are queued in the West approach and 5 in the East approach.

6. CONCLUSIONS

In this paper we have presented a simple model based traffic signal controller and compared its performance using two different traffic models: the notionally exact queue length returned by the Paramics plug-in and the approximate queue length returned by the Q tracker, with the latter giving a 23% improvement in vehicle delay when compared with the former.

By consistently overestimating the queue length the Q tracker based controller switches to green earlier than the real queue length based controller and gives longer green time which provides the bulk of the performance improvement. It will also 'gap-off' earlier providing additional performance improvement.

From this work it appears as if there is an optimal queue length for which phase switching should be triggered. It seems likely that this optimal queue length would be a function of traffic flow and could form part of the control parameters in a future study.

Accuracy of queue estimation can be further improved. The variance of estimation can be taken into account in the control policy. Results in this study suggests that the greater the variance, the longer the green extension to the favored queue.

7. ACKNOWLEDGMENTS

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8. REFERENCES


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