# Maximum queue length estimation at signalized intersections using shockwave theory and Kalman filter 

A.Wanuji.N.Abewickrema ${ }^{1}$, Mehmet Yildirimoglu ${ }^{1}$, Jiwon Kim ${ }^{1}$<br>${ }^{1}$ School of Civil Engineering, Faculty of Engineering, Architecture and Information Technology, The university of Queensland, St Lucia, Queensland 4072, Australia<br>Email for correspondence: w.abewickrema@uq.edu.au


#### Abstract

This paper proposes a combined framework of Lighthill-Whitham-Richards (LWR) shockwave theory with Kalman Filter (KF) for real time vehicular queue length estimation at signalized intersections on urban arterial roads. LWR shockwave theory was used as the base to identify traffic state changing points (e.g., capacity, jam density, free flow), which we call break points by relying on high resolution ( 2 seconds) traffic signal data. Once we identify the traffic state changing points, time at which these points occur can be used to reconstruct the shockwaves happening at the intersection in each signal cycle. Finally, these shockwave speeds were utilized in calculating the maximum queue length of each signal cycle. This model can identify traffic state changes that distinguish upstream arrival traffic flow from queue formation flow (jam density state). Thus, this approach can estimate time varying queue length even when the signal links are over saturated with long queues. Although shockwave theory successfully describes the complex queuing process, these models assume known vehicle inflows, which cannot be satisfied for most of situations. In our methodology we incorporate a different framework to estimate the vehicle arrivals by using 2 seconds vehicle detector data and adjacent Bluetooth detector data from the upstream intersection for real world applications. This estimation model can be applicable to scenarios when detailed "event-based" data are not available. The estimated maximum queue length has been evaluated using simulated ground truth data using AIMSUN. Evaluation results demonstrate that the proposed models can estimate long queues with satisfactory accuracy with the availability of only 2 seconds vehicle occupancy data, arrival flow and known signal timing data. Expansion to the base model is proposed using Kalman Filter (KF) to improve the reliability of the proposed model. Limitations of the proposed model are also discussed in the paper.


## 1. Introduction

Real-time queue length is a crucial information, which is increasingly needed for signal operation and signal optimization purposes. Essentially, two distinct model types have been proposed to tackle the real-time estimation of vehicle queues in signalized intersections. The first type is based on the analysis of cumulative traffic input-output to a signal link, was first proposed by Webster (1958) and later improved by several researchers. Nevertheless, this particular approach has significant drawbacks in estimating long queues that exceed beyond a specific detector location. Second type of models are constructed based on the analysis and modelling of traffic shockwaves. Shockwave theory was first demonstrated by Lighthill and Whitham (1955) and Richards (1956) for uninterrupted flow; and later expanded to signalized intersections. Even though shockwave theory can successfully explore the complex queueing process in both temporal and spatial dimensions, in real world applications the main drawback is that it assumes a known and steady vehicle inflow which is hard to infer without upstream detectors further away from the stop line. Without such arrival state information, existing
shockwave models cannot be utilized to estimate intersection queue lengths (Liu et al., 2009). In recent years, many researchers have utilized trajectory data readily to infer key traffic parameters, i.e., traffic volumes and the fundamental diagram (FD) parameters (e.g., free flow speed, capacity, jam density). Nonetheless, it has been widely recognized that one challenge for traffic state estimation using vehicle trajectory data is its low penetration rate (Wang, Huang and Lo, 2019).

The objective of this paper is to develop a methodology to estimate long queues with the availability of high-resolution vehicle detector occupancy data, signal timing data and vehicle inflow. We are particularly interested in the maximum queue length that occurs in each signal cycle. In this study, we emphasize the fact that high resolution detector data, in our case 2 seconds occupancy data, could be utilized in identifying traffic flow pattern changes. We apply the shockwave theory together with such high-resolution traffic data collected from loop detectors to estimate maximum queue length accurately.

## 2. Methodology

### 2.1.Shockwave analysis and break point identification

The relationship between flow and density at any point of the road is known as the fundamental diagram (FD). FD can be fully calibrated with three parameters: capacity $q_{m}$, free flow speed $V_{3}$ and jam density $k_{j}$, as shown in Figure 1a. Other parameters can be derived from them, such as critical density $\left(k_{m}=q_{m} / u_{f}\right)$ and congested wave speed $\left(V_{2}=\left(q_{m}-0\right) /\left(k_{m}-k_{j}\right)\right)$.
Shock waves are an imaginary type of waves appearing at a road segment closer to an intersection due to the stop and go nature of vehicles. Accordingly, three main types of shock waves occur at a signalized intersection within one signal cycle namely, queue formation wave $\left(V_{1}\right)$, queue discharge wave $\left(V_{2}\right)$, and the departure wave $\left(V_{3}\right)$ respectively. If the queue is not cleared within one signal cycle, another shock wave called residual queue forming wave ( $V_{4}$ ) will be formed. Detailed formation of these shockwaves appears in many literatures such as (Skabardonis and Geroliminis, 2005) and (Liu et al., 2009) and will not be discussed in detail in this section. These shockwaves can be represented in a space time diagram aligned with the signal timing (red timing and green timing) of a signal cycle (refer Figure 1b).

In this study, break points are defined as the points in time at which the traffic state changes occur. These break points can be identified by exploring the high-resolution occupancy data obtained via vehicle loop detectors. In Figure 1b, points A, B and C illustrates the break points observed at the vehicle loop detector site placed upstream of the stop line. We utilized occupancy data recorded every 2 seconds from the STREAMS database to identify these defined break points at which traffic state variations occur. Our methodology is initiated based on the methodology proposed by (Liu et al., 2009). They utilize high-resolution "event-based" data which contains vehicle events and signal events. This study considers two shockwaves, namely the queue discharge $\left(V_{2}\right)$ and the departure wave $\left(V_{3}\right)$ to identify the intersection point corresponding to the maximum queue length $L_{\max }^{n}$. The study does not make use of $V_{1}$ as it heavily depends on the arrival flow which is not observable in their methodology.

In this study, we execute a similar approach in the absence of event-based data (only using 2 seconds occupancy data). The performance of the developed analytical models for the maximum queue length estimation in a signal cycle were further improved by utilizing them in a univariate Kalman filter framework explained in section 2.2.


Figure 1: a. Fundamental diagram, b. Shockwave diagram at a congested intersection
Figure 2 summarizes the implementation algorithm in calculating the maximum queue length. Once we get the 2 seconds occupancy data through simulation, with the available signal cycle timing information the algorithm separates the signal cycle to green and red phases and then defined threshold conditions are applied to identify points A, B and C. Next, the times at which these break points occur $T_{A}, T_{B}$, and $T_{C}$ are inferred and used to calculate the shockwaves. Finally, the maximum queue length at each signal cycle is calculated using the calculated shockwave speeds.


Figure 2: Implementation steps of queue length estimation algorithm
Break point identification is challenging using 2 seconds occupancy data compared to utilizing event-based data, but not impossible. Figure 3 depicts how A, B and C break points are identified using 2 s occupancy data. We defined separate threshold values for the occupancy data recorded to identify each of these break points. In detail, the time that point A appears $\left(T_{A}\right)$ is the moment that the queuing shock wave $V_{1}$ propagates backward to the location of the loop detector. Between $T_{r}^{n}$ (start of red phase) and $T_{A}$, the vehicles pass the loop detector with the traffic state
( $q_{a}^{n}, k_{a}^{n}$ ) while between $T_{A}$ and $T_{B}$, no vehicle can pass the loop detector because of the jam traffic condition $\left(0, k_{j}\right)$. Point A is not difficult to identify; as after $T_{A}$, the detector is occupied for a relatively long time, so the value of the detector occupancy time is relatively large. In this study, based on our observation, if there is an occupancy change from less than $100 \%$ to $100 \%$ occupancy and if the occupancy value is kept at $100 \%$ for more than 4 s (2 of 2-seconds time intervals) within red phase, it can be categorized as a " A " break point.
Point B indicates the time $\left(T_{B}\right)$ that the discharge shockwave passes the detector. Between effective green start $T_{g}^{n}$ and, $T_{B}$ the traffic state over the detector is $\left(0, k_{j}\right)$; after $T_{B}$, vehicles are discharged at saturation flow rate and traffic state changes to $\left(q_{m}, k_{m}\right)$. based on our observation, if the occupancy remains $100 \%$ at least for two consecutive time intervals and then drops to a lower value than $100 \%$ occupancy within green phase, it can be categorized as a "B" break point.
Identification of point "C" is the most challenging step. Point C indicates the time ( $T_{C}$ ) when the rear end of queue passes the detector. Shockwave $V_{3}$ act as the interface between saturation traffic state $\left(q_{m}, k_{m}\right)$ and the arrival traffic state $\left(q_{a}^{n}, k_{a}^{n}\right)$. Therefore, before point C appears, vehicles discharge at the saturation flow rate at the location of loop detector, i.e., the traffic state is $\left(q_{m}, k_{m}\right)$. After the wave propagates to the detector location, the traffic condition becomes to $\left(q_{a}^{n}, k_{a}^{n}\right)$. Based on our observations, having $0 \%$ occupancy for at least two consecutive 2 seconds time intervals ( 4 s ) in a green phase assure the appearance of point C. These identified break points are utilized to generate preliminary results and expect to analyze further in future works.


Figure 3:Break point identification using 2 seconds occupancy data

### 2.2.Queue estimation model using Kalman filter

As depicted in Figure 1b, it is understandable that any two shockwaves out of $V_{1}, V_{2}$ and $V_{3}$ can be used to estimate the maximum queue length happening inside a signal cycle. But which shockwaves to utilize in calculating the maximum queue length depends on the accuracy of identifying each break point and the available traffic state details to calculate the shockwave speeds. In our study, 3 models were developed to calculate the maximum queue length and only the basic model (model 1) utilized in the framework of Kalman filter will be discussed under the scope of this section.
Considering the shockwave diagram (refer Figure 1b), an approximation for the maximum queue length of the $\mathrm{n}^{\text {th }}$ cycle ( $L_{\text {max }}^{n}$ ) can be derived as:

Model $1=L_{\text {max }}^{n}=\frac{N^{n}}{k_{j}}+L_{D}$
Where $N^{n}=$ the number of vehicles detected between break point B and C.

A univariate Kalman filter was developed assuming a random walk model as the process model (equation 4 below) and equation 3 as the measurement equation neglecting the $L_{D}$ term (the detector was placed very close to the stop line). $n$ was considered as the measurement while the state variable was defined as the maximum queue length occurring in each signal cycle in meters.

Kalman filter equations.

$$
\begin{align*}
& \text { Process Model: } L_{\max }^{n+1}=L_{\max }^{n}+\omega  \tag{2}\\
& \text { Measurement Model: } N^{n}=k_{j} * L_{\max }^{n} \tag{3}
\end{align*}
$$

$\omega$ and $v$ are process noise and the measurement noise respectively.
The concept and formulation of Kalman filter can be found in Vigos, Papageorgiou and Wang, 2008.

## 3. Results and Discussion

Intersection of Skiff Road and Ferry Road (intersection M5020) in Gold Coast, Queensland was selected as our testing site. Through movement lane (middle lane) along the Ferry Road was considered in the calculation of the maximum queue length. With the availability of CCTV camera recordings and technical drawings of the intersection, we replicated the intersection M5020 using AIMSUN software, and the simulation was conducted for 1 hour, from morning 07:00am to 08:00am. In the AIMSUN modelling framework, we assume a link input detector, i.e., a detector placed sufficiently upstream so that input traffic flow to the traffic signal can be measured and it replicates our vehicle inflow estimation framework in the simulation model.

Figure 4 summarizes the results of model 1 without and without applying the Kalman filter and validated against the ground truth data. The results emphasis that utilizing Kalman filter framework increase the performance of the model. Comparing the Mean Absolute Percentage Error (MAPE) of the models with and without Kalman filter confirms the fact that the Kalman filter can incorporate the uncertainty associated with the measurements, process, and the state to give a better estimate. In Figure 4, y axis depicts the queue length in meters and $x$ axis represents the signal cycle number between ( 20 signal cycles) 07:00am to 08:00am.


Figure 4: Model results of maximum queue length estimation

## 4. Conclusion

This proposed methodology is applicable in situations with no event-based data or detailed trajectory data available but only with the availability of high-resolution detector data. In the real-world application, it is necessary to assume a fundamental diagram and calibrate the road sectional parameters such as capacity, free flow speed and jam density. Further, vehicle effective length plays an important role in the model output in which we have assumed a fixed value to convert number of vehicles into a length. It is advisable to conduct a calibration to estimate the vehicle effective length which will improve the results. When utilizing 2 seconds occupancy data, identification of point $A$ and $B$ is accurate than identifying of point C. Even though point C is identifiable, our results shows that it can cause large errors. This is due to the large fluctuation happening to the occupancy at the detector location once its traffic state changes from saturation condition to the free flow arrival condition. Due to this reason, this methodology will not capture the over-saturation conditions accurately. Another limitation with this methodology is the arrival vehicle flow should be known which in some cases might not be available. To improve the model accuracy and to mitigate the existing limitations, an expansion to the existing model using Kalman filter in the LWR framework was proposed. When utilizing the Kalman filter it is important to capture the system dynamics correctly to be reflected by the process and the measurement models. Possible expansions to the proposed Kalman filter are to consider more variables as measurements and to consider nonlinear models to explain the system dynamics with extended Kalman filter.

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