

Estimating Phase Duration For SPaT Messages

September 28, 2018

Shahana Ibrahim, EECS Texas A& M University

Dileep Kalathil, EECS Texas A& M University

Rene O. Sanchez, Sensys Networks, Berkeley, California

Pravin Varaiya, Life Fellow, IEEE, EECS University of California Berkeley

<https://arxiv.org/pdf/1710.05394.pdf>

Table of Contents

- Motivation
- Prior Work
- Our Contributions
- Data is Everything!!!
- Problem Definition
- Our Algorithm
- Results & Analysis
- Future Scope
- Conclusion

Autonomous Vehicles



- Active research going on in Intelligent Transportation
- How do we optimize the traffic flow once self driving cars are on road?
- Can we increase the fuel efficiency once everything is automated?
- We have lots of data. What do we do using that for addressing these questions?

Road Intersection Geometry

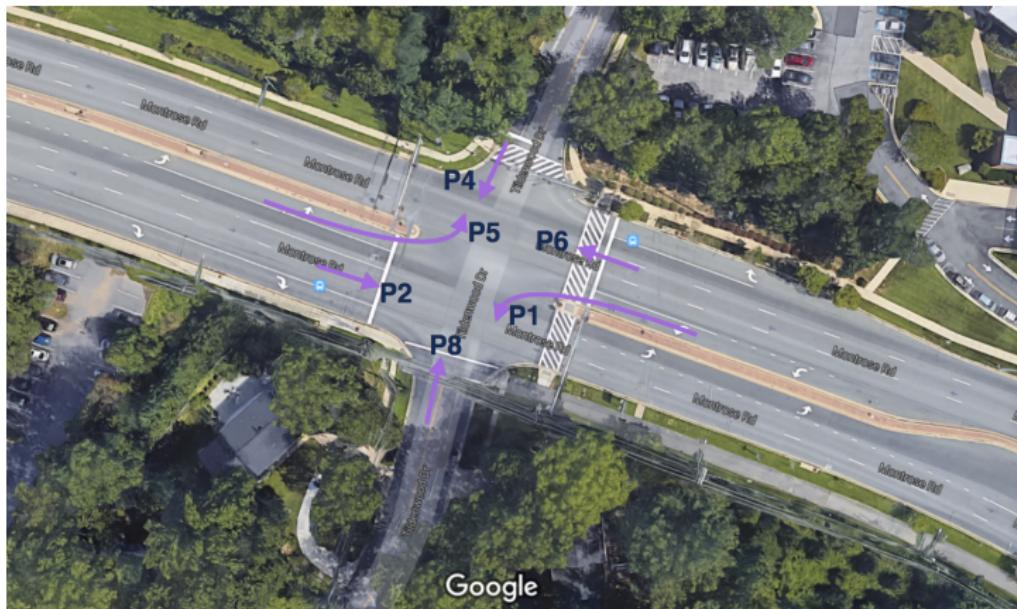


Figure: The intersection at Tildenwood Dr. and Montrose Rd.

Road Intersection Geometry Cont..

- The intersection is equipped with magnetic vehicle detectors at the stop bar
- Using vehicle detection data, each phase duration is typically actuated at the controller
- There are fixed, semi actuated and fully actuated traffic controllers used
- If the current signal phase and elapsed time is obtained from the controller, how do we get the estimate of the residual time of the current phase duration?

SPaT Messages

Definition

A SPaT (Signal Phase and Timing) message describes the current phase at a signalized intersection, together with the residual time of the phase, for every lane (hence every approach and movement) of the intersection

- SPaT Messages can be periodically broadcast by the intersection, say once per 100ms, typically with a 10ms accuracy
- For a fixed-time controller the SPaT information is definitive
- For an actuated controller, only an estimate of the residual time can be given

Why SPaT Messages!!!

- Several studies show eco-friendly speed advice is possible using SPaT data.
 - Velocity planning algorithms can be formulated using residual phase duration data
 - Results in less emissions and fuel consumptions
- Vehicle trajectory formulation in conjunction with MAP messages
 - MAP messages gives the physical geometry of different intersections
 - Vehicles can traverse without stopping at red light through a series of intersections
 - Results in less traffic

SPaT Messages Today??

- No intersection in the U.S. today broadcasts SPaT or MAP messages
- Very few cities have a Traffic Management Center that receives phase information from all its intersections

But Facts..

- Significant interest and activity going on in the automotive and ITS communities for standardization of SPaT and MAP messages
- Inexpensive to collect and process phase information locally at each intersection

So Future...

SPaT will become common in the era of self driving cars. So we need accurate estimates for residual phase duration in SPaT messages

Some Related Studies on SPAT

- [1] uses samples of GPS position to estimate phase duration , but used only fixed time signals, The absolute error reported is upto 6s
- [2] engages with smartphone to detect the signal light at an intersection and predict its phase duration. But the results were unimpressive with misdetection rates upto 12.4
- [3] uses a probabilistic phase duration prediction by taking a confidence bound on the frequency distribution. But this method is not efficient for predicting the residual time of the phase
- Several studies focusses on predicting the vehicle flow at arterial roads.

Problem Statement.

if t is the current time in cycle n during phase p_4, p_1, \dots , then $p_4(n) - t$, $p_1(n) - t \dots$ are the residual times of the phase that is included in the SPaT message

The SPaT problem

Let $I(t)$ be the information about previous phases available at time $t \in [0, L]$ during cycle n . The problem is to predict the residual times $p_k(m) - t$ of all phases k for all future cycles $m = n, n + 1, \dots$ given $I(t)$.

Measurement Site

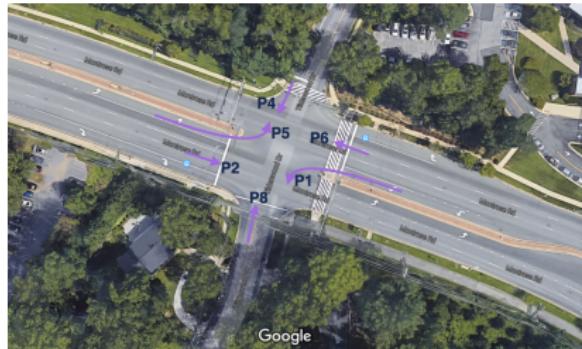
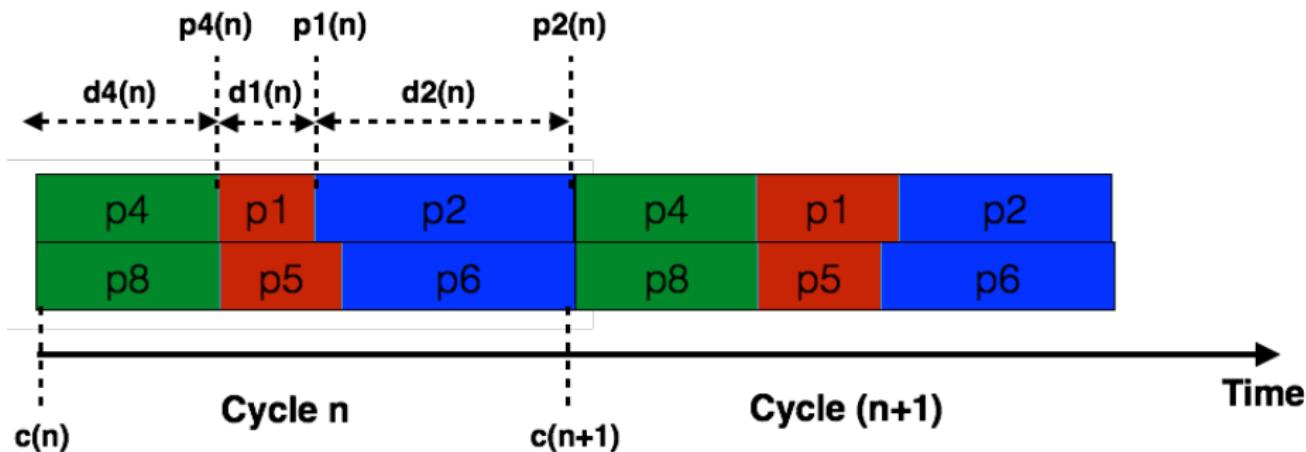


Figure: The intersection at Tildenwood Dr. and Montrose Rd.

- Cycle length is fixed by the timing plan at $L = 100, 110 \text{ or } 120 \text{ s}$
- Cycle is divided into nominal durations for each phase.
- Controller modifies these durations in each cycle depending on vehicle detections (actuated intersection)

Cycle and Phase Durations



At any given time t , predict: $p_4(n, t)$, $p_1(n, t)$, $p_2(n, t)$

Cycle and Phase Durations Cont..

If d_i is the duration of the phase p_i , the following identities hold for this intersection

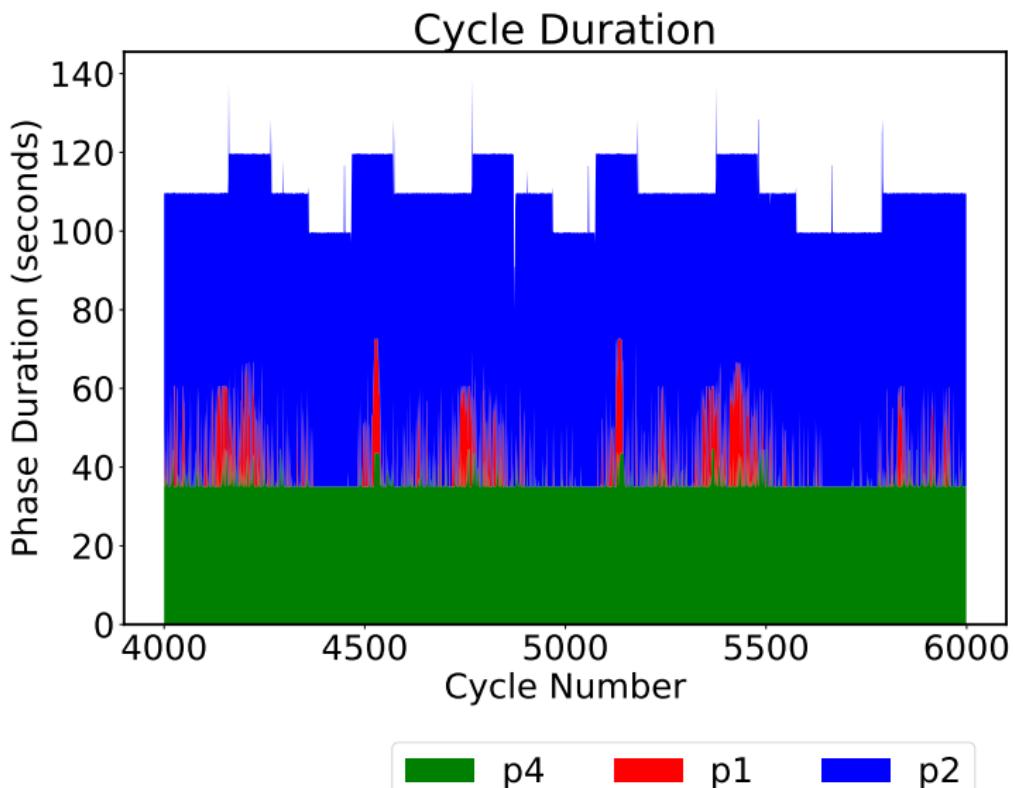
$$d_4 + d_1 + d_2 = d_8 + d_5 + d_6 = L, \quad (1)$$

$$d_1 + d_2 = d_5 + d_6, \quad (2)$$

$$d_4 = d_8. \quad (3)$$

Equation (1) recognizes L as the cycle length;

Simulation Data



Properties of Simulation Data

- Our study uses data for 36,000 cycles from September to October 2016.
- The phase data for a sample of 2,000 cycles (about 3 days) is shown in Figure.
- The minimum value of d_4 is the pedestrian clearance time of 36s; the duration of the phases is extended by 5s each time an additional vehicle is detected
- Large values of d_4 and d_1 occur only during the AM and PM peaks.

Phase Duration Distribution

Since $d_2 = L - (d_4 + d_1)$, it is enough to calculate pdfs of d_4 and d_1 .

Since d_4 and d_1 may be dependent, we need to calculate $d_4 + d_1$ also.

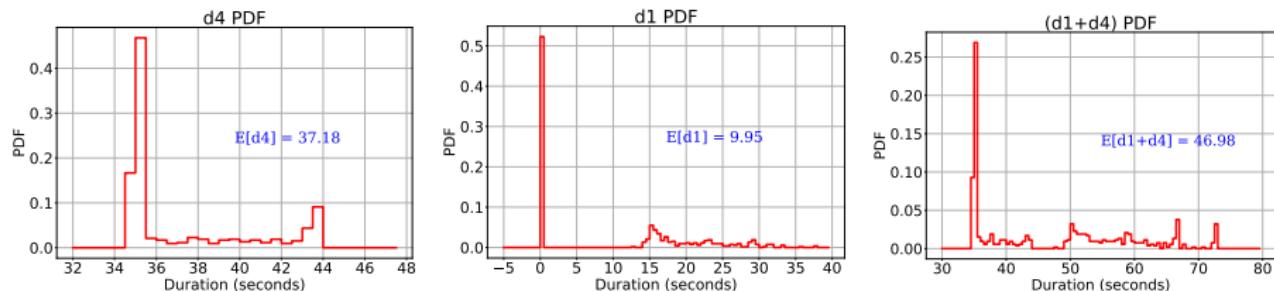


Figure: PDF of d_4 , d_1 and $(d_4 + d_1)$

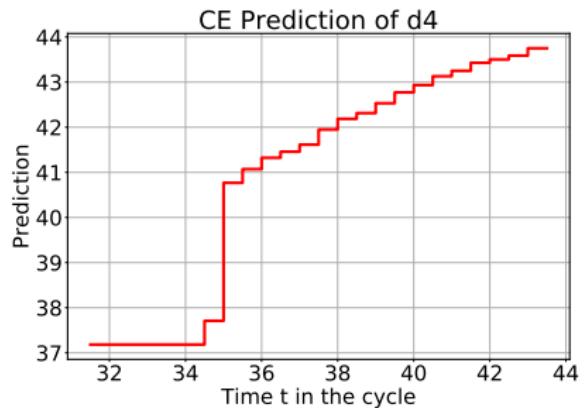
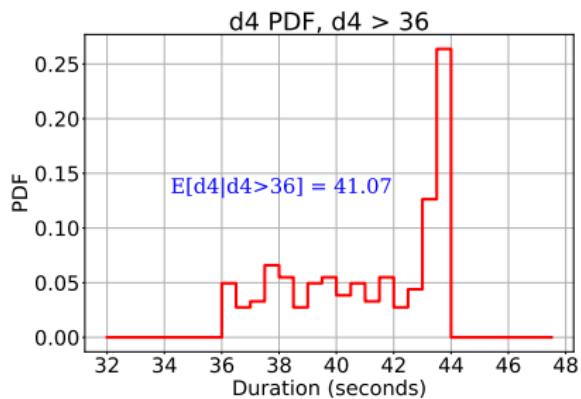
Conditional Expectation (CE) based Prediction

- At $t = 0$, given unconditional pdfs of d_4 , d_1 and $d_4 + d_1$, reasonable predictions are $\mathbb{E}(d_4)$, $\mathbb{E}(d_1)$ and $\mathbb{E}(d_4 + d_1)$ respectively
- At a later time t in the cycle, if we know d_4 is still actuated, then we have an extra information, that is $d_4 > t$. So a better prediction model is $\mathbb{E}(d_4)$ conditioned on the event $\{d_4 > t\}$

CE Prediction Model

Predicted d_4 at time t , $\hat{d}_4(t) = \mathbb{E}(d_4 | d_4 > t)$

Conditional Expectation based Prediction Cont..

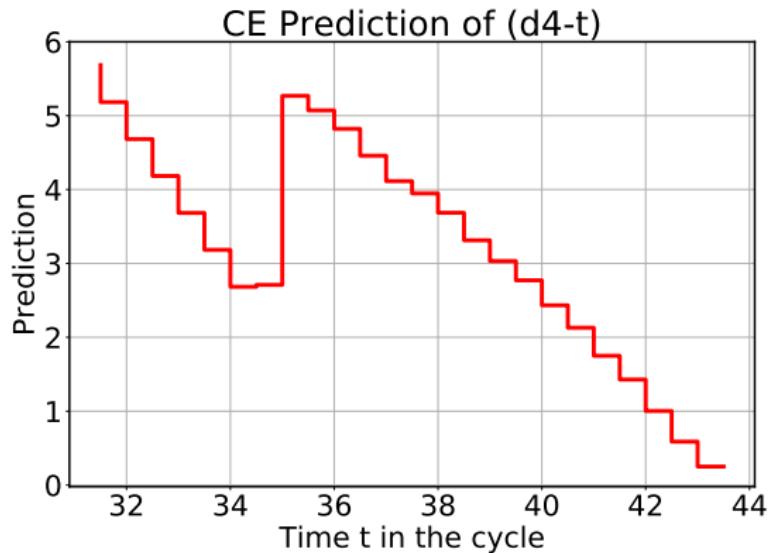


The first figure shows the conditional PDF for an example time, $t = 36$.

Conditional Expectation based Prediction Cont..

Residual time of p_4 at time t is predicted as

$$\hat{r}_4(t) = \hat{d}_4(t) - t \quad (4)$$



Caveats of CE Prediction

- Residual time prediction, \hat{r}_4 suddenly increases at around $t = 35$ by about 2.5s which may appear counter-intuitive
- For example, consider a driver waiting for phase p_1 to turn green after the end of p_4 . The residual time decreases initially. However, the driver will find that residual time suddenly extended by a few more seconds at $t = 35$ before decreasing again.
- This can create significant problems in designing a control strategies for eco-driving

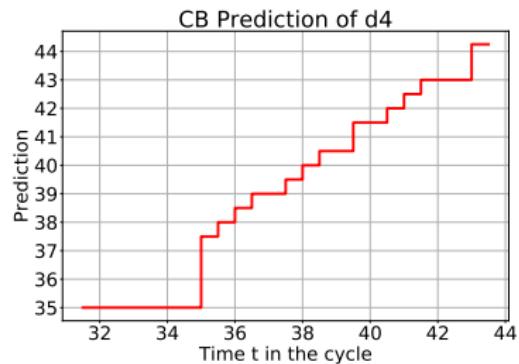
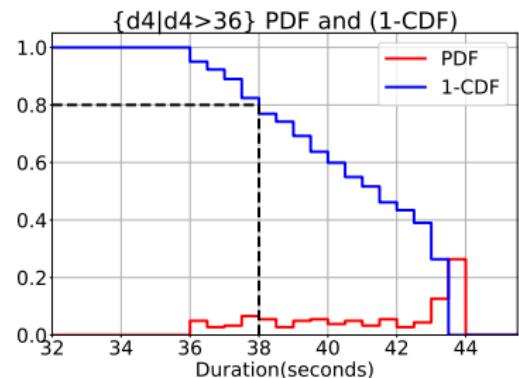
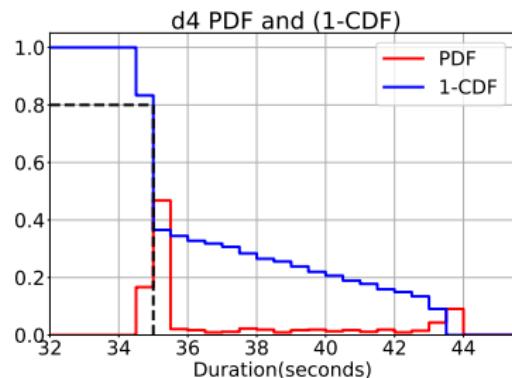
Confidence based (CB) Prediction

- Let α be the required confidence bound. We can define the confidence based prediction as the value d for which one can guarantee $\mathbb{P}(d_4 > d) = \alpha$.
- Let $F(d) = \mathbb{P}(d_4 \leq d)$ be the CDF of d_4 . Then $1 - F(d) = \mathbb{P}(d_4 > d)$. Then at time $t = 0$, one way to predict is finding the solution d such that $1 - F(d) = \alpha$.

CB Prediction Model

Predicted d_4 at time t , $\hat{d}_4(t) = \{d | (1 - F(d|d_4 > t)) = \alpha\}$

CB Prediction with Confidence Bound $\alpha = 0.8$



Prediction Errors

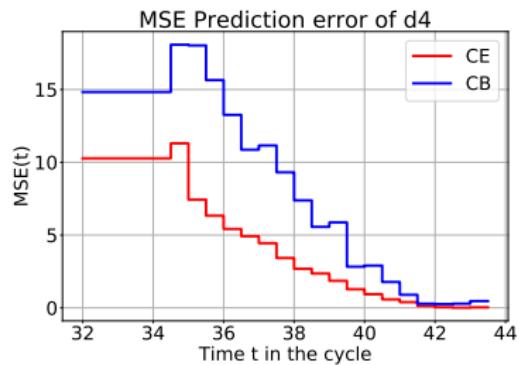
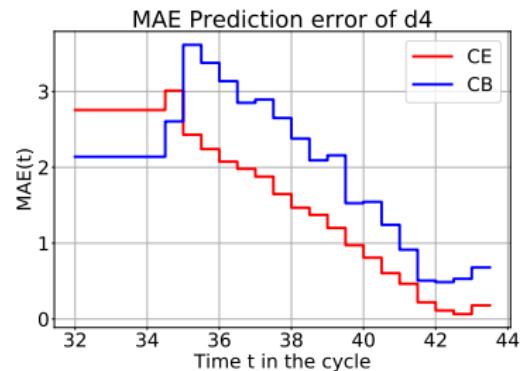
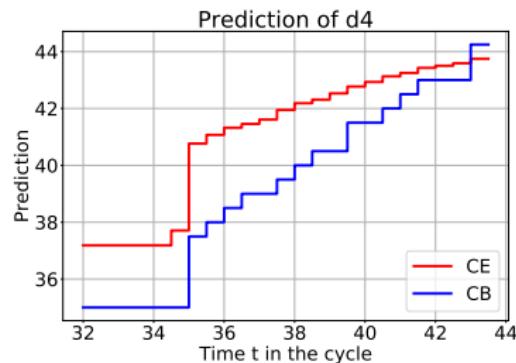
The mean Absolute Error (MAE) and Mean Square Error(MSE) of the prediction at time t are given by

$$\text{MAE}(t) = \frac{1}{n(t)} \sum_{n=1}^{n(t)} | \hat{d}_4(t) - d_4(\omega) | \quad (5)$$

$$\text{MSE}(t) = \frac{1}{n(t)} \sum_{n=1}^{n(t)} [\hat{d}_4(t) - d_4(\omega)]^2 \quad (6)$$

where $\omega = 1, \dots, n(t)$ are samples with $d_4(\omega) > t$

CE Prediction vs CB Prediction



Prediction as a minimizing loss function

- The optimal prediction $d^*(t)$ at time t is defined as

$$d^*(t) = \arg \min_x \mathbb{E}[l(x - d) | d > t] \quad (7)$$

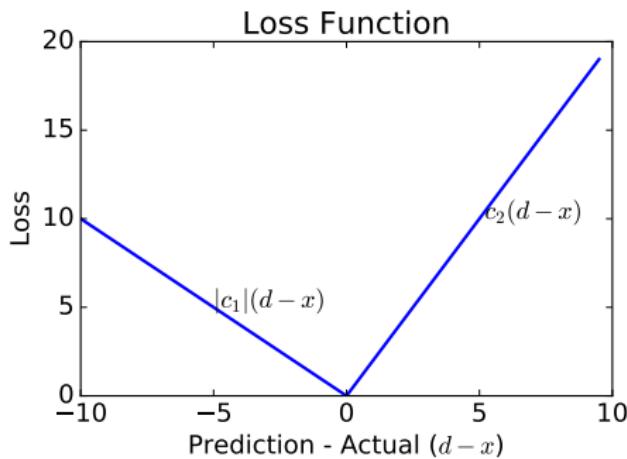
where $l(\cdot)$ is a specific loss function.

- For MSE, $l(y) = y^2$. For MAE, $l(y) = |y|$
- For MAE, both positive and negative error are judged equally harmful
- In reality, an overestimate of 'time to red' is more harmful than the same error in 'time to green'.

Prediction as a minimizing loss function

- We can have an asymmetric loss function as below

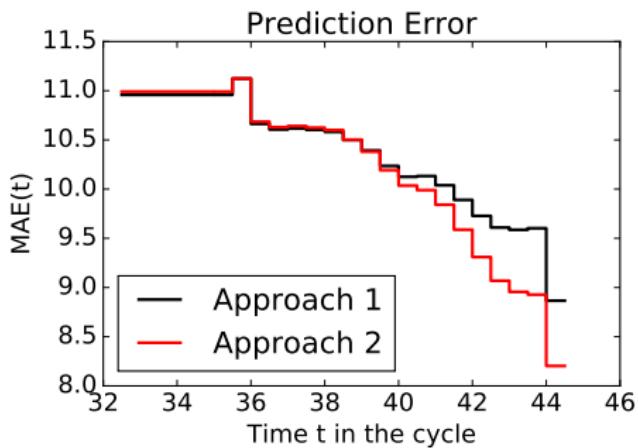
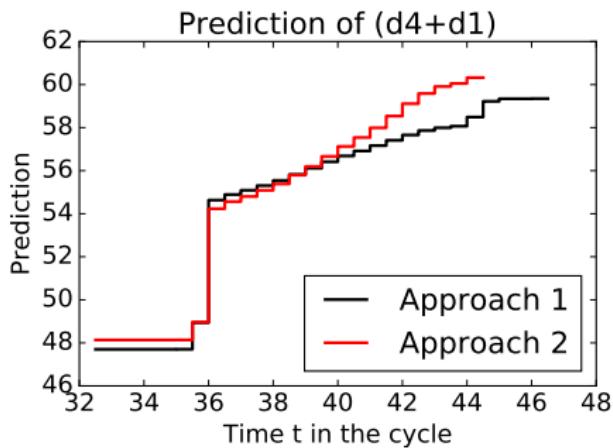
$$l(y) = \begin{cases} c_1|y|, & \text{if } y < 0 \\ c_2y, & \text{if } y \geq 0 \end{cases}$$



Prediction of other phases

- Prediction of residual phase duration d_1 given t seconds are elapsed in p_1 is similar to d_4 . $\hat{d}_1(t) = \mathbb{E}(d_1|d_1 > t)$
- Lets consider prediction of starting of p_2 while the driver is in p_4 , Here we have to predict $d_4 + d_1$ given $d_4 > t$.
 - Treat $d = d_4 + d_1$ as a single random variable and predict $d_4 + d_1$ as $\mathbb{E}(d_4 + d_1|d_4 + d_1 > t)$
 - Treat (d_4, d_1) as 2 dimensional random variable and obtain conditional distribution $\mathbb{P}(d_4 + d_1|d_4 > t)$. Predict $d_4 + d_1$ as $\mathbb{E}(d_4 + d_1|d_4 > t)$

Prediction of other phases Cont.



Another Intersection

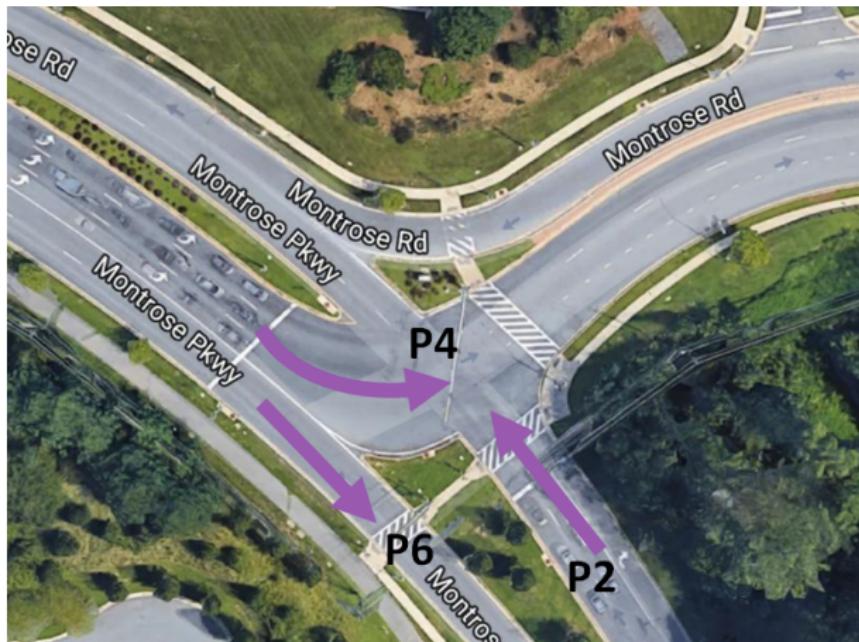
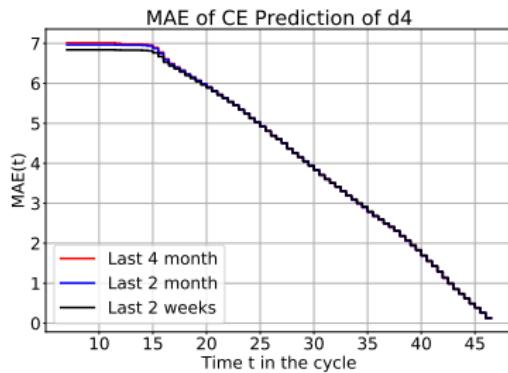
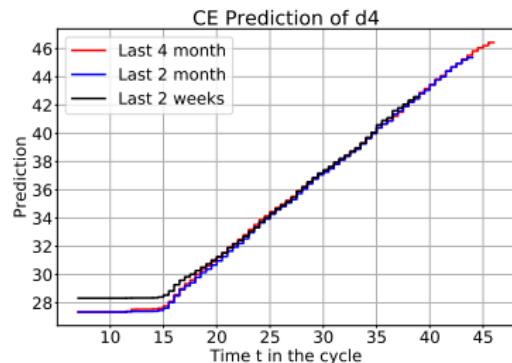
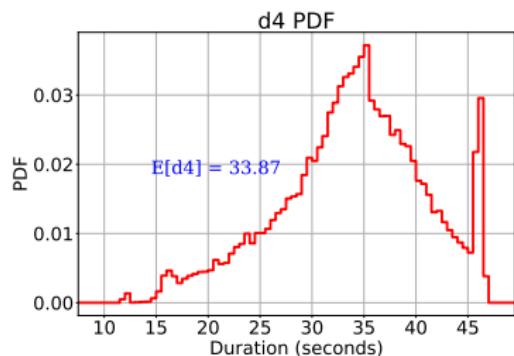


Figure: The intersection at Montrose Road and Montrose Pkwy.

Another Intersection-Results



Key Findings

- The algorithms predict the times for all future phase transitions, based on previous phase measurements and on the real time information that locates the current time within the current phase
- For actuated signals, conditioning the prediction on this real time information greatly reduces the prediction error
- For semi-actuated signals, as time increases, the estimate of the residual phase duration may increase or decrease, posing a challenge to construct fuel-minimizing speed profiles
- The best SPaT estimate is the one that minimizes the drivers own loss function

Future Work

- We can investigate vehicle detections to improve the phase duration estimations.

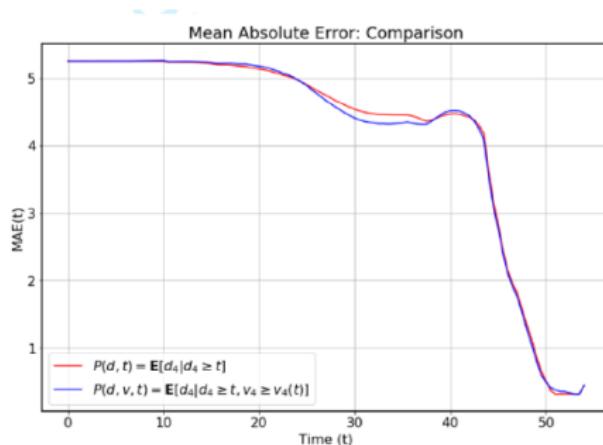


Figure: Prediction using Vehicle Detections

Future Work Cont...

- Using only vehicle detections will be realistic since managing the huge amount of data from Traffic Management servers can be avoided and GPS data is readily available. Learning algorithms on vehicle detections can be used to estimate cycle length, phase durations and predict the current phase and residual phase durations
- A generalized model which can apply for every intersections which may help in predicting the current phase and residual phase durations in multiple intersections.
- Optimising the vehicle flow through a series of intersections from the generalised model



Thank You

References

-  S. A. Fayazi, A. Vahidi, G. Mahler, and A. Winckler. *Traffic signal phase and timing estimation from low-frequency transit bus data*. IEEE Transactions on Intelligent Transportation Systems, vol. 16, no. 1, pp. 1928, 2015.
-  E. Koukoumidis, L.-S. Peh, and M. R. Martonosi *Signalguru: leveraging mobile phones for collaborative traffic signal schedule advisory* Proceedings of the 9th international conference on Mobile systems, applications, and services. ACM, 2011, pp. 127140
-  V. Protschky, S. Feit, and C. Linnhoff-Popien *Extensive traffic light prediction under real-world conditions*, 2014 IEEE 80th Vehicular Technology Conference (VTC Fall), 2014, pp. 15.