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Methodology for Evaluating Impact of Actuated Traffic Signal Control on Connected Vehicle Green Light Prediction

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ABSTRACT

Connected vehicles (CV) that communicate with traffic signals and notify the driver of expected signal status changes have emerged in the last few years. For fixed-time operations it is a deterministic exercise to predict the signal state for a given movement. However, under actuated-coordinated operation, there are stochastic variations of phase start and end times. When traffic engineers enable additional traffic responsive logic to accommodate for changes in demand, the phase timings become more challenging to predict. This paper proposes a methodology to evaluate traffic signal prediction algorithms for vehicle-to-infrastructure CV application. Data was gathered using video footage on minor and major movement of an intersection that operated in actuated-coordination. Data was collected for 176 cycles over two days. Results showed that the CV application can predict the mean start of green within +/−2.7s. The paper concludes by recommending the evaluation methodology and graphical summaries proposed be used as tools for traffic engineers and vehicle manufactures to characterize the stochastic nature of actuated traffic signals and manage expectations of motorists and other stakeholders.

Keywords: connected vehicle; time-to-green; probabilistic distribution; actuated-coordinated operation; vehicle-to-infrastructure

INTRODUCTION

During the USDOT Public Listening Summit on Automated Vehicle Policy held in March 2018, the Secretary of Transportation listed out three main visions: 1) safety, 2) infrastructure and 3) preparing for the future. Improved safety and reduced fuel consumption are imported impacts of CVs (US Department of Transportation 2018). This requires sound, robust and efficient infrastructure that can facilitate proper V2V and V2I communications. The traffic signal

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status and predicted traffic signal state is one recent development that works toward this vision. Two early applications of this technology are eco-driving and dilemma zone reduction, which need an adaptive and dynamic algorithm to provide accurate predictions.

The dynamic mobility applications proposed by the USDOT in the Multi-Modal Intelligent Traffic Safety System (MMITSS) bundle require various data elements from the SPaT message for their efficient operation (US Department of Transportation 2019). Although, the “time-to-green” or the prediction is an optional data element, the accurate prediction of traffic signal status is an important parameter for CV traffic signal applications, especially for the Intelligent Traffic Signal System and Transit Signal Priority listed by the MMITSS. In 2016, the automotive industry began deployment of traffic light status application in a production vehicle (Figure 1) (Howard 2016).

Fixed-time systems are deterministic and predicting start and stop times of phases can easily be achieved by synchronizing clocks on vehicles and traffic signals. Predicting actuated controller phasing is a significant challenge when signal timing changes in real-time with response to vehicles actuating traffic signal detectors. This research performs a comprehensive analysis that evaluates the performance of the “time-to-green” application on an intersection running actuated-coordinated system.

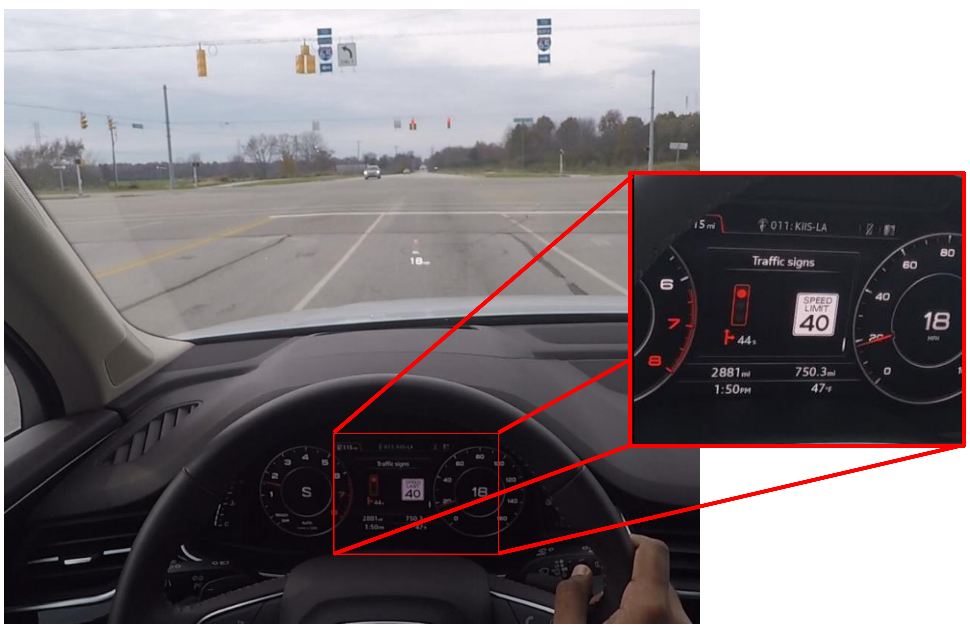

Figure 1. Dashboard with countdown timer for the next green

PREVIOUS LITERATURE

The conventional modes of traffic signal operations including fixed-time, semi-actuated coordinated and fully actuated systems are well documented (Bang 1976; Day et al. 2010; Urbanik et al. 2015). Adaptive traffic control systems (ATCS) which adjusts the timing intervals in real-time based on current traffic conditions, demand and system capacity have also been implemented for some time (Hunt et al. 1981; Lowrie 1982; Stevanovic 2010). Both the actuated systems and ATCS make use of vehicle detection infrastructure to improve efficiency, but the

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phase timings are also less predictable compared to fixed-time systems due to stochastic vehicle arrivals actuating the sensors throughout the day.

In the past decade, Automated Traffic Signal Performance Measures (ATSPM) for maintenance, asset management, and operations have been developed to assess, evaluate and make data-driven repairs, upgrades, and retiming decisions (Smaglik et al. 2007). The nature of the uncertainty of when a phase begins and terminates in sensor-actuated operation have been described by a number of tools (Day and Bullock 2011; Smaglik et al. 2007). These tools are widely used in a number of real-time dashboards (Day et al. 2014; Utah Department of Transportation 2018) and historic performance metrics (Li et al. 2017; Wu and Liu 2014) for human-in-the-loop timing plan adjustments to accommodate shifts in traffic demand.

Various studies have been performed using both simulation and real-world deployments to develop CV applications that interact with traffic signals. One such application that has gained considerable momentum is the Green Light Optimal Speed Advisory (GLOSA) system, the recommendation of an optimal speed to pass the upcoming traffic signal on green (Eckhoff et al. 2013). GLOSA requires a prediction of the traffic light status. Studies have used various modelling techniques ranging from linear programming and probability assignments (Bodenheimer et al. 2014) to Kalman filtering (Protschky et al. 2014) to predict the traffic light status at adaptive control intersections with more than 80% accuracy. However, these studies also identify the challenges encountered with actuated traffic signal controllers which are capable of changing the sequence and split time associated with each phase.

TRAFFIC LIGHT STATUS INFORMATION APPLICATION

This section describes the connected vehicle application (Figure 1) from end to end; the predicted traffic signal state change information is the key input to this application. A related desciption can also be found in (Wolf et al. 2019). The methodology behind the working concept of this application is illustrated in Figure 2 and outlined in the following sub-sections.

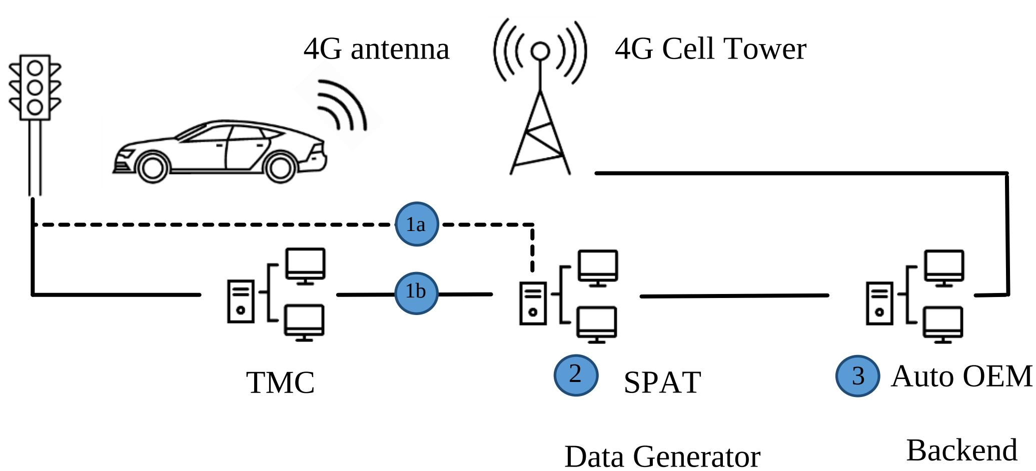

Figure 2. Real-time traffic light information system via cellular network. TMC = traffic management center; OEM = original equipment manufacturer

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Traffic Signal Data Collection

The traffic signal data collection sub-system (refer to 1a and 1b in Figure 2) is the interface to the traffic signal control infrastructure. The system polls data either directly (1a) or via the signal management system (SMS) at the traffic management center (TMC) (1b). It can collect the current timing plan, cycle second (if running on a coordination plan), phase call or detection call (pedestrian, bicycle, vehicle, transit) and Transit signal priority or preemption status. In this study, these data are received on 1 Hz frequency.

Signal State Prediction and SPaT Generation

Most traffic signal controllers do not provide information as to when they turn green/red, they only give information on their current state. Therefore, an external system (refer to 2 in Figure 2) is introduced that can work with these controllers. The created prediction SPaT (Signal Phase and Timing) message conforms to the industry standard SAE J2735 (SAE International 2016).

For actuated or adaptive signals, predicting the signal state changes becomes an essential task, and various methods have been documented (Bauer et al. 2015; Weisheit and Hoyer 2014). Overall, these methods must analyze both historical patterns and current traffic conditions including vehicle actuations, signal priorities, and preemptions, to provide the best estimate of future signal state change times. In this study, the primary prediction method is based on emulating the exact operations of traffic signal controllers (Bauer et al. 2016).

Clock Synchronization and Time Compensation

In contrast to broadcasting mechanism (US Department of Transportation 2016), this study takes advantage of the ambient cellular communication network to deliver the SPAT data. After the data is transmitted to the SPaT Generator, a central clock is maintained in the in-vehicle application to compensate for any transmission latency introduced by the cellular network. For every SPaT message received, in-vehicle application determines the latency and adjusts the in-vehicle display accordingly.

From the field deployment experiences in different metro areas across US (Audi Newsroom 2018), the clock drift issues are prominent in some cities and thus need larger compensations. As in some parts of the world, it is common practice to have the traffic signal controllers automatically synchronizing to a radio clock (e.g., DCF77 in Germany (PTB 2017)). In US, the controllers are sometime specified to synchronize to central system, it is not uncommon to see larger drifts and thus the compensations are heavier than others.

In-Vehicle Applications

Typical in-vehicle applications of SPaT data include eco-approach and departure systems, which, for example, provide the simple countdown timers to display the remaining red time; Figure 1 shows one such example on the dashboard. The system relies on receiving a map for the intersection layout. When the vehicle is matched to an approach it will show the remaining red time on the dashboard using a live SPaT message connection through the network as shown in Figure 2.

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PROBABILISTIC DISTRIBUTION OF GREEN FOR FIXED AND ACTUATED-COORDINATED TRAFFIC SIGNAL SYSTEMS

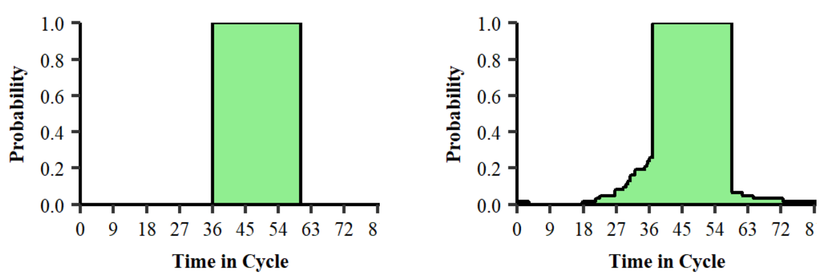
Fixed-time traffic signals typically operate on pre-defined schedules by time of day, day of week, and have fixed lengths of green time for each movement. In comparison, actuated signals depend on vehicle sensors to determine the amount of green time each movement gets, with limits determined by the time of day. In a coordinated system, there is a dedicated portion of the cycle that is green for the coordinated phases to allow for vehicle progression. When the coordinated system is also actuated, the time inside the dedicated portion of the cycle is flexible. A cyclic green time profile can be produced by using data from many cycles of an actuated-coordinated system over the same time of day period (Day et al. 2010). The probability of green is estimated using:

$$G_b = \frac{1}{N_C} \sum_{i \bmod C \in b} g_i \tag{1}$$

where G_b is the probability of green for bin b and N_C is the total number of cycles in the analysis period and g_i is the state of green for period i obtained from the high resolution traffic signal data. In this study, a bin size of 0.1s is used. Detailed computation on the probability estimation and their methodologies are well documented in the literature (Day et al. 2014, 2010; Mathew et al. 2019).

Figure 3 shows the cyclic green time profiles for two different types of signal operation of a coordinated movement over a one day period. The X-axis indicates the time in cycle and the Y-axis indicates the probability of green for a particular movement over all cycles of the analysis period. For the fixed-time operation illustrated in Figure 3a, the green time distribution is deterministic. For all of the cycles, the beginning of green (BOG) occurs at the cycle time of 36 seconds and the end of green (EOG) occurs at the cycle time of 60 seconds.

For the actuated-coordinated operation illustrated in Figure 3b, the BOG for at least one cycle occurs starting at the cycle time of 18 seconds. This is due to early return to green from one or more non-coordinated movements that have gapped out, or finished serving its demand before the allocated split time is used up, preceding it. Later into the cycle the probability of green increases, such that by 36 seconds, there is 100% probability of green, which is good for platoon progression. The EOG occurs for the majority of cycles at 60 seconds except for a few percent where there are no vehicles on the other non-coordinated movements.



(a) Fixed time (b) Actuated coordinated

Figure 3. Probabilistic distribution of green for fixed and actuated coordinated

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FIELD TEST TO EVALUATE PERFORMANCE OF PREDICTION APPLICATION

The previous section showed the variations in cycles and the probabilistic variations of the phase occurrences for two different types of traffic signal operation. This section develops a methodology to evaluate the performance of the traffic light indication application implemented in production vehicles that use V2I communications (Figure 1) to predict the phase occurrences.

As seen earlier, fixed-time systems are deterministic and easy to predict, but do not always perform efficiently in low or changing-demand scenarios, such as shoulder periods or late-night operation. However, fixed-cycle and optimized offset coordinated systems have significant benefits, such as reducing emissions and number of stops (Eckhoff et al. 2013; Katsaros et al. 2011). Actuated-coordinated systems introduce some flexibility to fixed-cycle operation, but are considerably more complex and challenging to predict time to next phase, hence it was decided as the test scenario to apply the phase probabilities methodology.

Data collection and methodology

Currently, the traffic light indication application is designed to provide time-to-green predictions as the vehicle approaches the traffic signal. This means that prediction is only displayed if the vehicle arrives at the intersection during the red phase. Hence, the ideal data collection procedure will be to drive the vehicle in multiple laps across the intersection. However, this is time consuming and the chances of making the red time is small on a well-coordinated system. An alternate solution is to park the vehicle on the right lane shoulder of the approach being evaluated at about 200 to 300 feet in advance of the stopbar. The application displays the prediction for the start of a movement based on a combination of the GPS coordinates of the vehicle and the status of the right/left turn indicator.

With the vehicle parked near the intersection, the countdown timer activates from the onset of red. This provides another opportunity to evaluate the performance of system at various time intervals before the actual prediction. In addition to the final countdown time (usually 4s), it was decided to compare the predictions at 30s, 20s and 10s horizons within the countdown. This will also be another indicator of the variations involved in the actuated-coordinated system.

US-231 & Cumberland Avenue in West Lafayette, Indiana was chosen as the test intersection. This is a typical four-legged intersection that runs actuated-coordinated with the major street US-231 (north and south) coordinated. The performance of predictions was tested for both major and minor movements – northbound through (NBT, phase 2) and westbound left (WBL, phase 3) – for a period of 4 hours between 09:30 and 13:30. A total of 176 traffic signal cycles were evaluated. Figure 4 illustrates the phasing and sequencing diagram at this intersection. During the timing plan between the 9:00 and 15:00, the intersection operated with a cycle length of 82s.

Figure 5a shows the vehicle location during data collection. For testing the NBT movement, the vehicle was parked on the NB right lane shoulder (Figure 5b). For the WBL movement, the vehicle was parked on the WB right lane shoulder with the left turn signal turned on. Figure 5c shows the data collection setup inside the research vehicle. Video data collected at 30fps from two time-synchronized cameras was used to compare the actual event and prediction. The "dashboard cam" recorded the traffic signal countdown prediction (similar to Figure 1) on the dashboard and the "traffic signal cam" captured the actual status of the traffic lights at the intersection.

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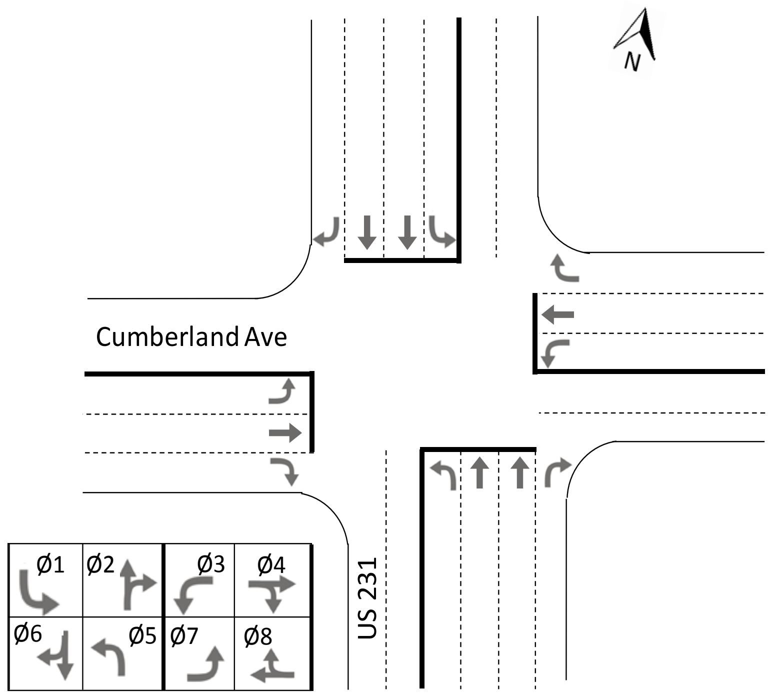

Figure 4. US 231 and Cumberland Ave intersection diagram

Figure 6 shows an example of the data extraction process during which the two videos were compared to each other. The timestamp (shown on the top left corner in Figure 6a) of the red signal countdown timer at pre-defined intervals of 30s, 20s, 10s and final display (usually stops at 4s to avoid driver distraction before the start of green) was extracted using a video editing tool. The predicted time of green was then estimated by adding the respective time (30s, 20s, 10s, and final display) to the timestamp. For example, in Figure 6a, the final step of the countdown timer (4s) disappears at the timestamp 12:26:05.467. The predicted green time timestamp is calculated to be 12:26:09.467 after the addition of 4s. This is compared with the timestamp when the signal actually turns green in the field (12:26:10.367 from Figure 6b), to estimate the residual (given by Equation 2) and determine whether the prediction was early, on time or late. In this case, the residual for the final prediction is -0.9s, which indicates that the final prediction was early by 0.9s.

$$\textit{Residual} = \textit{Predicted green start time} - \textit{Actual green start time} \quad (2)$$

RESULTS

Table 1 shows the results of the prediction residuals from 176 cycles observed on both NBT and WBL movements. Samples indicate the number of cycles where a prediction was observed. For example, 103 cycles (out of 176 cycles) had a prediction at 30s for the NBT movement. On average, the final prediction was late by 1.9s for NBT and early by 0.3s for WBL. Looking at the median values for both the movements, the final predictions were within 0.7s of the actual time. Results also show that the final prediction can vary between 1.17s and 2.75s for the NBT movement at 95% confidence intervals. Similarly, for the WBT, the final prediction can be

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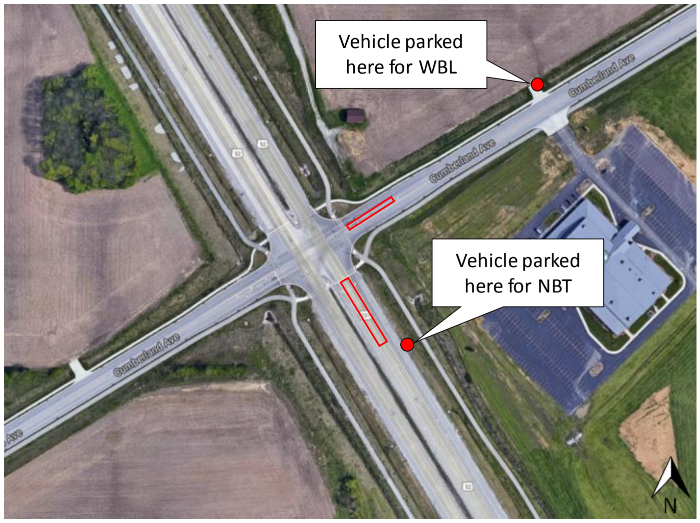
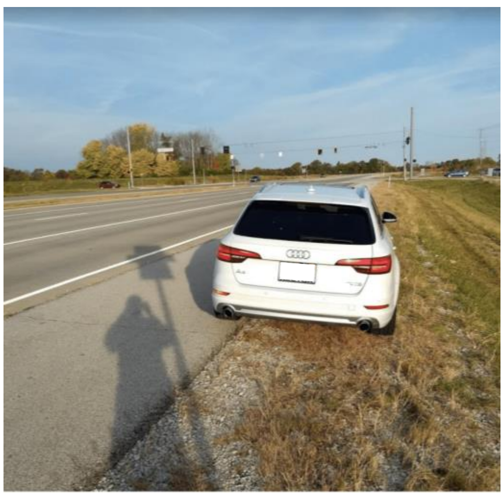
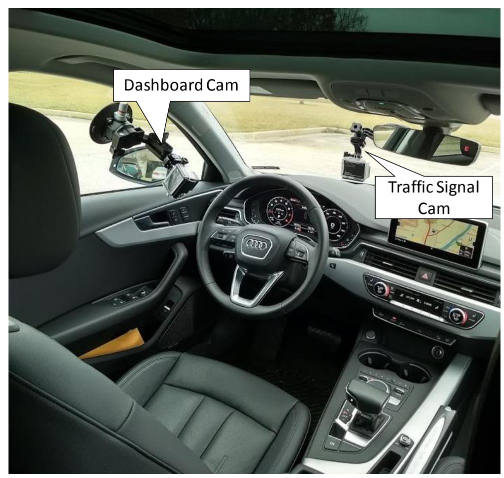
between -1.24s and 0.63s. Overall, more than 80% and nearly 60% of the predictions were within +/- 5s for NBT and WBL movements, respectively.



(a) Overview of vehicle location



(b) Vehicle parked near NB shoulder



(c) Data collection setup inside the vehicle

Figure 5. Data collection setup

Figure 7 and Figure 8 shows the scatter with lines plot of the residuals for NBT and WBL respectively. The late predictions at the far-right end of the tail (callout i) are mostly due to the previous phase gapping out. In contrast, early predictions on the left end of the tail (callout ii) are due to vehicles arriving late into the split on the previous phase that extends the green time.

Comparing the results across the 30s, 20s, 10s and final prediction, one would expect the results to be inversely proportional to the time from actual event. The mean and standard deviation of the residuals decreases from 30s to 10s, however, they both increase for the final prediction. This is likely due to the green extensions and gap-outs from the actuated-coordinated system, which provide efficient allocation of green time, but makes it challenging to predict when phases will terminate due to a detector “gap out.”

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(a) Final red signal countdown time (4s) before it disappears at 12:26:05.467

(b) Actual start of green at 12:26:09.567

Figure 6. Extracting timestamps for prediction tests

Table 1. Prediction Residuals

Prediction	**30s**		**20s**		**10s**		**Final (usually 4s)**	
Movement	NBT	WBL	NBT	WBL	NBT	WBL	NBT	WBL
Samples	103	132	108	137	134	138	145	152
Mean (μ)	2.379	0.109	1.951	0.042	1.250	-0.358	1.961	-0.306
Median	1.033	-0.717	0.933	-0.633	0.583	-0.55	0.776	-0.584
Std Dev (σ)	6.189	6.354	4.337	5.740	3.217	5.146	4.859	5.857
95% CI	[1.184, 3.574]s	[-0.975, 1.193]s	[1.133, 2.769]s	[-0.919, 1.003]s	[0.705, 1.794]s	[-1.216, 0.501]s	[1.170, 2.752]s	[-1.237, 0.625]s
Within ± 1s	19.42%	15.15%	28.70%	18.425%	29.85%	26.81%	22.76%	23.03%
Within ± 5s	66.99%	56.06%	80.56%	59.12%	86.57%	64.49%	80.69%	59.87%
Within ± 10s	86.41%	88.64%	94.44%	90.51%	99.25%	93.46%	93.10%	91.45%

CONCLUSIONS

This study evaluated the accuracy of a vehicle-to-infrastructure (V2I) application, known as the traffic light status information, which predicts the start of green as the vehicle approaches the traffic signal for the vehicle's movement. Tests were conducted for the minor and major movements of a four-legged intersection that ran actuated-coordinated operation. Results showed that the application can predict the mean start of green within +/- 2.7 seconds (at 95% confidence

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intervals). However, on a cycle-by-cycle basis, it was observed that nearly 80% of the phase indications could be predicted within +/- 5s even with the stochastic vehicle detection and real-time controller logic.

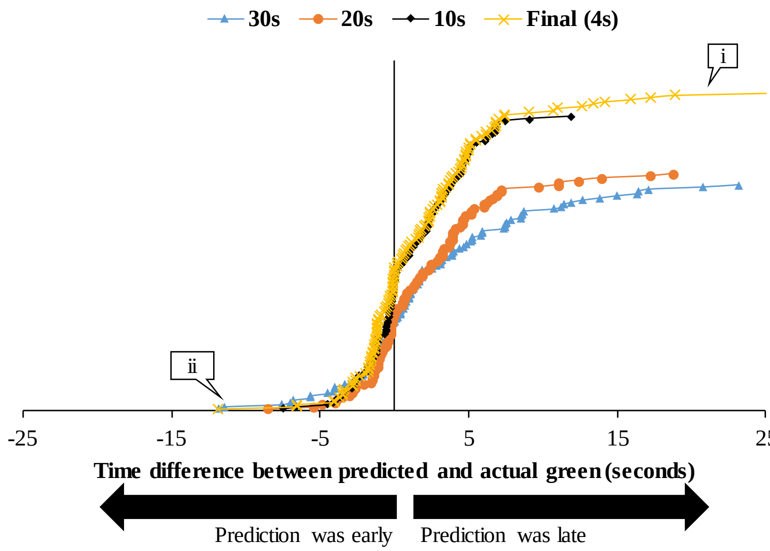

Figure 7. Residual plot for NBT

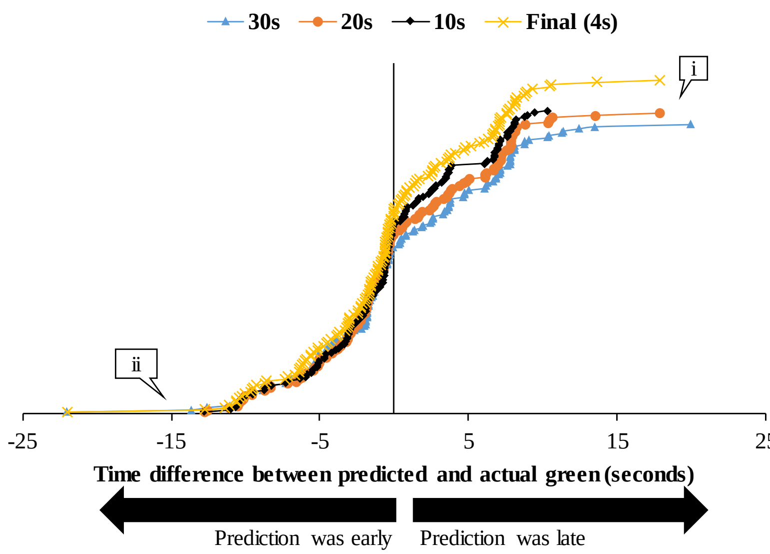

Figure 8. Residual plot for WBL

As connected and autonomous vehicle applications gain ground, traffic signal prediction will be important to facilitate safe, efficient, and economic driver advisory and eventual automated controlling of vehicles. However, modern signal controllers are adaptive to changing traffic conditions, so the signal states become more challenging and unpredictable. Some of these effects do lead to inaccuracies in any prediction protocol. For fixed-time operations (Figure 3a) it is an arithmetic exercise to determine the future signal state. However, under actuated-

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coordinated conditions Figure 3b), there is significant stochastic variation of the phase on and off times due to the random arrival of vehicles. Longer term, the authors anticipate these quantitative graphics and analysis methodology developed in this study will help facilitate dialog between automotive manufacturers, signal controller vendors, and agencies. For instance, this may result in a "phase-next" data flag provided by signal controllers to inform the vehicle of a deterministic window to update their phase predictions 5 to 7s prior to start of the next phase.

A precondition for safety critical applications involving SPaT messages, such as autonomous driving is to know if the time window can be relied upon. As connected vehicle (CV) technology becomes more widely implemented in production vehicles, it is vital to have a technology that provides an accurate estimation of the signal status. The automotive industry is accustomed to tight tolerances; however, modern traffic signals operate much more stochastically. Accurate prediction of traffic signal status will be imperative for CVs to implement eco-driving and Green Light Optimized Speed Advisory (GLOSA). In cases where bad predictions are frequent, other data elements such as confidence levels can assist in the application design for safety concerns, such as hiding any low confidence predictions.

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