A methodology for signal timing estimation based on low frequency floating car data: Analysis of needed sample sizes and influencing factors

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Abstract
The objective of this paper is to analyze the estimation quality of a staged methodology, that allows the estimation of signal timing information like cycle length, green and red time intervals for time-dependent fixed-time controlled and actuated intersections based on low-frequency and sparse floating car data (FCD). The paper exemplifies, based on simulated dataset, the estimation approach, which assumes as a principle condition the daily repetition of similar signal plans, whereby identical daytime and workday periods are aggregated to reach a sufficient trajectory density. The established concept utilizes efficiently small amounts of FCD trajectories that cover typical sampling intervals between 15-45 seconds. The introduced approach considers three processing stages. Firstly, map matching, data decomposition and stop line estimation are required. Secondly, trajectories’ stop line crossing times are calculated, whereby crossing times of all trajectories are iteratively projected by the application of a modulo operation into the time scale of potential cycle lengths. A statistical data analysis is carried out to estimate cycle lengths and daytime slices with similar signal program patterns. Finally, the last stage of the used approach considers the precise estimation of red and green time intervals based on a histogram analysis. The paper conclusively analyzes the signal program estimation quality considering different degrees of saturation and trajectory sample sizes.

Keywords: FCD, Floating Car Data, signal timing estimation, low frequency
1 Introduction

Stops at traffic lights significantly influence the road network capacity and impact the emissions of motorized traffic strongly. Increasing traffic demand urge infrastructure operators as well as the automotive industry to act. On the one side minimizing stops and hence reducing delays and emissions in road networks could be achieved by the optimization of traffic lights (Pohlmann et al., 2010). On the other side drivers could also contribute to emission reduction while driving with foresight and using the advice of a Green Light Optimized Speed Advisory (GLOSA) (Eckhoff et al., 2013). Assistance concepts like GLOSA or even simpler automatic start/stop functions need a reliable estimate of signal switching times at signalized intersections. Actual methodologies focus on the processing of signal switching data provided by centralized traffic control systems. Other approaches are based on the processing of local traffic signal data in combination with a bilateral short range communication between vehicle and infrastructure to transmit forecasted switching information (Barthauer et al., 2014; Braun et al., 2009). This concept requires large investments which are hardly financeable by road authorities. During the recent years the increasing availability of floating car data (FCD) caused by the popular use of modern smartphone navigation software offers a promising data source to estimate signal timing information like cycle length and green/red time interval based on this ubiquitous data source.

Until now there has not been much research focusing on signal timing estimation that considers temporary sparse probe vehicle data, so called low-frequency FCD, supplied typically by commercial data providers (Axer et al., 2015; Fayazi et al., 2015; Liu et al., 2012). Therefore, further effort is needed to investigate the capabilities of signal timing estimation by taking into account low-frequency FCD with low penetration rates. This paper is connected to research from (Axer et al., 2016; Axer et al., 2015) that provides an offline-approach to estimate signal timing information for periodic signal controlled intersections, based on a sparse historical low frequency floating car dataset. The used methodology for signal timing and phase estimation will be exemplified in detail, taking into account data samples from a microsimulation model. Furthermore, the usage of a microsimulation allows later an analysis of the estimation quality and important influencing factors.

2 Related work

The problem of the estimation of signal timing and phase information based on vehicle trajectory data has been analyzed under consideration of different data requirements and methodical approaches (Fayazi et al., 2015; Kerper et al., 2012; Liu et al., 2012). Until now methods introduced have in common, that they are using FCD with relatively high penetration rates and/or high sampling frequencies. The main characteristics of sparsity and density differ strongly from typical data situations being available in European cities.

Kerper et al. (2012) performed a first feasibility study for fixed-time controlled intersections using only simulated FCD with a high sampling frequency of 1 Hz and also a high penetration rate that differs from typical commercial FCD. The basic principle lies in the determination of green time interval beginnings by observing the acceleration process of vehicles in relation to their stop line distance. Cycle length information gets continuously calculated based on the time difference of consecutive green time interval beginnings. To be able to determine the cycle length online, the algorithm needs at least two qualified trajectories during a time period of a constant signal program. Green and red times get calculated for each cycle by the analysis of crossing and stopping times of each vehicle. This process requires typically a very dense data source.

Fayazi et al. (2015) developed referring to Kerper et al. (2012) an approach using low-frequency but high periodic trajectories provided by a bus transit system in San Francisco. The study considers the combined data of two high frequently used bus routes which allowed the collection of 4289...
trajectories per month on one particular intersection movement. Trajectories that show the driving
sequence of deceleration, stop and acceleration allow the calculation of the red time interval. To filter
these specific trajectories, the algorithm calculates in a first instance the delay time of each trajectory.
Furthermore, each qualified trajectory provides even rough information of the green interval beginning
for each phase by means of a simple dynamic driving model that tries to estimate the beginning of
acceleration, using a constant acceleration rate. Assuming again a fixed-time controlled intersection
the time interval between consecutive green interval beginnings could be estimated, as it needs to be a
multiple of the cycle length. The authors showed that a precise online cycle length estimation needs at
least two qualified trajectories in approximately 5 min. Red and green time interval estimates need
even to be observed by multiple vehicles to ensure representative results. The main advantage of the
introduced approach lies similar to Kerper et al. (2012) in the capability of time continuous analysis of
consecutives trajectories, that enables the detection of an adapted signalization, i.e. modified cycle
length, green and red time.

In contrast to the introduced methods, the algorithm called “POVA” from Liu et al. (2012) aims at
the online signal timing estimation for actuated and adapted signal control. The traffic light state
estimation requires a historical dataset that combines driving speed, distance to stop line and the most
likely traffic state in the moment of FCD generation during vehicles’ approach. The likelihood of a
traffic state, linked to stop line distance and driving speed, has been calculated by a maximum a
posterior (MAP) estimation. Recently generated probe data get compared to the historical dataset to
find out the most likely traffic state, by maximizing the similarity between historical state series and
actual state series. Having a closer look on the used data source reveals, that Liu et al. (2012) could
utilize at 62 % of all intersections in the test site of Shanghai. whereby 120 trajectories or state reports
in a period of two hours could be used. That means, the floating car data source is capable to supply in
average one trajectory every minute.

Axer et al. (2015) developed a FCD driven approach, that is capable to infer cycle length and
red/green time intervals for time-dependent fixed-time and even slightly actuated controlled
intersections. As a basic principle, the approach analyzes the moment in time, when vehicle’s
trajectory crosses the intersection’s stop line as well as the moment, when vehicles remains with low
momentary driving speed in front of the stop line. The methodology requires similar and recurring
signal program patterns for equal day time periods. That means, at all hours of a workday for an
extensive time period (i.e. year or half-year), the intersection’s signal program behaves nearly
identical. Therefore, the developed approach tries to estimate offline the mostly observed signal
program for typical day time situations (also named as a time slice in this paper) based on a historical
floating car dataset.

As crossing and stopping vehicles are the exploited information in this approach, their sample sizes
and their distributions need to have a fairly large impact on the signal program estimation quality.
Therefore, the objective of this paper is also the analysis of the interdependencies between trajectory
sample sizes, movement’s degree of saturation and the signal program estimation quality. In advance
to this analysis, chapter 3 summarizes the approach used for signal program estimation.

3 Signal program estimation

3.1 Pre-requirements & assumptions

The methodology described in the following subsections is valid for fixed-time control and even
actuated signal control, where cycle length and phase sequence stay constant and traffic signal clock is
managed by a central traffic control computer that guarantees a constant synchronization between
clock and cycle. The method assumes, that at the same time of day the traffic controller shows a
periodical signalization. In case of an actuated signal control, in which green time intervals could be
actuated in a pre-defined frame (earliest green beginning, latest green end) the methodology has the capability to detect the most common green time interval. The terms suggested are reasonable because at daily recurrent situations with very high traffic demand, the most amount of FCD is generated and even actuated traffic control behaves nearly like a fixed-time controlled intersection.

3.2 Stage I - Basic trajectory pre-processing

The first stage covers the pre-processing of raw data – namely the map matching, intersection data selection and the needed estimation of the stop line position for each intersection’s approach. Concerning the path inference and map matching process this paper is oriented mainly on the research from Lou et al. (2009) and Axer et al. (2015), where the most probable path of a consecutive series of trajectory’s data points \( p_1 \rightarrow p_2 \rightarrow \ldots \rightarrow p_n \) is obtained. The map matching algorithm first projects trajectory’s raw data points based on the Euclidian distance function to the surrounding road network – the so called candidate point generation process. A consecutive shortest-path algorithm finds routes between adjacent candidate points (candidate graph generation). A search algorithm gets finally involved to find the path through the candidate graph by maximizing a global performance measure. The map matched data needs to be selected for a certain intersection and logically decomposed into all occurring driving directions. This process could easily be done in a first instance by a simple database query that creates logical data subsets, since trajectories for a certain driving direction need to travel along a known sequence of network links. Decomposed data is analyzed to estimate stop line positions, needed for later processing. The stop line position estimation is a very sensitive process for the later crossing time calculation, as faulty stop line information will lead directly to erroneous crossing times. Axer et al. (2015) have already tested the inferring of the stop line position from aerial images. Nevertheless, a map matched trajectory set for a certain driving direction could be exploited to derive a data-driven estimate of the stop line as a second reference, as trajectories’ data points with slow momentary driving speed lower than 3 km/h should reach highest density in the near of the stop line (Axer et al., 2016).

3.3 Stage II - Classification of similar day times

The second stage covers two processes. Firstly, data needs to be pre-selected for a time period (weekdays) where signal control is assumed to stay constantly. Secondly, for this selected time period the method tries to find time slices (hours of the day) in which signal program looks identically. In the following, the authors are assuming, that a traffic signal program stays constant during an entire year on all weekdays from Mon. to Fri. During each workday, signal program changes systematically to different cycle lengths and/or different red/green time intervals. In preparation for explaining the next steps, we have developed a simulated model for a signalized intersection that uses three different signal programs over a total simulation runtime of 48 hours, whereby program sequence is repeated after the first 24 hours for the second day (see Table 1). The objective is now to investigate the cycle length that fits best to the overall time period of one day. In other words, which cycle length could be observed mostly by our historical trajectory subset, when all trajectories between Mon. to Fri. of the entire year are aggregated to one large subset? Axer et al. (2015) have shown, that under the introduced conditions, each trajectory \((k)\) passing the stop line reveals a cyclic periodical behavior

<table>
<thead>
<tr>
<th>Program Nr.: [-]</th>
<th>Time of day [24-hour clock]</th>
<th>Cycle time [s]</th>
<th>Green beginning [s]</th>
<th>Green end [s]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Program 1</td>
<td>0 - 6; 10 - 15; 19 - 24 h</td>
<td>60</td>
<td>0</td>
<td>30</td>
</tr>
<tr>
<td>Program 2</td>
<td>6 - 10 h</td>
<td>90</td>
<td>0</td>
<td>46</td>
</tr>
<tr>
<td>Program 3</td>
<td>15 - 19 h</td>
<td>85</td>
<td>0</td>
<td>43</td>
</tr>
</tbody>
</table>

Table 1: Traffic program configuration (simulation case)
when projecting all timestamps of complete trajectory \( \tilde{t}_k \) from real time scale into the time scale of the correct cycle length \( c \). This projection uses the following modulo operation and needs a pre-defined reference time \( t_{ref} \).

\[
\tilde{t}_{k,c} = \text{mod}_c(\tilde{t}_k - t_{ref})
\]

Projecting trajectories’ timestamps into the wrong cycle length leads to a non-cyclical repetition. This periodical effect provides the basis for the estimation and is shown in Figure 1 (top), where data has been obtained by a microsimulation model and the correct cycle length has been 60 secs. Having introduced the cyclicality of trajectories under correct cycle length, one could expect that in case of an incorrect cycle length, the distribution of stop line crossing times \( \tilde{t}_{c,cross} \) for all trajectories would follow a uniform distribution with the parameters \( a=0, b=c \). If the cycle length is correctly chosen, the distribution of \( \tilde{t}_{c,cross} \) would deviate dramatically from this theoretical uniform distribution, as vehicles should cross mainly the stop line only in the green time interval.

The deviation between empirical distribution and theoretical uniform distribution in particular could be exploited by the application of the A-D-Test (Anderson-Darling-Test) (Anderson et al., 1954) that evaluates the goodness-of-fit between the theoretical cumulative density function (CDF) and empirical cumulative density function (ecdf) of \( \tilde{t}_{c,cross} \) based on the A-D distance (see Figure 1 - bottom). The objective of the A-D Test is to disprove the hypothesis that empirical cumulative density function arises from the assumed theoretical uniform distribution by considering a critical p-value. Having reached a p-value (\( p \)) less or equal than 0.05 allows statistically to disprove the assumed similarity. In addition to this critical p-value the empirical distribution that reveals the highest dissimilarity between ecdf and CDF is searched. Because cycle length is usually located in a limited range, one could simply iterate the introduced A-D-Test over a reasonable cycle length range between 30 and 120 secs in order to find results, where p-value does not exceed 0.05 and A-D distance reaches very high values. Figure 1 (bottom) illustrates calculated A-D distances over different cycle
lengths for the introduced simulated signal program. The A-D distance reaches a global maximum for a cycle length of 85 secs, while the cycle lengths of 60 secs and 90 secs differ also strongly from all other tested cycle lengths.

The sample sizes of trajectories, needed to identify the correct cycle length based has been analyzed in Axer et al. (2016) and depends highly on the underlying ratios between green time interval and cycle length per movement. For further processing, we assume a minimal needed sample size of \( \rho = 100 \) crossing times to be able to estimate correctly at least the cycle lengths for different time slices of the day. Since the previously calculated A-D distances show a global maximum for a cycle length of 85 secs (see Figure 1), this cycle length will be used for ongoing processing first, as it indicates the cycle length that could be observed mostly by the simulated trajectory subset. Figure 2 (top) shows all trajectory stop line crossing times \( t_{c=85,cross} \) over the daytime period after applying modulo operation (Eq. 3). Between 15:00 to 19:00 h crossing times \( t_{c=85,cross} \) show a well-defined non-uniform distribution, whereas \( t_{c=85,cross} \) follows on all other times obviously again a uniform distribution.

To be able to detect the start and the end of a time slice with a very similar signal program, we propose to create a discrete crossing time matrix. The complete daytime period is divided into 60 minutes (column index \( j \in [1; n] \)) and the cycle length is divided into classes of 5 secs duration (row index \( i \in [1; m] \)). It should be mentioned, that these class widths could be adapted to the overall sample size of \( t_{c,cross} \) for further research. Figure 2 (bottom) represents the result of this discretization process by using grey colors for different cell states. Each cell \( (B_{ij}) \) represents one of the following states: crossing vehicles \( (B_{ij}=1=\text{light grey}) \), no crossing vehicles \( (B_{ij}=0=\text{dark grey}) \), insufficient data \( (B_{ij}=Na=\text{grey}) \). The state \( (B_{ij}=Na) \) is assigned in that case, in which \( \rho \) is smaller than the pre-defined minimum sample size of 100. To be able to reliably assign the cell states, one has to consider two elementary issues. Firstly, Figure 2 shows only a simplified example, where vehicles are crossing the stop line just during the green time. In reality, vehicles could even cross illegally the stop line during

![Figure 2](image_url)

**Figure 2:** Distribution of \( t_{c} \) for a selected cycle length of 85 sec (top); Discretized crossing time matrix - with \( m = 17 \) and \( n = 24 \), light grey = crossing vehicles, dark grey = no crossing vehicles, grey = inefficient data (bottom)
the red time or the intersection could be temporary maintained – so cyclical behavior could be
interrupted. Furthermore, the map matching process and the spatial inaccuracy of GPS could lead to
erroneous crossing times that need to be handled for a correct assignment of matrix states \( B_{ij} \). Secondly, the existence and the amount of these erroneous crossing times are unknown, which implies
that a pre-defined threshold value, that incorporates a minimal needed amount of crossing times for
each cell, could not guarantee a correct state assignment by compensating erroneous crossing times.
To overcome this problem efficiently, the used approach establishes the state assignment of \( B_{ij} \)
column-wise based on a critical density \( \rho_{j,\text{crit}} \) that needs to be exceeded, to set \( B_{ij} \) to state one. Figure
3 (left) illustrates therefore a histogram of crossing times covered by one particular column \((j=16\) from
Figure 2) of the crossing time matrix, whereby each column covers data of a 60 min wide time period
and the histogram bins \((i)\) are again set to 5 sec. One could state, that the density of the crossing time
distribution starts rising at the end of the cycle, reaches a maximum at the beginning of the cycle and
decreases to zero between 50 to 75 secs. To estimate an appropriate density threshold value that filters
potentially erroneous crossing times (noise) occurring densities are classified into 10 equidistant
classes (see Figure 3 right). The densities could be divided into two groups, whereby each density
group is represented by a local density maximum. As higher densities should only occur during the
green time, the higher density group belongs to the green time interval. On the opposite, lower
densities correspond to the red time interval of the cycle that could contain potential noise. The most
frequent and likewise lowest density (see Figure 3 right) could simply be used as a noise indicator. If
the local maximum of the low density group shifts to higher densities, the data distribution needs to be
covered by a higher amounts of erroneous crossing times.

If absolutely no erroneous crossing times (noise) could be sampled and the crossing time
distribution follows perfectly a uniform distribution, Figure 3 (right) should reveal only two clear
peaks exactly in the first and the last bin of the histogram. In this simulative example the crossing time
distribution raises relatively fast but drops slowly. This effect could be also observed in reality and is
highly correlated to the movement’s degree of saturation, which will be analyzed later on chapter 4. In
this situation the low density maximum is surrounded by other small densities. Nevertheless, the upper
boundary of the class with the most frequent and likewise lowest density could be approximately used
as an estimator for the needed critical density \( \rho_{j,\text{crit}} \) value (see Figure 3 right; dashed vertical line). To
level smaller density variations as best as possible, densities have been smoothed slightly by the
application of a moving average with a Epanechnikov smoothing kernel (window size = 3) (Wand et

\[ \text{Figure 3: Histogram of crossing time distribution and density threshold - dashed horizontal line (left);}
\]
\[ \text{Histogram of occurring densities and inferred density threshold - dashed vertical line (right)} \]
al., 1994). This introduced critical density approach has been applied for each $B_{ij}$ by calculating $\beta_{j,\text{crit}}$ column-wise for the complete matrix.

Figure 2 indicates that between 22:00 to 06:00 h not enough crossing times could be sampled in this simulation, whereby between 15:00 to 19:00 h one could clearly identify an area of cells, where vehicles are crossing only during a certain time interval. In this specific daytime period the rest of the cycle length is not used for stop line crossings over a time window of approx. 35 sec. Next, one has to consider the constructed matrix row-wise ($i$) to infer time slices with constant signal programs. Summing up all cell states for one particular row ($i$) cumulatively allows the identification of transitions between different signal programs, since the cumulative sum of cell states for one row ($i$) stays constant, where the cell state was set to zero and increases linear, where cell state was set to one. The transitions between a constant and non-constant part of the cumulative sum reveals therefore signal switching times over the daytime period. (see Figure 2 bottom, vertical dashed lines). Mathematically the state $B_{ij}=\text{Na}$ is handled as $B_{ij}=0$. The explained procedures need to be repeated for all remaining best cycle times that have been inferred (60 and 90 secs). At the end of stage II one has derived a list of the signal program switching times, whereas between the switching times signal program could be assumed to be very similar. In this example the inferred switching times for each tested best cycle is shown in Table 2. As each tested best cycle length will generate an individual list of signal switching times, all inferred switching times are needed to be cleaned, to remove duplicates. The combination of consecutive switching times allows finally the generation of time-slices with similar signal programs that will be used in the ongoing last processing stage III.

### 3.4 Stage III - Time-sliced crossing times analysis

Up to now one has already inferred time slices, where cycle length, red and green time are nearly constant. Stage III is dedicated to the estimation of more exact red and green time intervals for each of these calculated time slices. For this purpose, the crossing times distribution of a previously inferred time slice is analyzed in more detail. To explain the developed methodology based on a realistic example, stage III uses again data from the same simulated intersection (Program 3, see Table 1). The crossing times vector over a previously derived time slice with a known cycle length will be called $\overrightarrow{t_{ts,te}}$ ($ts =$ beginning of time slice, $te =$ end of time slice). The vector $\overrightarrow{t_{ts,te}}$ summarizes analogously all times of stopping data points up to 10 m upstream of the calculated stop line position, where the momentary GPS-speed has been lower than 3 km/h. The data provisioning of $\overrightarrow{t_{ts,te}}$ needs to be considered as an optional data input, because momentary GPS-speeds are not a standard feature of every floating car data source.

As a part of a histogram analysis, both vectors $\overrightarrow{t_{ts,te}}$ and $\overrightarrow{t_{st,te}}$ are discretized into classes of one second. Next, one could assume that red and green time intervals need to be coherent time intervals each time – i.e. no gaps during red and green time interval. Furthermore, it is reasonable to assume, that most of the vehicles will report crossing times in the near of the green time beginning and most of the stopping times will be reported at the end of the red time interval – hence the effect of the crossing time peak will be exploited in the following. The delay between real green beginning and first stop line crossing has been analyzed heavily in literature under the term of start-up loss time. Bester et al. (2002) have summarized several empirical researches, done in the last years. As a result of their field

<table>
<thead>
<tr>
<th>Best cycle length [s]</th>
<th>Detected switching times for tested best cycle length:</th>
<th>Uniquely detected switching time [24-hour clock]</th>
</tr>
</thead>
<tbody>
<tr>
<td>85</td>
<td>0, 6, 15, 19, 22, 24</td>
<td>0, 6, 10, 15, 19, 22, 24</td>
</tr>
<tr>
<td>60</td>
<td>0, 6, 10, 15, 19, 22, 24</td>
<td></td>
</tr>
<tr>
<td>90</td>
<td>0, 6, 10, 22, 24</td>
<td></td>
</tr>
</tbody>
</table>

Table 2: Detected switching times for dependent on best cycle length.
campaign one could say, that start-up loss time lies on average between 2.7 to 3.2 seconds. Therefore, we assume that the crossing time peak will be reached approximately 3 secs after the real green time beginning.

Due to the fact that \( t_{gt,ste} \) and \( t_{st,ste} \) could include only a relatively small amount of samples, it is suitable to apply a smoothing function on the generated histograms (see Figure 4). After having smoothed both histograms the used methodology tries to classify each cycle second again to a binary state of one or zero. In terms of the green time histogram the state one classifies a cycle second to green, state zero classifies a state to red. The same approach is also applied for the red time histogram.

To be able to handle again noisy histograms, the used classification process considers in principle the same critical density approach as already explained in stage II. Below this critical density all cycle seconds are set automatically to zero. This threshold could be also interpreted as a filter. In the context of this paper noise is defined as uniformly distributed crossing or stopping times that could lead to a systematic density offset during histogram analysis. This noise could occur, when a time slice of \( t_{gt,ste} \) or \( t_{st,ste} \) covers more than one traffic signal program for a few minutes. When working with the introduced critical density threshold, a temporary density drop in histogram could lead to time gaps during the second-wise state classification process. In these particular situations density could become lower than the critical density for a short time period and the green time interval could be shortly interrupted (faulty gap). The very same situation could happen when a small amount of drivers

Figure 4: Histogram of crossing times (top left); Histogram of stopping times (top right); Classified states for green and red time intervals (bottom)
crossed the stop line during the red time interval, as they could lead to a short density increase in the green time histogram (faulty peak). To overcome these faulty situations, it is necessary to compensate implausible green time and red time interrupts. This is done by an iterative rule-based algorithm, that fills gaps or compensates faulty peaks smaller or equal to 3 secs if the gap or the peak is surrounded by constant states for longer than 1 sec. If the application of this algorithm is not able to reconstruct a coherent red and green time interval (without interrupts), no plausible green or red time estimate could be provided.

One can clearly see in Figure 4 (top left) that in the illustrated example the density of the smoothed crossing time distribution starts increasing round about 8 secs to early. This error is caused by the linearization of low-frequency trajectories and could reach in worst case scenarios without the application of filter techniques the FCD sampling interval (i.e. 15 secs). To be able to adjust this systematic situation one has to infer the cycle second, where density reaches a global maximum during the crossing time distribution and adjust this identified cycle second systematically by minus 3 secs – this adjusted point in time will be the beginning of the green time interval.

Depending on the existing data situation of $t_{\text{gste}}$ and $t_{\text{rste}}$ it could also happen, that parts of the inferred red time interval overlap slightly the inferred green time interval and vice versa. This effect is caused by slow moving data points, which occur likewise during the red time interval and the beginning of the green time interval, when vehicles start their acceleration process. Another challenging situation considers the estimation of the green time interval’s end (see Figure 4). In many cases the movement’s degree of saturations decreases gradually after having reached a maximum (see Figure 4 - top left). This effect leads, especially in combination with the critical density approach, to an underestimation of the real green time interval’s end. Until now, two different kinds of techniques should be mentioned to handle those situations. First, one could exclude time intervals, where both states are overlapping. Second, one could assume, that the real end of the interval lies in the middle between overlapping intervals or in the middle of the gap between the intervals. In this paper and the second solution is used for further analysis.

The methodical part of this approach gets finalized by Figure 4 (bottom), which shows red and green time intervals, that could be inferred for the part of the signal program (see Table 1 for reference signal program) with a cycle length of 85 secs.

![Figure 5: Distributions of crossing times - simulated populations; scenario a) low saturation - left; scenario b) high saturation - right](image_url)
4 Estimation quality and influencing factors

The objective of this chapter is the analysis of the quality of signal program estimation for two differently simulated data scenarios. As a result of this chapter the authors would like to infer required sample sizes to ensure a reliable signal timing estimate for a day time slice with a nearly similar signal program. If a signalized intersection reveals multiple different, but daily recurrent signal programs, the sample sizes inferred in this chapter need to be provided by a real FCD source for each day time slice. As already explained in chapter 3.4, the shape of the crossing and stopping time distributions ($t_{cste}$ and $t_{sste}$) have a fairly large influence on the estimation quality. As the density threshold approach (see chapter 3.4) is based on the simplified assumption of a uniform crossing time distribution, a nearly linear reduction of crossing vehicles over the green time will impair the estimation of a valid density threshold, which is needed to filter higher noise ratios in the crossing time histogram. It is well known, that the vehicle flow rate of highly saturated movements will decrease only slowly after the beginning of the green time interval and vice versa for low saturated movements (Branston et al., 1978). Therefore, we have simulated two signalized movements with different degrees of saturation. In simulation scenario a) the maximum degree of saturation reaches only $x = 4\%$ and in scenario b) the saturation reaches $x = 54\%$. Furthermore, a saturation flow rate of $S = 2000$ veh/h, a cycle length of $c = 85$ secs and a green time interval of $g = 63$ secs (incl. yellow state) have been assumed. The simulated data covers a trajectory population of approx. 190,000 vehicles for each scenario, whereby uniform random samples have been selected and analyzed by the signal timing estimation process, explained in chapter 3.4. This experiment has been replicated 500 times for different trajectory sample size and additional noise ratios. As a quality indicator for the estimation process authors have calculated the percentage of correctly estimated cycle seconds for each replication (see Figure 6).

One could conclude, that different noise ratios impair primarily scenario b), as the overall shape of the crossing time distribution (see Figure 5) deviates more from the assumed simplified uniform distribution, needed to assess a valid density threshold. In contrast to this, scenario b) converges in average to a slightly higher estimation quality of approx. 97.5\%, whereby scenario a) reaches a maximum estimation quality of approx. 95\%. The overall higher quality in b) could be explained by the higher degree of saturation. In such movements both data sources, crossing and stopping vehicles are present, while at lower saturated movements stopping vehicles hardly appear. In these simulated

![Figure 6: Ratio of correctly estimated cycle seconds; scenario a) low saturation - left; scenario b) high saturation - right](image-url)
scenarios the average proportions between crossing and stopping vehicles have been for scenario a) at 3.7 and for scenario b) at 5.6. One should remember again, that a stopping vehicle is defined as a data point up to 10 m upstream of the stop line position, where momentary GPS-speed has been lower than 3 km/h. One could state, that higher saturated movements contain richer information than lower saturated movements, which allow a better estimation quality for low noise ratios. Both scenarios exceed a high estimation quality of 95 % by a sample size of circa 500 crossing vehicles, even if the distributions are disturbed by noise. In addition to the mean estimation quality authors have also analyzed the standard deviations of the estimation quality, which could not be illustrated in this paper for the sake of brevity. For scenario a) the standard deviation for 500 sampled crossing vehicles is about 2 %, even if additional random vehicle crossings of 40 % are present. The standard deviation of the estimation quality for b) is lower than 4 %. To evaluate the reliability of the proposed estimation process, the ratios of failed estimates have been calculated. A failed estimate occurs for instance, when input data for the estimation process is too sparse and/or if the noise ratio has been too high, which could lead to no coherent red and green time intervals. Last but not least Figure 7 indicates, that in case of a high saturation and 40 % random crossings (noise) the floating car data source needs to provide about 1500 trajectories to get a ratio of failed estimates lower than 5 %, whereby the same ratio could be reached in scenario a) by using only 500 trajectories.

5 Conclusion and further research

Referring to the research of Axer et al. (2016) this paper exemplifies the developed signal phase and timing estimation process by taking into account a simulated dataset. Furthermore, the authors analyzed for the very first time the impact of different sample sizes, degrees of saturation and noise ratios. The developed approach revealed a high and reliable estimation quality, even if input data is covered by relatively high noise ratios. The actual estimation methodology indicates less reliable results in case of non-uniform crossing time distributions, that could be observed in situations in which movements’ saturation is about 50 %. In case of very low or very high degrees of saturation the crossing time distribution will probably tend to be again uniformly distributed, which guarantees more reliable estimates. However, further research is needed to investigate the influence of GPS position accuracy and different traffic actuated signalization strategies.

Figure 7: Ratio of failed estimates; scenario a) low saturation - left; scenario b) high saturation - right
References


