# Turning Rate Estimation at a Signalized Intersection Using Probe Data

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**Abstract**: Knowing the turning rates at an intersection can contribute to the improvement of signal control parameters and correct estimation of vehicle delays. This study proposes a methodology for estimating turning rates at an intersection under oversaturated traffic conditions. Data from detectors and infrared beacons (probe data) are used with a traffic simulator to reproduce average probe travel times for different turning ratio values. Turning rates were estimated by observing the change in the parameters describing the linear relationship between the entry time and average probe travel time for different turning rates and comparing them with the values from virtual probe and detector data. The methodology works well with simulated data.

*Keywords:* Turning rate estimation, Infrared beacon data, Probe vehicles

## 1. INTRODUCTION

Delays at intersections should be the basic performance index for traffic signal control, however, measuring or estimating the delay properly enough is a difficult task. According to Kuwahara and Tanaka (2008), heavy traffic congestion that leads to a 10-20 km queue can be caused by even just 10-20% excess demand and so even small modifications in capacity and travel demand can impact traffic flow significantly.

In Japan, among the most common equipment used in collecting traffic data are ultrasonic wave detectors. Located at 150, 300, 500, and 1000 m distances from the stop line (Traffic Bureau, National Police Agency, *et.al*), these provide traffic information which are used to adjust parameters of adaptive traffic signals. For roads with dedicated right turn lanes, detectors are located 30 m from the stop line. To control traffic signals, detector data is used to calculate the congestion length and then an algorithm that minimizes total delay is used to compute the green split for major and minor streets (Usui and Kobayashi, 2006).

The authors turn their attention to delays between vehicles from a single approach. When multiple phases are assigned to one approach, there are instances where vehicles in one phase experience significantly longer delays than the others. To measure and eventually minimize these delays, it is therefore important to determine the turning behavior or directional demand per approach. One typical case is that of an intersection with a dedicated right-turn lane and a separate phase for right-turning traffic shown in Figures 1 and 2, respectively. In Japan, the green split of right-turn traffic is adjusted based on the time gap between successive vehicles observed by the detector at the right-turning lane. However, the

minimum and maximum green times are fixed, resulting to the following problems which were identified by Kiryu, *et. al.* (2000):

a.  green periods are "wasted" when there is no right-turn demand;
b.  queue left-over occurs when maximum green time is not long enough;
c.  when a vehicle is in a stationary queue in the detection zone, it appears as though there are no passing vehicles.

In that study, the proposed solution was to use image processing vehicle detectors to observe the actual number of right-turners. While this study produced good results, such detectors are not available in all intersections. Other practical solutions should therefore be explored.

This study wishes to find out if the turning rate of vehicles in an intersection can be estimated using available data. By available data we mean those coming from ultrasonic wave detectors and Infrared (IR) beacons.

Ultrasonic wave detectors can give traffic volume data and time occupancy in a given link. These information are used to estimate travel times which are provided to drivers via Japan's Vehicle Information and Communication Systems (VICS) (Ishii and Ito, 2006). IR beacons permit two-way communication between the vehicles and the traffic management center. The IR beacon sends DOWNLINK data containing traffic information while vehicles with on-board (OB) units send back UPLINK data which contain an ID number, time of passing, and information on present and previously passed beacons (Mashiyama, *et al.*, 2003). In this paper, vehicles with OB units will be referred to as *probe vehicles* and the UPLINK data will be referred to as *probe data*.

Since the travel time of probe cars between beacon locations can be obtained, we can draw a rough image of the prevailing traffic conditions given a high enough number of probe cars. As of 2011, around 54,000 IR beacons have been installed all over Japan (Universal Traffic Management Society of Japan) and in some Japanese areas, the percentage of probe cars has reached to around 10% of the total traffic volume.

Several studies have been conducted on the application of probe data in traffic management. Oda, *et al.* (2010) used 100 taxis with OB units to determine the feasibility of using scarce probe data to reflect actual traffic conditions. They found that probe data can be successfully used if accumulated over a sufficient time period. They did not use detector data but still indicated its importance in improving their results. Mashiyama, *et al.* (1999) formulated a method for estimating the turning rate of vehicles passing an intersection but the results had significant errors due to the small number of probe vehicles and data transmission errors in IR beacons. Therefore, it is considered that these data sources can be utilized for improving the performance of the adaptive traffic control.

The objective of this paper is to propose a methodology for estimating the turning rates at an intersection using probe and detector data. The methodology involves the use of a traffic simulator. Chapter 2 of this paper discusses the settings and details of the simulation. Chapter 3 explains the estimation method used as well as the results.


## 2.  TRAFFIC SIMULATION

Suppose that for a given lane approaching an intersection one vehicle arrives every *t* seconds daily for the time duration ΔT. The total number of arriving vehicles *X* is constant but the turning behaviors vary. This means that there are days when more vehicles want to turn right, or days when most vehicles want to go straight. In one cycle, the traffic signal first assigns the right-of-way to both through and left-turn traffic, then to the right-turn traffic.

Suppose also that one of these vehicles is a probe car and it arrives at exactly the same time each day sometime in the middle of duration ΔT. The travel time $tp$ of this probe car between the beacons at the origin and destination links can be measured. It is easy to see that $tp$ can have a wide range of values depending on the turning behavior of the cars that arrived before it. For example, if the cars preceding the probe car wanted to turn left and as a result all of them weren't able to cross the intersection within one cycle (i.e. residual queue was formed),then $tp$ would have a higher value than when the residual queue was not formed for the same number of preceding vehicles. From here we can say that certain turning rates give rise to certain values of $tp$ and so we can estimate the turning rates if we know $tp$.

In the proposed turning rate estimation methodology, we try to find the set of turning rates which are likely to produce the observed probe travel times. Monte Carlo simulation is used to generate probe travel times under different turning rate combinations.

## 2.1 Virtual Probe and Detector Data

The arrival times of probe and detector data are the primary inputs to the simulation. Actual field data was not yet available for this study so detector and probe data were generated using simulation. The resulting vehicle travel times will be referred to as results of "virtual calculation" and the collected probe and detector data will be referred to as "virtual data". It should be emphasized that the proposed estimation methodology should accept real-world probe and detector data as its inputs. In conducting this study, several assumptions and simplifications were made. These are:

a. The IR beacon and detector are in the same position in every link.
b. Data obtained from the IR beacon and detector has a one second resolution.
c. 10% of the vehicles have OB units (this value is acceptable value in some regions in Japan)
d. There are no data transmission errors for both IR beacon and detector.
e. All vehicles are passenger cars.
f. The simulation is conducted 100 times for every set of turning rates.

The study area is the four-legged intersection shown in Figure 1. The upstream link has three major lanes and one dedicated right turn lane. Detectors are provided on each lane as shown in Figure 1.

The Advanced & Visual Evaluator for road Networks in Urban areas (*AVENUE*) traffic simulator was used (Horiguchi, *et.al.*, 1996). *AVENUE* is a "Q-K" type of simulator, meaning it allows the users to input the key parameters of the fundamental diagram which are maximum flow, jam density and free flow speed (Table 1). As a result, the vehicles behave accordingly to meet with these set values. This is different from commonly used simulators which let the users input values related to specific driver characteristics.
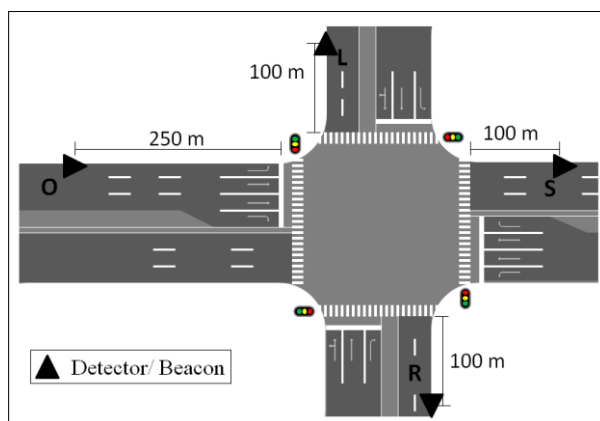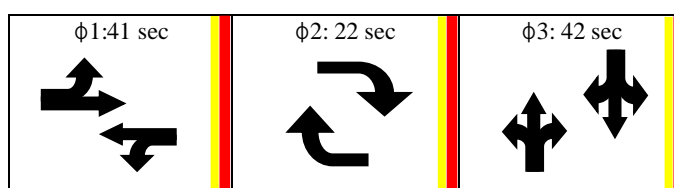
Figure 1. Layout of study area



Figure 2. Traffic Signal Phasing plan (1 cycle: 120 seconds)

Table 1.Simulation parameters

| Maximum flow (pcu/hr/lane) | |
|---|---|
| Left-turn lane | 1500 |
| Other lanes | 1800 |
| Jam Density (veh/km) | 180 |
| Free Speed (km/hr) | 50 |
| Traffic demand (veh/hr) | 2400 |

The following variables are defined:

$X_O$ : total traffic volume entering link O

$X_{Oj}$ : traffic volume travelling from links O to $j$ (where $j \in$ L, R, S)

$\hat{X}_{Oj}$ : estimated traffic volume travelling from links O to $j$

$p_{oj} = X_{Oj}/X_O$ : turning rate of vehicles travelling from links O to $j$

$\hat{p}_{oj} = \hat{X}_{Oj}/X_O$ : estimated turning rate of vehicles travelling from links O to $j$

$\alpha_{oj}$ : turning rate of probe vehicles travelling from links O to $j$

$t_i$ : passing time of each vehicle at the detector in link O (where i=1,2,3,…, $X_O$)

Only heavy traffic condition was considered because light traffic conditions will not significantly affect the average travel times even if the turning rates are changed. To generate the virtual probe and detector data, a total traffic demand $X_{O=}400$ vehicles which is slightly greater than the link capacity was set. These vehicles arrived randomly within 10 minutes. To allow the traffic to build-up to a congested state, 240 seconds was set to be the start-up time. The probe vehicles were scheduled to enter after the start-up time. The turning rates of all vehicles and probe cars were arbitrarily set to the values found in Table 2. Note that these values have been arbitrarily assigned.

Table 2. Turning Rates of Traffic Data from Virtual Calculation

| Destination | Turning rates | | Volume | |
|---|---|---|---|---|
| | $p_{Oj}$, all vehicles | $\alpha_{Oj}$, probe vehicles | All vehicles (probe and non-probe) | Probe vehicles (10% of total) |
| **Left** | 25% | 30% | 100 | 12 |
| **Right** | 20% | 20% | 80 | 8 |
| **Straight** | 55% | 50% | 220 | 20 |

## 2.2 Lane-changing in Simulation

In the study area and also in real-world conditions lane changing is permitted throughout the length of the link except at distances closer to the intersection. Lane-changing behavior cannot be modeled directly in *AVENUE* and so to simulate it appropriately, a lane-changing zone separating links with different lane restrictions was created. The lane restrictions on the downstream side (right side) of the zone are indicated by the solid white arrows in Figure 3.
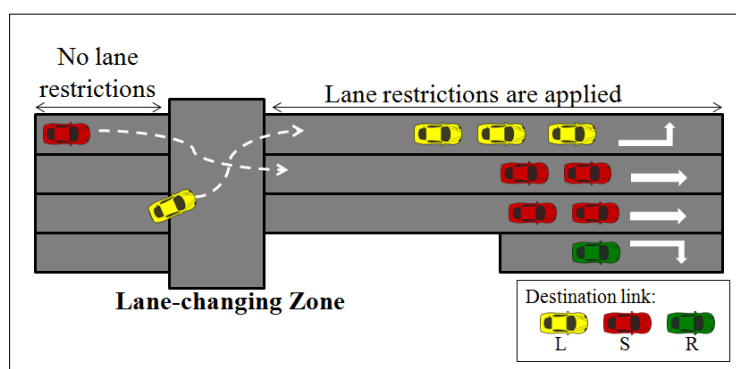


Figure 3. Lane-changing zone in *AVENUE*

In *AVENUE*, vehicles can only switch between lanes at the lane-changing zone. When the traffic condition is very heavy and there are too many vehicles that want to switch lanes, this zone becomes a bottleneck point where vehicles get stuck on the upstream lanes. This affects the entry time of the incoming vehicles and leads to unrealistic results. To prevent such situation from happening, the lane-changing zone was placed a significant distance away from the intersection.

## 2.3 Monte Carlo Simulation

It was mentioned earlier that the probe car travel times have varying values depending on the turning behavior of the cars preceding them. To generate the probe travel times which are likely to ensue from a given set of turning rates ($p_{Oj}$), we conduct Monte Carlo simulation where the destination of each non-probe car is changed or re-assigned each simulation trial. Such destination re-assignment is conducted 100 times and the average travel time of the probe cars is used in the estimation process. Preliminary tests conducted by the authors show that the standard deviation of the travel times between 100 and 1000 simulation trials do not significantly vary so 100 trials are reasonable. More details are explained in the succeeding sections.

From the virtual probe and detector data the following are known: $X_O$, $t_i$, $\alpha_{Oj}$, $p_{Oj}$ and $X_{Oj}$ (for $j \in$ L,R,S). In the real world scenario only $X_O$, $t_i$, $\alpha_{Oj}$ can be collected so variables $p_{Oj}$ and $X_{Oj}$ are just used to check if the estimation results are correct.

The total length of link O is 300 meters but for the Monte Carlo simulations Link O is shortened to 250 meters which is the distance of the detector from the stop line. This was done so that the entry time of each vehicle into the simulation is equal to the detected times $t_i$. This is reasonable if the queues formed do not extend beyond the detector location which is the case for the traffic demand used.

At first, turning rates are assumed for all directions. These will be denoted by $p'_{Oj} \in \{p'_{OL}, p'_{OR}, p'_{OS}\}$. Each set of turning rates correspond to one simulation *case*. The initial values of $p'_{Oj}$ are given by $\alpha_{Oj} \in \{\alpha_{OL}, \alpha_{OR}, \alpha_{OS}\}$. In each *case*, 100 simulation trials are conducted where the destinations of non-probe vehicles are changed per trial. Note that in all trials and *cases* the probe car destinations and entry times are never changed. The steps are summarized in the flow chart in Figure 4. A total of 11 *cases* are considered (see Table 3) and finally sensitivity analysis is applied to the output data to yield the estimated turning rates and volumes ($\hat{X}_{Oj}$ and $\hat{p}_{Oj}$).
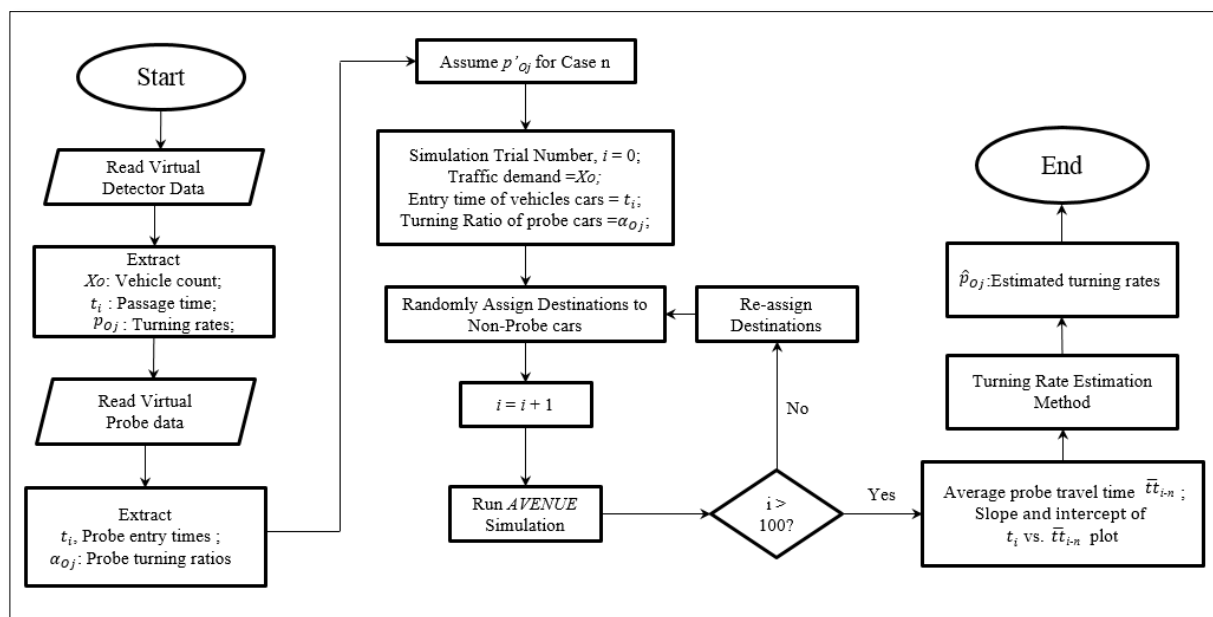


Figure 4. Simulation flow chart

### 2.3.1 Destination re-assignment

In the destination re-assignment process, a destination array $D$ with elements $D(i,j)$ is created where $i$ is the vehicle entry time in multiples of two seconds (Note: two seconds is the minimum headway) and $j$ is the lane number. Each element $D(i,j)$ takes only one of the following values: 0, L, R, or S. $D(i,j)$ is zero when no vehicles have been detected at time $i$ and lane $j$ in the virtual data. The non-zero elements of $D$ having row and column indices $i$ and $j$ are extracted to form a linear array $N$. For every $N(k)$ and $N(k+1)$, index $i$ of $N(k) \leq$ index $i$ of $N(k+1)$. If $i$ of $N(k) == i$ of $N(k+1)$, then $j$ of $N(k) < j$ of $N(k+1)$. I.e. the elements of $N$ taken from $D$ are arranged in ascending order (row first, then column). The elements of $N$ are rearranged to form array $N'$ using the *permute* function of Matlab. The elements of $N'$ are then returned to array $D$ maintaining the original indices from $N$.

### 2.3.2 Changing turning rates

The probe turning rates $\alpha_{Oj}$ from virtual data are used as initial values in estimating $p_{Oj}$. For Case 1 indicated in Table 3, we conduct simulation by setting turning rates equal to $\alpha_{Oj}$. We assume that the values of $p_{Oj}$ are within $\pm 10\%$ of $\alpha_{Oj}$. Note that this range is set merely for reducing the number of calculations and any range of values can be used. In conducting the sensitivity analysis for this study, we consider other *cases* where the turning rates are within 10% of $\alpha_{Oj}$. A summary of all the cases are provided in Table 3. Only the turning rates of the vehicles bound for link L and S were varied in this study because changing those for link R will require additional treatments and considerations such as the effect of oversaturation in the right turning lane on adjacent lanes. This issue will be addressed in future work.

Table 3. Cases considered in Monte Carlo Simulation

|  | Assumed Turning Rate for all vehicles %, $p'_{Oj}$ | | Vehicle Volume (probe and non-probe) | |
|---|---|---|---|---|
|  | L ($p'_{OL}$) | S ($p'_{OS}$) | L | S |
| Case 1 | 30% | 50% | 120 | 200 |
| Case 2 | 31% | 49% | 124 | 196 |
| Case 3 | 33% | 47% | 132 | 188 |
| Case 4 | 35% | 45% | 140 | 180 |
| Case 5 | 37% | 43% | 148 | 172 |
| Case 6 | 39% | 41% | 156 | 164 |
| Case 7 | 29% | 51% | 116 | 204 |
| Case 8 | 27% | 53% | 108 | 212 |
| Case 9 | 25% | 55% | 100 | 220 |
| Case 10 | 23% | 57% | 92 | 228 |
| Case 11 | 21% | 59% | 84 | 236 |

## 3. SENSITIVITY ANALYSIS

### 3.1 Trends in Probe Travel Times

Under light traffic conditions the travel time of vehicles per cycle is independent of the traffic demand because on the average, vehicles are travelling at free flow speed. Under oversaturated conditions, the time it takes for vehicles to cross the intersection becomes longer as the demand increases, following a linearly increasing trend over time. This trend continues even if the upstream traffic demand is reduced. If the demand continues to increase, the upward trend will continue until some maximum value is reached. On the other hand, a downward trend will be observed when the traffic condition transitions from oversaturated back to undersaturated. We quantify these trends by fitting a least-squares line to a scatter plot of the vehicle entry times versus the average travel time of probe vehicles (Figures 4a and 4b). The entry time is defined as the time when each probe car passed the upstream beacon location at Link O while the probe travel time is taken as the difference between each probe car's passing time at the downstream and upstream beacons. Because this method is based on trend lines, the estimation methodology proposed in this study requires that travel times

follow a linearly increasing or decreasing trend which is continuous.

When dealing with traffic data collected over long time periods, time intervals where the aforementioned trends exist must be selected before conducting the sensitivity analysis. In this study we consider a linearly increasing trend which reflects an oversaturated traffic condition. Notice that most vehicles are experiencing delays greater than the average delay, $R/2$ where $R$ is the red light interval. The trend lines shown in the figures are only for the probe vehicles. The following variables are considered in analyzing the results:

$\overline{tt}_{i\text{-}n}$ : average travel time of probe vehicle $i$ from the 100 simulation trials in Case $n$

$t_i$ : the entry time of a vehicle $i$ to link O (also the passing time in the detector in Link O from virtual data)

Note that only probe travel times are considered because their entry times and turning rates can be obtained from real-world data.
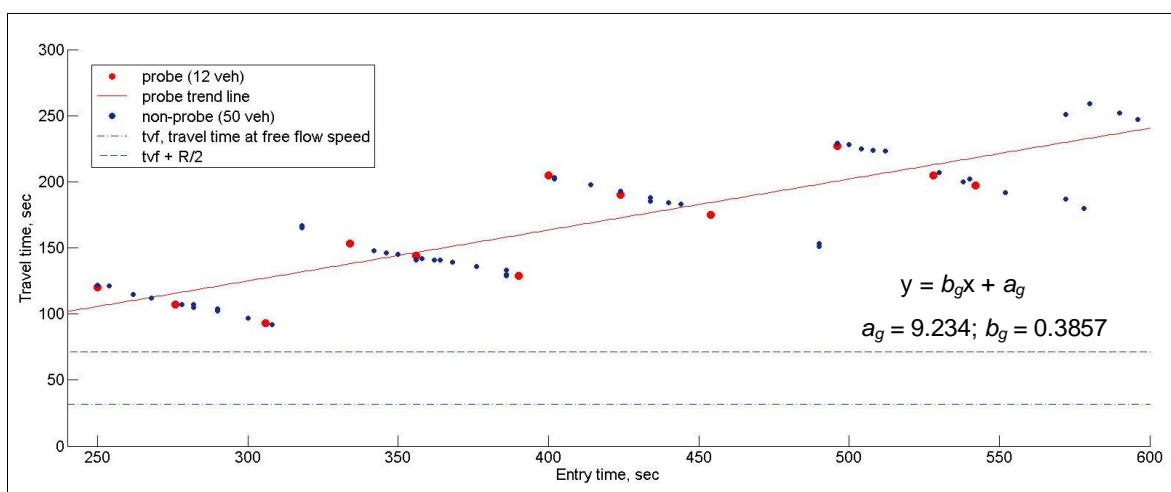


Figure 4a. Travel times for vehicles bound for link L from Virtual Calculation
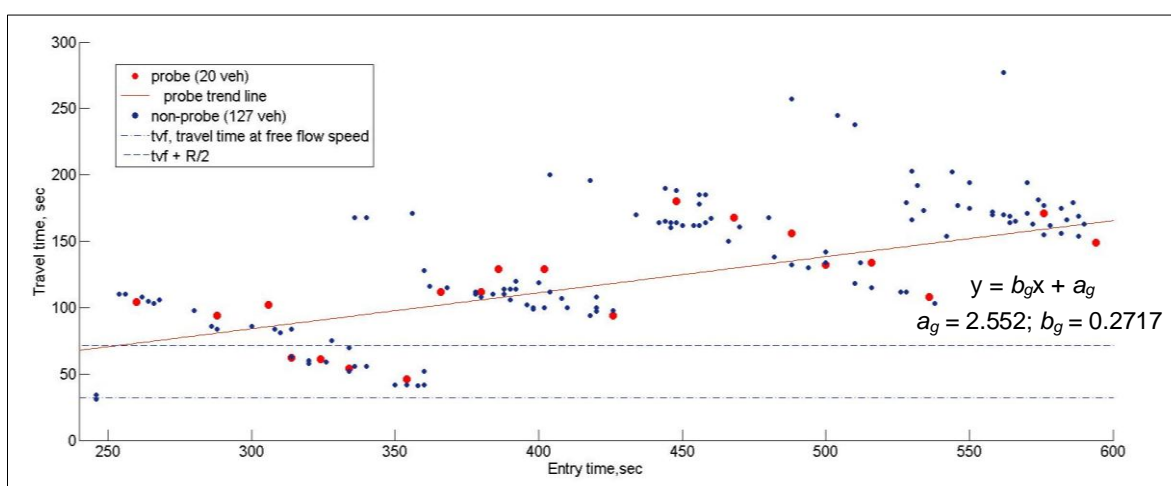(*Trend line is plotted only for probe vehicles*)



Figure 4b. Travel times for vehicles bound for link S from Virtual Calculation
(*Trend line is plotted only for probe vehicles*)

## 3.2 Comparison of Slopes and Intercepts

For each of the 11 cases we construct the scatter plots of $t_i$ versus $\overline{tt}_{i\text{-}n}$. Our goal is to check which set of turning rates produce travel time trends that best resemble the plots from the virtual calculation. The plot for each destination is drawn separately. We use linear regression and determine the trend line $y = a + bx$ of each plot. We then remove the difference in dimensions between the intercept $a$ and slope $b$ using a standardization procedure with the following equation (the same equation also applies for the slopes to obtain $b'_n$):

$$a'_n = \frac{a_i - \bar{a}}{\sigma_a} \tag{1}$$

where,

| | |
|---|---|
| $a_n$ | : intercept of the scatter plot for Case $n$ |
| $\bar{a}$ | : the mean of $a_n$, where $n$=1:11 |
| $\sigma_a$ | : standard deviation of $a_n$, where n=1:11 |
| $a'_n$ | : standardized intercept for Case $n$ |

The standardized intercept of the virtual data scatter plot $a'_v$ is also computed using both $\bar{a}$ and $\sigma_a$. Again, the same applies to the intercept $b'_v$. The figures below show the resulting plots for both destinations.
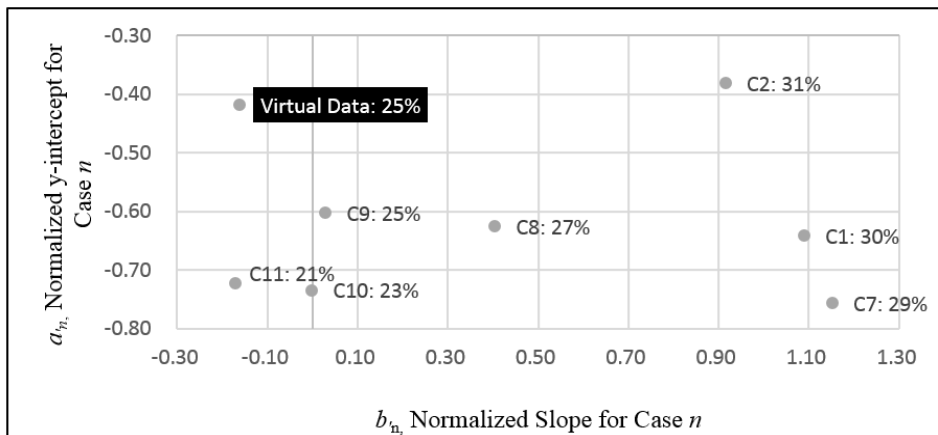


Figure 5a. Scatter plot of normalized slopes and intercepts for probe vehicles bound for link L
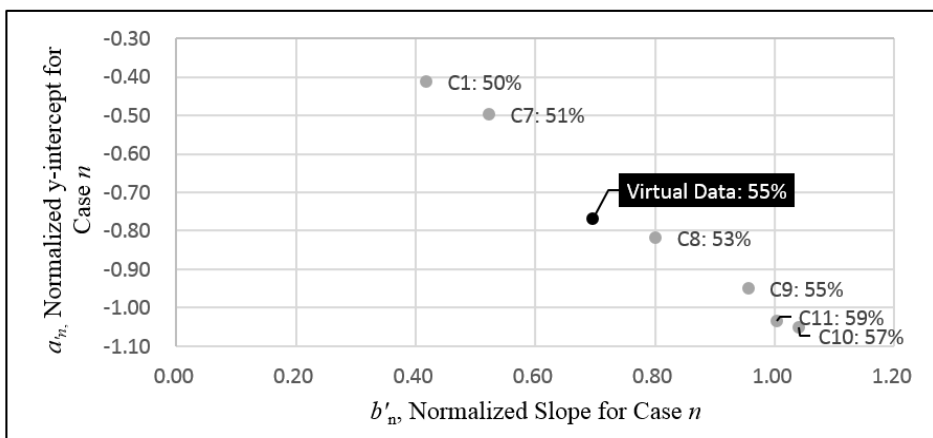


Figure 5b. Scatter plot of normalized slopes and intercepts for probe vehicles bound for link S

### 3.3 Combining the Results for Destinations *L* and *S*

The standardized slopes and intercepts are then plotted separately and the Euclidean distance $\delta_{nj}$ between the ordered pairs $(b'_n, a'_n)$ and $(b'_v, a'_v)$ is obtained using the following equation:

$$\delta_{nj} = |b'_n - b'_v| + |a'_n - a'_v| \qquad (2)$$

where:

      $\delta_{nj}$      : Euclidean distance for case *n*, destination *j*
      for destination *j*:
      $a'_n$, $b'_n$ : standardized intercept and slope of case *n* plot
      $a'_v$, $b'_v$ : standardized intercept and slope of virtual data plot

In Figures 5a and 5b, the values of $\delta_{nL}$ and $\delta_{nS}$ are interpreted as measures of how close the trend of Case *n* is to that of the virtual data. Notice that in Figure 5a, the closest point corresponds to Case 9 (i.e. $p'_{OL} = 25\%$) while in Figure 5b the closest point corresponds to Case 8 (i.e. $p'_{OS} = 53\%$). To reconcile these, a scatter plot of $\delta_{nL}$ versus $\delta_{nS}$ is constructed in Figure 6. We conclude that the case with turning rates corresponding to that with the least Euclidean distance from the origin is the one that is most likely to resemble the probe travel time trends from virtual data. The turning rates with nearest distance to the origin correspond to that of Case 9 with $p'_{OL} = 25\%$ and $p'_{OS} = 55\%$. These are equal to the virtual data turning rates $p_{OL}$ and $p_{OS}$, respectively.
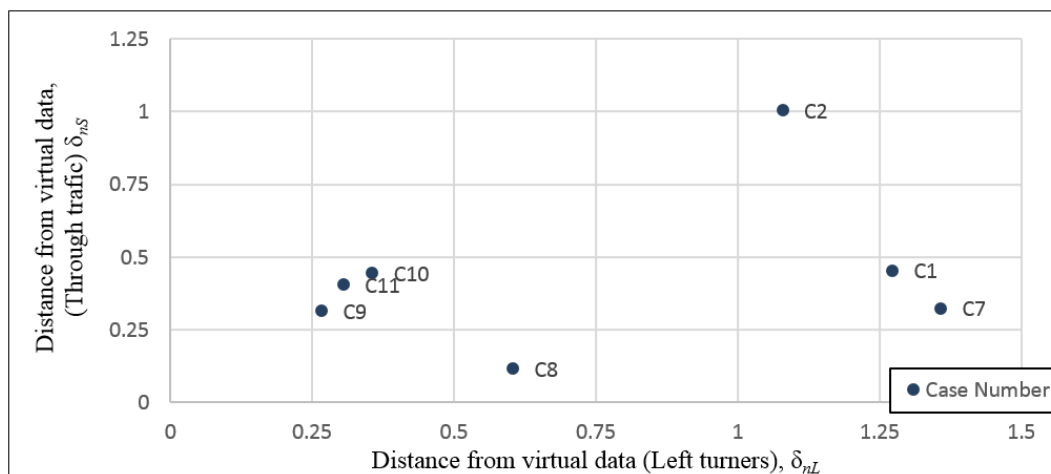


Figure 6. Euclidean distances of $(b'_n, a'_n)$ from $(b'_v, a'_v)$ for destination L and S

From the results just shown it can be seen that the estimation method works well even for a low percentage of probe vehicles (10%). For the virtual data used in this paper, the turning rates were estimated with no error. However, estimation errors within around ±4% have been observed for different virtual data. Also, since many simplifications were applied in this study (refer to Chapter 2) errors may occur when these simplifications are removed. Based on the results shown, it can be said that probe and detector data can be used to estimate turning rates to a certain accuracy. Methods to improve the estimation accuracy as well as calibration techniques should be developed when actual data become available.

### 3.4 Application to Real-World Data

The previous section demonstrated that the proposed estimation method can correctly estimate turning rates under the conditions and assumptions presented. The following points must be considered when applying this methodology to real-world data:

a. In the real-world case, the IR beacon and detector do not have the same location. This means that the passing time of the probe vehicles on the detectors cannot be easily determined. The proposed methodology must be adjusted in order to overcome this simplification.

b. Other factors that can affect driver behavior such as the presence of cyclists, pedestrians, parked cars, etc. were not considered in this study. The differences in vehicle lengths were also not considered. These should be accounted for during calibration of the simulator.

c. This method must be expanded to cases where oversaturation does not occur in all directions (e. g., oversaturation only for Left-bound traffic or under-saturation only for Right-bound traffic).

For this method to be practical, the authors only used data sources which are already available in Japan (i.e.) probe vehicle and detector data. Several methodologies are available to measure the input parameters to the *AVENUE* simulator in the real world. Historical probe information can also be used as a reference in order to detect oversaturated traffic conditions.

### 4. CONCLUSIONS

This study showed the possibility of utilizing detector and limited probe data to estimate turning rates at an intersection using the methodology developed by the authors.

The basic idea of the methodology is that certain turning rates give rise to certain values of probe travel times. Based on the volume and passing time information collected from virtual detectors and beacons, Monte Carlo simulation was conducted for 11 turning rate combinations and the average directional probe travel time for each case was calculated. The linearly increasing trend in travel times under oversaturated conditions, represented by the slope and y-intercept of the plot of entry time versus probe travel time was shown to have adequate sensitivity to changes in turning rates. Thus, by measuring these trend line parameters, the turning rates can be estimated. Once the turning rates are known, the average travel times and delay can also be estimated and used for controlling traffic signals.

For future work, the authors plan to validate this methodology with real-world data. Adjustments will be made to modify the simplifications made in this paper. The methodology will also be extended to consider under saturated traffic conditions.

### ACKNOWLEDGEMENTS

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