Methodology for Estimating Volume and Average Travel Times in an Intersection Using Probe Data

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Knowing the delay at an intersection is important for optimizing traffic signal parameters. This study proposes a methodology for estimating the turning rate, average travel times, and delay of cars from one intersection approach by utilizing vehicle counts from detectors and limited probe car travel times obtained from IR beacons. Monte Carlo simulation was conducted to generate the distribution of average travel times as well as the trend in the delay of probe cars. The estimated turning rates were obtained by probability analysis and based on these turning rates the average travel times and delay are calculated via Monte Carlo simulation. The methodology is shown to yield good results when tested with virtual data.

Key Words : *Monte Carlo simulation, Beacon data, Probe cars, Turning rate estimation, Travel Time estimation*

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[1]), 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*[2]), 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[3]).

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. 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[4]):

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 aims to estimate turning rates and average travel times in an intersection 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[5]). 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 onboard (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.*, 2000[6]). 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[7]) 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[8]) 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[9]) 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 determine if turning rates and average travel times at an intersection approach can be estimated by combining detector data with probe data. An estimation methodology is proposed. 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 procedures for estimation using probability analysis, and Chapter 4 presents an application of the estimation method by means of a scenario analysis.

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.

(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. Data obtained from the IR beacon and detector has a one second resolution.
b. 10% of the vehicles have OB units (this value is acceptable value in some regions in Japan)
c. There are no data transmission errors for both IR beacon and detector.
d. All vehicles are passenger cars.

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 and beacons are provided on each lane as shown.

Table 1

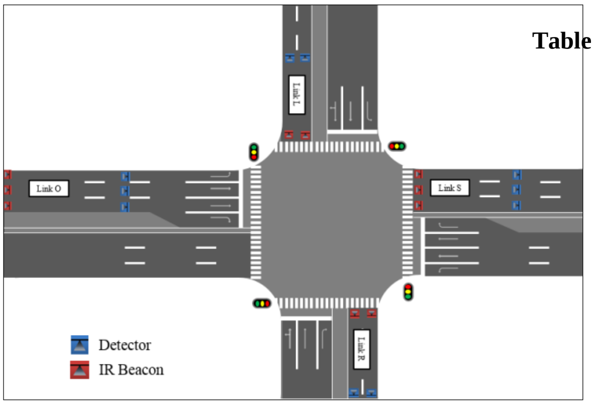

Fig.1 Layout of study area

The Advanced & Visual Evaluator for road Networks in Urban areas (*AVENUE*) traffic simulator was used (Horiguchi, *et.al.*, 1996[10]). *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. 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.

The developers of *AVENUE* conducted a study which aimed to validate the results of the traffic simulation model with field data (Horiguchi, et. al., 1995[11]). The study area was composed of a small street network with 6 intersections and the field data was collected between 7:50-9:10 (peak morning period). They used "reasonable" values of saturation flow rates within the range 1600 to 1800 veh/hr/lane and found that the hourly throughputs in each lane were very similar for simulation and field data. In one part of the study, the developers compared the average travel times of floating cars (computed over one hour) with the average travel times from simulation (measured every 5 minutes). The travel times were measured for cars that travelled from links A to F (passing through intersections B, C, D, and E). They found that the simulation results were close to average floating car results. The difference between average simulation and floating car travel times were not provided in that study but are estimated visually by the author to be less than 1 minute.

It is therefore reasonable to assume that the simulation-based methodology proposed in this study can be adapted to real-world data with simple calibration techniques. To eliminate minor discrepancies between the field and simulated data, we deal with average travel times instead of individual travel times. 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
α_{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)

(2) Monte Carlo Simulation

From virtual probe and detector data the following are known: X_O, t_i, α_{Oj}, p_{Oj} and X_{Oj} (for j $\in$ L,R,S). In the real world scenario however, only X_O, t_i, α_{Oj} can be collected so variables p_{Oj} and X_{Oj} are just used to check if the estimation results are correct. The Monte Carlo Simulation procedure can be summarized into 2 levels:

Level 1: Case Generation

In this level, 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 is defined as one simulation *case*. For each direction, the possible value of the turning rate ranges from 0-100%. In this research, the range of possible turning rates for each direction is limited to within ±10% of the probe turning rates from virtual data to lessen the number of computations. However, when applying this methodology to a real-world case, a wider range of assumed turning rates can be used. Once the desired number of cases are decided, we proceed to Level 2.

Level 2: Simulation trials

For each *case*, 100 simulation trials are conducted where the destinations of non-probe vehicles are changed via the destination re-assignment process. Note that in all trials and *cases* the probe car destinations and entry times are never changed. Based on preliminary tests involving many trials, results show that the standard deviation of the travel times between 100 and 1000 simulation trials do not vary significantly so 100 trials are reasonable. The two levels are illustrated in the figure below.

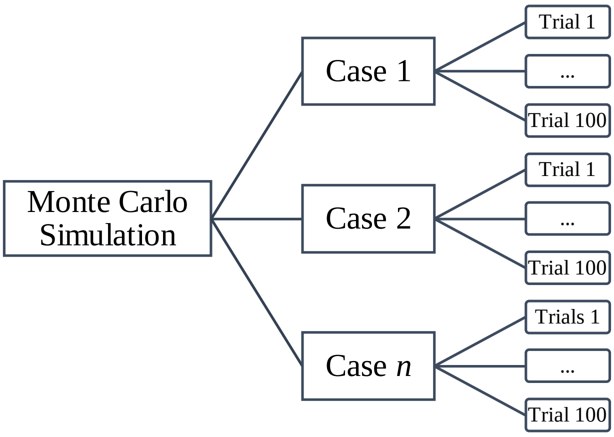

Fig.2 Hierarchy of operations in the Monte Carlo Simulation

(3) Destination re-assignment

After assuming the turning rates p'_{Oj}, a destination array D with elements $D(i,j)$ is created where i is the vehicle entry time in seconds 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 number of non-zero cells containing L, R, or S are based on the assumed turning rates. An example is given below. For simplicity, probe cars are not included in the example.

Total demand: $X_O = 10$

Assumed turning rates per direction:

$$p'_{OL} = 20\%$$
$$p'_{OR} = 30\%$$
$$p'_{OS} = 50\%$$

$$\mathbf{D} = \begin{bmatrix} L & L & 0 \\ R & R & R \\ S & 0 & S \\ S & 0 & S \\ 0 & S & 0 \end{bmatrix}$$

The non-zero elements of D having row and column indices i and j are extracted to form a linear array N. The elements of N taken from D are arranged in ascending order (by row first, then column). This means that for every $N(k)$ and $N(k+1)$, index i of $N(k)$ $\le$ index i of $N(k+1)$. If i of $N(k) == i$ of $N(k+1)$, then j of $N(k) < j$ of $N(k+1)$.

N= [L L R R R S S S S S]

The elements of N are rearranged to form array N' using the *permute* function of Matlab.

N'= [S R S R S S S L R L]

D is updated by replacing its non-zero elements with the values of ***N'***. The elements are arranged in the same order as when ***N*** was first extracted from ***D***.

$$updated\ \mathbf{D} = \begin{bmatrix} S & R & 0 \\ S & R & S \\ S & 0 & S \\ L & 0 & R \\ 0 & L & 0 \end{bmatrix}$$

After the destination re-assignment process, matrix ***D*** will be converted to the input file format of *AVENUE* and the simulation is conducted with the new vehicle destination assignments.

(4) Estimation of Turning Rates

After each trial, the following parameters are obtained: average travel time of probe cars (per direction) and travel time trend.

Since travel times are approximated by the simulator, we use average values of the probe car travel times to approximate the average travel time of all vehicles. Due to the limited number of probe cars (10%), deviation of the average probe travel time from that of the entire population of cars is expected. Figure 3 shows the outcome of 100 Monte Carlo trials for a Volume/Capacity ratio of 1.33 for the Right direction. For each x-value, the average travel time of the right-turning probe cars and all the right-turning cars are plotted. Note that the deviations between them can vary by as much as ~30 seconds. We therefore need another parameter, the travel time trend.

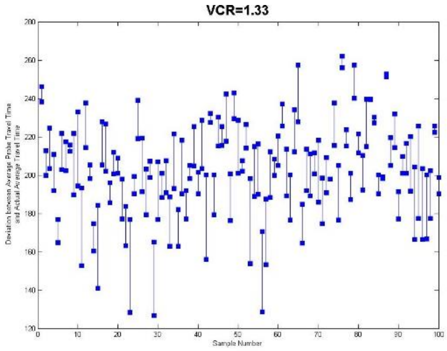

Fig.3 Deviations between average travel times of probe cars and all cars

The travel time trend is a measure of the temporal change in the individual travel times. This trend line is obtained by getting the slope of the Entry time vs. the Travel time between beacons. Figure 4 below illustrates such trend. Local trends in travel times can be observed per signal cycle but notice that when the traffic conditions becomes "heavy", the average travel time per cycle increases as well.

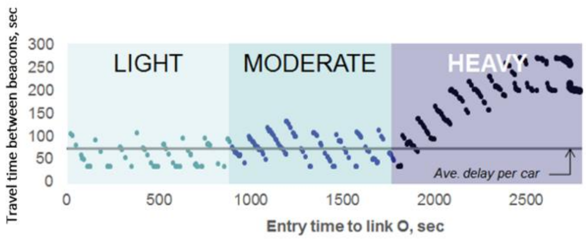

Fig.4 Trends in travel times

The slope is calculated by linear regression and setting the y-intercept = free flow travel time between beacon points. Given the trend line equation below:

$$y = mx + b$$

where:
x: variable representing arrival time in seconds
y: variable representing travel time in seconds
m: slope of xy plot
b: y-intercept of xy plot

we define delay as the excess in travel time due to the traffic signal and queuing. This is simply the difference between actual travel time and free flow travel time. If we set the intercept *b* to be equal to the free flow travel time, we have:

$$\text{delay} = y - b$$

Thus we now have a slope value that is a function of delay:

$$\text{delay} = mx \qquad (1)$$

The authors found that in the estimation analysis, measuring the slope obtained by constraining the intercept had a more stable result than the slope with unconstrained intercept. Because the slopes are obtained from the best-fit lines of only the probe cars, there are instances where the arrival times of probe cars are arranged in such a way that the resulting slope becomes negative or close to zero. By constraining the intercept, a positive slope is always achieved and higher values of travel time always yield higher values of the slope. This will be very useful for the probability analysis to be explained in the succeeding section.

3. PROBABILITY ANALYSIS

In this analysis, the probability distribution of the average probe travel times for each direction are constructed. Following the Central Limit Theorem, we know that the average probe travel times follow a normal distribution. Suppose that the average travel time of probe cars μ_t was obtained from field data. The turning rate which is most likely to have produced μ_t is calculated by the following procedure:

Step 1: Conduct Kolmogorov-Smirnov test

For one direction, when the probability distributions have been constructed for each case, a one-sample Kolmogorov-Smirnov (KS) test is conducted to check if μ_t, the average travel time from virtual data, comes from each of the case distributions. If the hypothesis that μ_t is likely to have come from such distribution is rejected, then that distribution is excluded from the analysis.

Step 2: Probability Calculation

Calculate the mean and standard deviation of the 100 trials for each case. Then calculate the value of the probability density function if μ_t belongs to the normal distribution with mean μ'^{n}_{t} and standard deviation σ'^{n}_{t}. μ'^{n}_{t} and σ'^{n}_{t} are the means and standard deviations of the average probe travel time for case *n*, respectively.

Since the normal distribution is a continuous function, the probability density function cannot be obtained for a single point. If $\boldsymbol{X}$ is a random variable representing the average probe travel time, we introduce some constant Δ and calculate $P(\mu_t - \Delta < \boldsymbol{X} < \mu_t + \Delta)$ if $\boldsymbol{X} \sim$ Normal $(\mu'^{n}_{t}, \sigma'^{n}_{t})$. Δ is arbitrarily assigned to be equal to $\mu_t/100$. The turning rate estimate is corresponds to the case which has the maximum probability density, P_{max}. Figure 5 gives an example of the probability analysis process. Based on this example, the turning rate corresponding to Case B is considered to be more likely to have produced the average probe travel time μ_t.

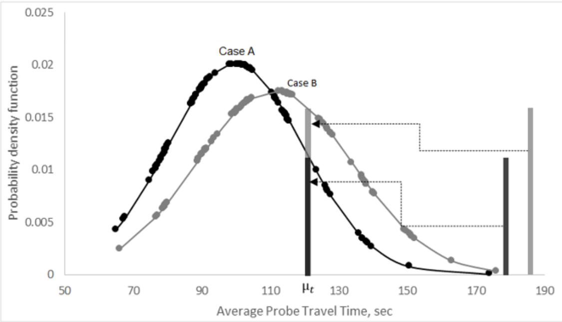

Fig.5 Calculation of probability if virtual data belongs to the Case *n* distribution

Step 3: Compare results of Average Travel Time and Slope

The second step is conducted using both average travel time and slope values. The probability densities for each parameter are normalized by expressing the density for each case *n* as a percentage of the sum of the densities for all cases using the following equation:

$$P'_{j,n} = \frac{P_{j,n}}{\sum_{n=1}^{N} P_{j,n}} \tag{2}$$

where:

$P_{j,n}$: For direction j and case n, $\mathrm{P}(\mu_t - \Delta < \boldsymbol{X} < \mu_t + \Delta)$ if $\boldsymbol{X}$ ~ Normal $(\mu'^{n}_{t}, \sigma'^{n}_{t})$.

$P'_{j,n}$: The normalized value of $P_{j,n}$

The normalized probabilities are calculated. The probabilities for all directions corresponding to one case are added. The maximum normalized probability sum, P'_{max}, is then determined. P'_{max} is calculated by considering the average travel time distributions as well as the slope distributions and the results for each are compared. For example, if P'_{max}(average travel time) > P'_{max} (slope), then the turning rates of the case where P'_{max}(average travel time) was computed from is considered as the final turning rate estimate.

Once the turning proportion is known, Monte Carlo simulation with 100 trials is again conducted. The average travel time estimate is the average travel time of all vehicles for all the trials.

4. SCENARIO ANALYSIS AND RESULTS

We now apply the estimation methodology by generating different virtual data and considering different traffic conditions. We test three scenarios where the total demand is the same but the traffic condition for the Right and Straight traffic are varied in each scenario. For simplicity, the Left-turn traffic demand is held constant. The settings used in creating the virtual data are outlined below:

Virtual Simulation Settings

Cycle length	: 100 seconds
Total demand	: 400 vehicles
Probe penetration	: 10%
Vehicle entry duration	: 15 mins (9 cycles)

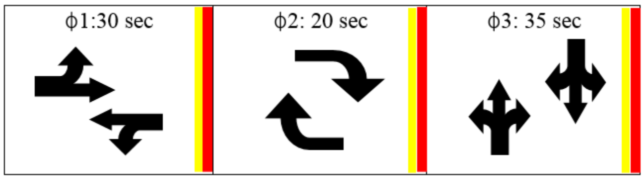

Fig.6 Signal Timing Setting

Table 2 Assumed Turning Rates in Monte Carlo Simulation

Turning Rates, %			
Case #	Left	Right	Straight
1	30	8	62
2	30	10	60
3	30	12	58
4	30	14	56
5	30	16	54
6	30	18	52
7	30	20	50
8	30	22	48
9	30	24	46
10	30	25	45
11	30	26	44
12	30	28	42
13	30	30	40
14	30	32	38
15	30	34	36

Table 3 Traffic Volume and Turning Rates of Probe Cars Virtual Data

Destination	Turning Rates, %	Volume
Left	25%	10
Right	20%	8
Straight	55%	22

Table 4 Demand by Capacity Ratios of the Scenarios Considered

Scenario	Demand/Capacity	
	Right	Straight
1	0.71	0.80
2	1.07	0.68
3	1.33	0.59

There is no scenario where Straight Demand/ Capacity ratio is greater than one because the capacity of the Straight direction is greater than the original total demand of 280 vehicles for both Right and Straight. The following diagram gives an overview of the processes involved in each scenario.

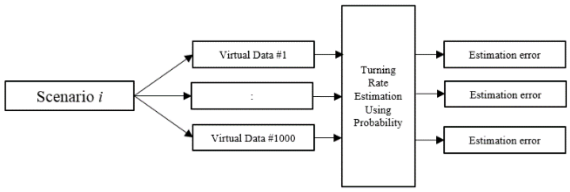

Fig.7 Process flow for the Scenario Analysis with 1000 Virtual Data Inputs

Figures 8 and 9 show the distributions of the 1000 virtual data generated for each scenario. These distributions are for the average probe travel times. Note that for the Right direction, the distribution becomes wider at larger V/C ratios. This is because the average probe travel times can greatly vary depending on the order at which vehicles bound for certain directions arrive. For example, if a probe vehicle is preceded by a platoon of through vehicles, then there is a high chance that it will have to wait longer to reach the right-turn lane. For the Straight probability plot with lower demand, the probability distributions overlap because most vehicles are able to travel close to the free flow travel times.

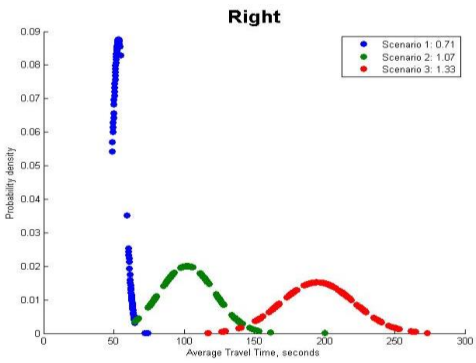

Fig.8 Probability distribution of average probe travel times for the three scenarios (Right-turn)

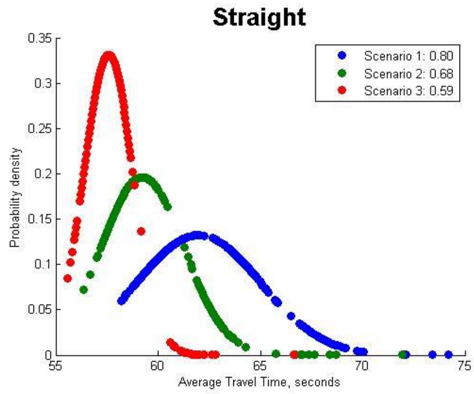

Fig.9 Probability distribution of average probe travel times for the three scenarios (Through)

For each scenario, the estimated travel time and actual travel times were compared using equation (3). The percent errors were then grouped by magnitude as shown in Figures 10 and 11

$$\% \text{ error} = \frac{|est.ave.travel\ time - actual\ ave.travel\ time|}{actual\ ave.travel\ time} \text{ x } 100\% \qquad (3)$$

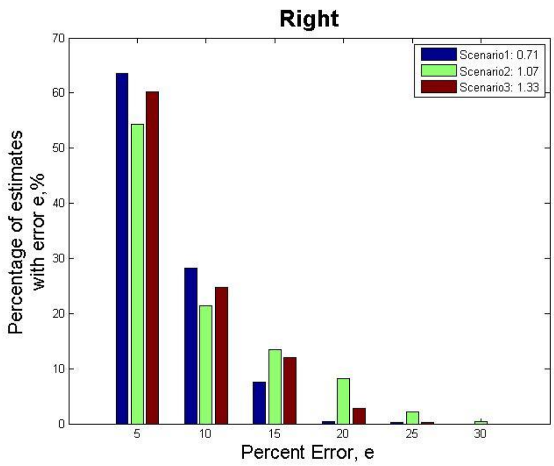

Fig.10 Percentage errors for the Right-turn traffic scenarios

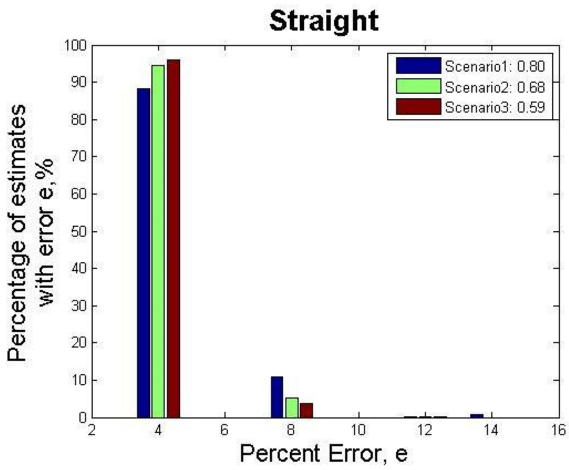

Fig.11 Percentage errors for the Through traffic scenarios

The mean of the percentage errors for each scenario were computed. Figures 12 and 13 show plots of the mean percentage error with the 95% confidence interval.

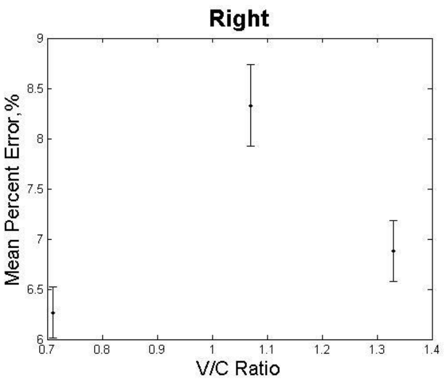

Fig.12 Mean percentage errors for Right traffic

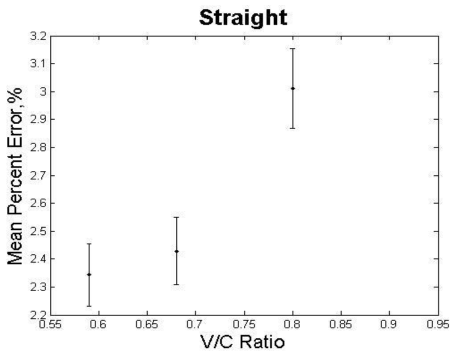

Fig.13 Mean percentage errors for Straight traffic

Figures 10 and 11 show the percentage of correct results corresponding to certain values of the percent error,e. Errors are expected because for a given turning rate, there are many possible average travel times as shown in Figures 8 and 9.

Table 5 Estimated Average Travel Times for different Demand/Capacity ratios

Demand/Capacity ratio		Estimated Average Travel Time, sec	
Right	Straight	Right	Straight
0.80	0.77	66.91	57.78
0.89	0.74	74.00	57.27
0.98	0.71	85.83	56.86
1.07	0.68	109.29	57.12
1.11	0.67	123.06	57.31

Because a range of possible average travel times exist under a given turning rate, estimation errors are possible. In Figure 10, Scenario 2 has the most number of results which have errors greater than 10%. At Demand/Capacity ratios less than 1, the increase in average travel times is gradual. The table below shows the estimated average travel times of right-turn traffic for different Demand/Capacity ratios. Notice that high changes in the average travel times begin between right-turn ratios 0.89 and 1.11. This means that errors in turning rate estimation can lead to relatively high errors in the average travel time even for a relatively low error in turning rate estimate.

For the estimates in the Straight direction, errors are not so high because the estimated average travel times for each case do not vary significantly. Even if the turning rate estimates are overestimated or underestimated, the errors remain small.

Based on the results obtained, it can be said that the methodology works well. However, the results may vary when actual data is used. For future work, this method should be validated using real-world data.

5. CONCLUSION

In this study, a methodology for estimating the average demand and delay in an intersection was developed. The main components of this method are the following: a.) Monte Carlo simulation algorithm for generating probability distributions of average travel times and slopes and b.) turning rate estimation method using probability analysis. A trial implementation of the method was conducted by using virtual data from simulation. The results show that on the average, the percentage errors of the average travel time estimates for the scenarios considered are below 10% which indicates the potential of this method to work well. For future work, validation of this method's performace should be done with real-world data to check the veracity of the assumptions used.

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