Applying Travel Time Reliability for Pre-Evaluation of Expressway Congestion Improvement Schemes*

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1. Introduction

Travel time reliability is a preferred measure to evaluate the level of service of expressway segments as it reflects mobility and road user satisfaction at the same time. Correspondingly, it is well suited for assessing the efficiency of congestion improvement schemes. By now, applications of travel time reliability are limited to before/after studies and road users' information provision. However, road authorities are more interested in evaluation of the impacts of alternative improvement schemes on travel time reliability, prior to implementing them in real conditions.

Most of existing approaches to estimate travel time reliability are mainly relying on empirical data. Hence, regarding the unavailability of such data in present time (before implementation), by far, the most one could get is the estimates of reliability measures for the existing conditions. A methodology is presented to estimate travel time reliability that is based on modeling travel time variations as a function of demand, capacity, weather conditions and accidents. Once travel time reliability is modeled, given the model inputs, travel time reliability can be estimated without empirical data, which enables road authorities to pre-evaluate the impacts of improvement schemes on reliability and level of service.

2. Background and literature review

Travel time variations on expressways are the result of interactions between demand, capacity, weather conditions, accidents, work zones and traffic composition. Such interactions were investigated by a number of studies. Tu, *et al.* (2007)[1) 2)] investigated the impact of inflow and adverse weather on travel time variations on Dutch freeways. They quantified threshold inflows above which travel time variability increases sharply while adverse weather was found to lower the threshold values. Elefteriadou and Cui (2007)[3)] developed separate models to estimate travel time reliability for different scenarios of traffic conditions and non-recurring events on freeway segments. However their models were site specific and could not be applied elsewhere. The significance of capacity and bottleneck operations with respect to travel time reliability is also highlighted by several studies[4)]. As breakdown of traffic of traffic flow and consequently the capacity (capacity reliability) of a roadway are proven to be random events, probability of breakdown should necessarily be included in travel time reliability models. However, only few studies attempted to clarify the nature of such a relationship[5)]. This study aims to build up such a model that estimates travel time reliability as function of probability of breakdown, demand variations, accidents, weather conditions and traffic composition as the root sources of (un)reliability.

3. Methodology

Figure 1 shows the general framework of the proposed simulation model. For an expressway segment, traffic conditions are modeled over a year and patterns of demand and capacity are generated for each five minute interval (365*24*12=105,120 intervals) by applying Monte-Carlo simulation technique. Weather condition and its impacts on capacity and demand variations are simulated according to available meteorological data during the analysis period. Accidents are generated randomly based on a model that links accident rate to traffic density. However, the relationship between adverse weather and accident likelihood is not considered so far. The whole year analysis is performed by comparing demand and available capacity for each scenario, and queue length is estimated for each time interval through shockwave analysis. Travel times are estimated using speed-flow relationships developed for expressways and buffer time index is estimated as a measure of travel time reliability.

A two lane segment of Tomei expressway between Nagoya and Tomei-miyoshi (Tokyo Bound, 9.7 km) is selected as the test bed for this study and analysis period is the whole year of 2003.The next section describes the way that the model is calibrated based on the characteristics of the test bed.

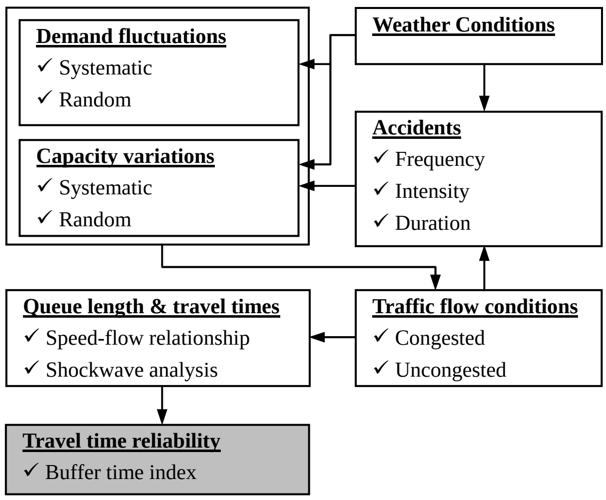

Figure 1: Framework of the simulation model

*Keywords: *Travel time reliability, Level of service, Buffer time index, Breakdown probability*

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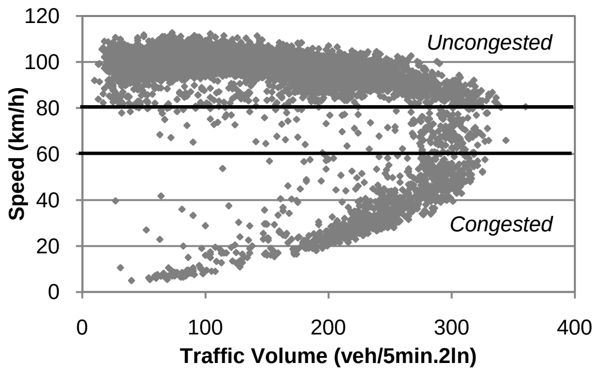


Figure 2: Empirical fundamental diagram

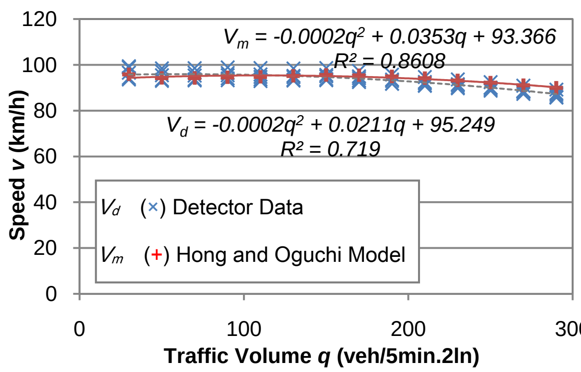


Figure 3: Comparison of estimated and observed speeds (Uncongested)

4. Model components

4.1. Demand

In this study, demand represents the arriving traffic flow that has both regular and stochastic characteristics. Daily and hourly demand values are estimated from test bed's AADT based on a methodology first proposed by Brilon (2000)[6] and further extended by Nakamura, *et al.* (2007)[7] on Japan expressways. Following the same approach, 5-minute aggregated traffic counts from 2002 to 2004 were analyzed. Considering several variables to account for the impacts of rain, month of the year, day of the week and hour of the day, the daily and hourly demand values were estimated for the year 2003. The short term stochastic variation of demand is also considered by applying a multiplicative normal distributed term with an expected value of 1 and standard deviation of 0.1.

4.2. Capacity

Empirical studies revealed that freeway capacity is a random variable and Weibull distributed [4]:

$$F_c(q) = 1 - e^{-\left(\frac{q}{\beta}\right)^{\alpha}} \tag{1}$$

Where α and β are the shape and scale parameters of the distribution function and $F_c(q)$ is the capacity distribution function. Inano (2008)[8] has estimated shape and scale parameters of the capacity distribution function of several bottleneck sections on Japan expressways. Considering the independency of different breakdown events, the probability of breakdown on a segment with n bottlenecks can be estimated from Equation (2):

$$F_c(q) = 1 - \prod_{i=1}^{n}\left[1 - F_{c,i}(q_i)\right] \tag{2}$$

Where $F_{c,i}$ (q_i) and $F_c(q)$ are the capacity distribution function of the bottleneck i and a segment with n bottlenecks respectively. For the test bed of this study, estimations from Equation (2) delivered a Weibull distribution with shape and scale parameters of 14.5 and 383 (veh/5 minute*2ln).

Chung, *et al.* (2006)[9] investigated the impacts of rain on the capacity of several highly congested segments of Tokyo Metropolitan Expressway. Accordingly to adjust simulated capacities due to weather conditions, adjustment factors of 0.94 and 0.91 are applied for the hourly rainfall of 1 to 3 mm and 3 to 10 mm respectively. For heavier rain falls, adjustment factor of 0.89 is applied. In addition, Capacity values need to be adjusted relative to the proportion of the heavy vehicles in traffic flow. Assuming the passenger car equivalent factor of 1.7, Japan Road Association[10] approach is adopted to estimate adjustment factors.

Queue discharge flow (QDF) was proven to be lower than breakdown flow[4]. Using the distribution of breakdown flow rates (observed immediately prior to breakdown) and the distribution of queue discharge flow, an average drop of 3% to 24% is derived by a couple of investigations[4]. However, average capacity drop of 10% is adopted for the purpose of this research that is consistent with Inano (2008)[8].

4.3. Speed-flow relationship

Traffic density is the key parameter of shockwave analysis and can be estimated if average speed is known. Knowing the volume, speed-flow models developed by Hong and Oguchi (2008)[11] were used to estimate speed during uncongested conditions. Using developed models, after defining the distribution of the vehicles on different lanes, the 85th percentile speed for each lane is estimated. As it is preferable to estimate average speeds rather than 85th percentiles, in order to define required adjustments for the purpose of this study, we obtained average speeds (V_d) relative to each traffic volume category, from 5 loop detectors on the test bed and compared the values with estimated 85th percentile speeds (V_m) derived from Hong and Oguchi (2008)[11] models. Regarding **Figure 2,** only samples with average speed of above 80 km/h were considered for this purpose. As shown in **Figure 3,** the difference between observed and estimated speeds increases as traffic flow approaches capacity area. Equation (3) is applied to convert estimated 85th percentile speeds to average values according to traffic volume:

$$\Delta V = V_d - V_m = -0.0142q + 1.883 \tag{3}$$

A speed-flow relationship for congested conditions is developed through investigation of 5 minutes average speeds and traffic volumes of the congested flow in 2003. Regarding **Figure 2**, speed threshold of 60 km/h was set for congested conditions. **Figure 4** shows the average speed of congested flow corresponding to traffic volume categories after excluding transient state observations.

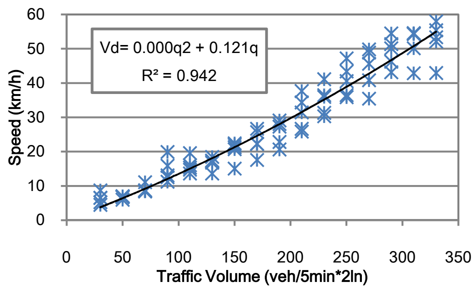


Figure 4: Speed-flow relationship (congested)

A second order polynomial function was found satisfactory to represent speed-flow relationship during congestion.

4.4. Accidents

Hikosaka and Nakamura (2001)[12)] investigated the relationship between accident rate and traffic flow conditions on various segments of Tomei Expressway and developed models to estimate accident rate relative to traffic density. These models are used in this study to generate accidents according to traffic conditions. Traffic conditions are categorized into several categories according to density levels and Equations (4) and (5) are used to estimate accident rate for uncongested and congested conditions respectively. Consequently, number of accidents is estimated from Equation (6) relative to section length l and traffic throughput q_i corresponding to density category i:

$Unc\cdots\cdots$:

$$AR_i = 0.0488{k_i}^2 - 2.983k_i + 60.465 \qquad (4)$$

$Congested$:

$$AR_i = 0.0416{k_i}^2 - 3.1716k_i + 97.142 \qquad (5)$$

$$AN_i = \frac{AR_i \times l \times \sum_i q_i}{10^8} \qquad (6)$$

Where AR_i (AN_i*10^8 / veh.km) is the accident rate, k_i is density and AN_i is the number of accidents for density category i.

To define accident duration, clearance time of 268 accidents occurred on Tomei Expressway in 2003 was analyzed and a Weibull function with shape parameter of 1.13 and scale parameter of 66 (minute) was found to best describe the distribution of the clearance time. Derived parameters were used for random generation of accident clearance times. Accidents could be located randomly on shoulder or main lanes. To estimate capacity reductions due to accidents, adjustment factors of 0.81 and 0.35 are adopted from HCM 2000 for the accidents occurring on shoulder or the main lane respectively.

4.5. Measurement of queued vehicles

As demand exceeds available capacity, since density is known, number of queued vehicles can be estimated through shockwave analysis. Speed of the shockwave w is estimated from Equation (7) and queue propagation rate Q (veh/5 minute) is estimated from Equation (8):

$$w = \frac{q_1 - QDF}{k_1 - k_2} \qquad (7)$$

$$Q = (q_1 - QDF) - k_1.w \qquad (8)$$

Where q_1 and k_1 are traffic volume and density of the upstream (uncongested) and QDF and k_2 are queue discharge flow and density of the congested flow.

5. Travel time and reliability estimation

In this study, buffer time index (BI) is used as a measure of travel time reliability:

$$BI = \frac{95^{th}\,TT - \overline{TT}}{\overline{TT}} \times 100 \qquad (9)$$

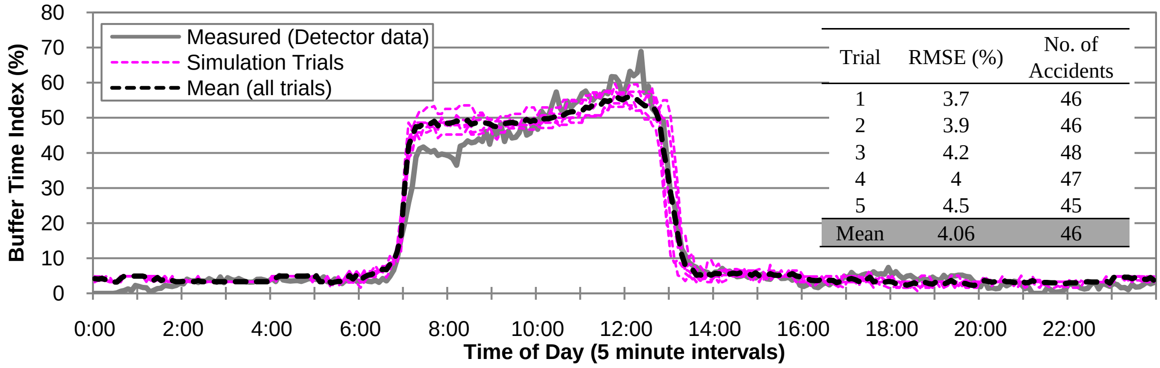
Where 95^{th} TT and $\overline{TT}$ are 95^{th} percentile and average travel time respectively. To estimate buffer time index, travel times should be estimated for each interval during analysis period. For uncongested intervals this could be done by dividing the segment length into the speed at desired time intervals whereas for congested intervals, it is necessary to locate a virtual bottleneck along the segment. Equation (10) is proposed to estimate travel time TT during congested intervals which accounts for congested and uncongested portion of the segment by using different speeds:

$$TT = \frac{Min\left({}^{Q}\!/_{k_2}, \delta.l\right)}{v_2} + \frac{l - Min\left({}^{Q}\!/_{k_2}, \delta.l\right)}{S} \qquad (10)$$

Where v_2 is the speed of the congested flow and S is the speed limit of the segment. Given Q as the number of queued vehicles and k_2 as the density of congested flow, Q/k_2 yields queue length in km. δ is an adjustment factor ($0 < \delta < 1$) that is multiplied to the section length l to define the location of the virtual bottleneck. δ can be defined through an iterative procedure by minimizing the root mean square error (RMSE) of estimated buffer time index from model and detector data. Assuming the virtual bottleneck is located between the midpoint and endpoint of the segment, the following steps describe a procedure to define δ:
Step1: Estimate travel times and buffer time index for each time of day using detector data. Step 2: Set δ =0.5. Step 3: Run the simulation for 5 times and estimate travel times and buffer time index from the simulation model. Step 4: Compare estimated buffer indices from steps 1 and 3 and calculate the RMSE (equation 11) for each trial. Step 5: Set δ=δ + 0.1; if δ >1then go to step 6 else go to step 3. Step 6: Plot δ versus RMSE and select the δ value corresponding to minimum RMSE.

$$RMSE = \sqrt{\frac{\sum_{k=1}^{n}(BI_{mi} - BI_{di})^2}{n}} \qquad (11)$$

Where BI_{mi} and BI_{di} is estimated buffer time index at interval i from model and detector data respectively. n is the number of samples. To estimate travel times from



Trial	RMSE (%)	No. of Accidents
1	3.7	46
2	3.9	46
3	4.2	48
4	4	47
5	4.5	45
Mean	4.06	46

Figure 5: Comparison of measured and simulated buffer time indices for the test bed (Weekdays/Non-holidays)

detector data, "Piecewise Linear Speed Based" (PLSB)[13] trajectory algorithm was applied for each 5-minute interval. Using above procedure for weekdays and non-holidays, δ is estimated as 0.67.

6. Results and validation

A sample output of simulated demand, capacity and resulted queues over a week are shown on **Figure 6**. The simulation model was run for several times and buffer time index was estimated for weekdays and non-holidays of 2003 and compared with the values obtained from detector data. For each trial, RMSE and corresponding number of predicted accidents are shown on **Figure 5**. Peak period starts from 7 am to 1 pm during which travel time unreliability varies from 40% to 70%. Therefore the model can correctly predict the beginning and the end of the peak periods and the extents of congestion. To make an intuitive comparison, average values of estimated buffer time index from several simulation trials is also estimated likewise the corresponding RMSE. The average RMSE is lower than 5 % which is not high, considering the stochastic nature of the input variables. Low values of RMSE, implies the applicability of the proposed methodology to estimate travel time reliability for planning applications. According to available accident records, 49 accidents occurred on the test bed on 2003, while several trials of simulation, predict 47 accidents (**Figure 5**), which are very close. Thus the methodology can also be used to evaluate the safety impacts of congestion improvement schemes.

7. Conclusions and future work

The proposed methodology enables road authorities to evaluate the impacts of congestion improvement schemes on travel time reliability and accident rate, prior to putting them in action. The model could also be applied to evaluate the impacts of root sources on (un)reliability. For the segments, where detector data are not available, more generalized forms of speed-flow relationship are required. Additional investigations are necessary to evaluate the capacity reductions due to accidents on Japan expressways.

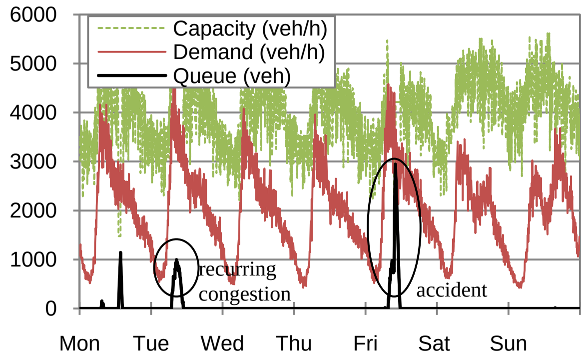


Figure 6: Demand, capacity and resulted queues

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