APPLICATION OF TRAVEL TIME RELIABILITY FOR PERFORMANCE ORIENTED OPERATIONAL PLANNING OF EXPRESSWAYS

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Evaluation of impacts of congestion improvement schemes on travel time reliability is very significant for road authorities since travel time reliability represents operational performance of expressway segments. In this paper, a methodology is presented to estimate travel time reliability prior to implementation of congestion relief schemes based on travel time variation modeling as a function of demand, capacity, weather conditions and road accidents. For subject expressway segments, traffic conditions are modeled over a whole year considering demand and capacity as random variables. Patterns of demand and capacity are generated for each five minute interval by applying Monte-Carlo simulation technique, and accidents are randomly generated based on a model that links accident rate to traffic conditions. A whole year analysis is performed by comparing demand and available capacity for each scenario and queue length is estimated through shockwave analysis for each time interval. Travel times are estimated from refined speed-flow relationships developed for intercity expressways and buffer time index is estimated consequently as a measure of travel time reliability. For validation, estimated reliability indices are compared with measured values from empirical data, and it is shown that the proposed method is suitable for operational evaluation and planning purposes.

\textbf{Key Words:} quality of service, congestion relief schemes, travel time reliability, buffer time index

1. INTRODUCTION

Travel time reliability is a preferred measure to evaluate the quality 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 as it reflects operational performance of expressway segments. 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. One barrier to this potential application is the inherent limitations of travel time reliability estimation methods. 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 implementing the congestion improvement scheme), by far, the most one could get is the estimates of reliability measures for the existing conditions.

In this study, first an empirical method to estimate travel time reliability is described briefly through a field study. Then a novel methodology is presented to estimate travel time reliability based on modeling travel time variations as the function of demand, capacity, weather conditions and accidents. Finally, proposed methodology is validated by comparing estimated reliability measures with the values measured through the field study. Proposed methodology considers stochastic variations of demand and capacity dynamically and makes it possible to estimate travel time variations over the time. Hence, travel time reliability can be estimated and
used for assessing the efficiency of congestion relief schemes prior to their implementation.

2. LITERATURE REVIEW

Reliability is relatively new to the realm of traffic engineering. There are several definitions used for travel time reliability, but the following definitions have been well documented in the literature\(^1\): i) The range of travel times experienced during a large number of trips; ii) The impact of non-recurring congestion on travel conditions (duration, extent and intensity); iii) The likelihood that a trip maker’s expectations being met (variability between the expected and actual travel time). Lint et al.\(^2\) compared several existing commonly used travel time reliability measures based on empirical data from a densely used freeway in the Netherlands and found that all measures are highly inconsistent. As a result, without objective and quantitative criteria, a choice for any reliability measure in road network performance analysis will remain subject to debate.

Travel time variations on expressways are the result of interactions between demand, capacity, weather conditions, accidents, work zones and traffic composition. All these components have some stochastic characteristics. The interaction can be complex and varies greatly from day-to-day. Such interactions were investigated by a number of studies. Tu, et al.\(^3\),\(^4\) evaluated the impact of inflow variations and traffic composition as the root sources of (un)reliability. Tu, et al.\(^6\) proposed a methodology that incorporates breakdown probability into travel time reliability. But their methodology is unable to produce common reliability measures which are based on travel time distributions, and cannot be used to evaluate travel time reliability prior to implementation of congestion relief schemes. This study aims to develop such a model that estimates travel time reliability as the function of probability of breakdown, demand variations, accidents, weather conditions and traffic composition as the root sources of (un)reliability.

3. EMPIRICAL APPROACH

Availability of continuous travel time data is an essential prerequisite for empirical reliability estimation methods. In this study, travel times were estimated for each 5-minute interval during analysis period from spot speeds collected by double loop detectors by using the “Piecewise Linear Speed Based” (PLSB) model proposed by Lint and Zjipp\(^8\). The following section describes the characteristics of the test bed and available data.

(I) Test bed and analysis period

The test bed of this study includes two consecutive segments of Tomei Expressway that runs from Tokyo to Nagoya (Tokyo bound). Each segment has 2 lanes with on/off ramps in the beginning and the end. Analysis period is the whole year of 2003. As shown in Fig.1, segment A is 9.7 km long and located between Nagoya and Tomei-Miyoshi interchanges. Segment B is 5.0 km long and located between Tomei-Miyoshi and Toyota interchanges. There are 7 double loop detectors installed on the test bed reporting aggregated spot speeds and traffic counts every 5 minutes. Detector data were used to estimate travel times and reliability trends over the analysis period. Weather data were available from 2002 to 2005 and accident records on the test bed were collected for the year 2003.
Travel time reliability measurement

In this study, buffer time index ($B_{Isj}$) is used as a measure of travel time reliability:

$$B_{Isj} = \frac{95^{th} TT_{Isj} - \overline{TT}_{Isj}}{\overline{TT}_{Isj}} \times 100$$

(1)

where $95^{th} TT_{Isj}$ and $\overline{TT}_{Isj}$ are the 95th percentile and average travel time in interval $s$ of the day category $j$, respectively ($s=1, 2, ..., 288; j=1$ for all days; $j=2$ for weekdays/non-holidays; $j=3$ for weekends/holidays). Travel times were estimated for segment A, segment B and the whole test bed. As shown in Fig.2, considering travel time distributions for segment A, segment B and the whole test bed, buffer time index was estimated every 5 minute during the analysis period for three categories of days: i) All days including weekends and holidays; ii) Weekdays/non-holidays; iii) Weekends/holidays. To estimate buffer time index at any desired time interval in Fig.2, in the case of all days, distribution of travel times including 365 samples are considered (daily travel times at the same time interval). Considering 130 weekends and holidays in 2003, for weekdays/non-holidays and weekends/holidays, 235 and 130 samples are included, respectively.

Although directional average annual daily traffic (AADT) is almost equal for both segments, travel times on segment A are obviously more unreliable comparing to segment B. The difference is more conspicuous on weekdays/non-holidays, where demand increases every morning during the peak periods. While buffer time index is sometimes up to 70% on segment A during the peak periods, travel times on segment B seem to be relatively reliable as buffer time index does not exceed 15%. On weekends/holidays, travel condition on segment A is significantly unreliable in the morning between 10 am and 1 pm where buffer time index rises drastically up to 100%. Such unreliable travel times are the result of increased demand for travel on some weekends/holidays and such special vacations in Japan as Obon (mid August) and Golden Week (end of April and beginning of May). Segment B also has unreliable travel conditions on weekends/holidays in the morning between 10 am and 1 pm. However since the maximum buffer time index is about 50%, travel condition is more reliable on segment B comparing to segment A.

Segment A is located in the upstream of segment B. As it will be discussed in section 5, there are several bottlenecks on segment A. As a result, the traffic volume which is arriving to segment B during the congested periods is actually the queue discharge flow from segment A plus/minus the vehicles entering or leaving the test bed from on/off ramps. The arriving traffic flow to segment B during congested periods on segment A is apparently not high enough to cause traffic breakdowns in most of the cases. Thus, travel times are much more reliable on segment B comparing to segment A. Such a phenomenon implies the significant impact of expressway segments with several bottlenecks on the whole network's travel conditions.

Some congestion relief schemes may culminate in less variable travel times and improve reliability trends shown in Fig.2. On the other hand, safety may improve as a result of improved traffic conditions after implementation of a congestion relief scheme. However the extents, to which travel time reliability or safety will improve, cannot be evaluated using the same empirical method due to unavailability of required data. The following section describes a framework that can be used to evaluate impact of congestion improvement schemes on reliability in advance.

4. MODELING METHODOLOGY

Fig.3 shows the general framework of the proposed simulation model. i) For an expressway segment, traffic conditions were modeled over a year
by estimating hourly traffic demands and capacities. Patterns of demand and capacity were generated for each 5-minute interval (365×24×12=105,120 intervals) by applying Monte-Carlo simulation technique. ii) Weather condition and its impacts on capacity and demand variations were simulated according to available meteorological data during the analysis period. iii) Accidents were generated randomly based on a model that links accident rate to traffic density. However, the relationship between adverse weather and accident likelihood was not considered yet. iv) A whole year analysis was performed by comparing demand and available capacity for each scenario, and queue length was estimated for each time interval through shockwave analysis. v) Travel times were estimated using speed-flow relationships developed for expressways. vi) Finally, buffer time index was estimated as a measure of travel time reliability.

Regular patterns of demand were modeled by analyzing historical traffic volume data based on the month of the year, day of the week and weather conditions.

Capacity was considered as a random variable in the proposed methodology. Since traffic breakdown may happen on different locations on each segment, the capacity distribution function for each segment was estimated by incorporating the capacity distri-

Fig.2 Measured buffer time index from empirical data.
Demand and capacity were compared at each 5-minute interval. If demand exceeds available capacity, shockwave analysis and speed-flow relationships were used to estimate the resulting queue length and the required time for queue dissipation.

After initial assessment of traffic conditions at each time interval, accidents were generated based on a model that relates accident rate to traffic density. Separate models were used for congested and uncongested conditions.

Travel times at uncongested intervals were estimated given the speed of traffic flow and segment length. Travel times at congested intervals were estimated considering the segment length, queue length and the position of the bottleneck. Impacts of queue discharge flow from segment A and queue spillbacks from segment B was considered while estimating travel times at congested intervals. Finally, distribution of travel times at each time interval was considered and buffer time index was estimated as a measure of travel time reliability.

A simulation model was developed for the whole test bed and was calibrated by using the above-mentioned procedure according to the characteristics of each segment of the test bed in 2003. Calibration process and model components are described elaborately in the proceeding section.

5. MODEL COMPONENTS

(1) Demand

In this study, demand represents arriving traffic flow during uncongested periods which has both regular and stochastic characteristics.

a) Regular patterns

Daily and hourly demand values are estimated based on a methodology first proposed by Brilon\(^\text{10}\) and further extended by Nakamura, et al.\(^\text{11}\) on Japan expressways. The main hypothesis is that the regular patterns of demand can be modeled as a function of day of the year and weather conditions.

Daily traffic demand ratio \( (DD_d) \) is defined as the quotient of daily traffic demand divided by directional annual average daily traffic \((AADT)\). Considering the time of the day, the hourly traffic demand \((HD_{dh})\) on a day category of \(d\) is estimated from equation:

\[
HD_{dh} = DD_d \times HDC_{dh} \times AADT
\]  

(2)

where, \(HDC_{dh}\) is the hourly traffic demand coefficient (ratio of hourly traffic demand to daily traffic demand). To estimate \(HDC_{dh} \), the 5-minute traffic counts were analyzed in 2003 which is the analysis period of this study. Daily traffic demand was estimated by aggregating the 5-minute traffic counts for each day in 2003 and then hourly traffic demands were estimated by aggregating the 5-minute traffic counts for each uncongested hour in 2003.

b) Stochastic characteristics

Stochastic characteristics of traffic demand were considered in estimation of daily traffic demand and within hour demand variations. Hourly traffic demands were divided by corresponding daily traffic demand and hourly traffic coefficients were estimated for each hour. Congested hours were not considered because the traffic volume during these periods is influenced by traffic conditions in the upstream or downstream and does not represent the real demand. Estimated values were then categorized for each hour based on the day category and the median was considered as the hourly traffic demand coefficient for each hour of a specific day category. Equation (3) is used to estimate daily demand ratios according to day, month and weather condition categories:

\[
DD_d = \alpha_m + \beta_d + \gamma_r + \mu + \varepsilon
\]  

(3)

where, \(\alpha_m\) is dummy of month with 12 categories (January to December); \(\beta_d\) is dummy of day with 9 categories (weekdays, Sunday/holidays and special days); \(\gamma_r\) is dummy of rainfall with 4 categories (no rain, 1-30mm/day, 30-90mm/day and above 90mm/day); \(\mu\) is a constant value and finally \(\varepsilon\) is the random error term with a normal distribution and mean of zero. There are several categories defined for input variables in equation (3). Thus, to provide enough samples for each category of input variables, the detector data from 2002 to 2004 were analyzed and model parameters in equation (3) were estimated. The 5-minute traffic counts were aggregated.
for each day to estimate the daily traffic demand ratios from 2002 to 2004. Model parameters and goodness of fit index ($R^2$) for study segments are summarized in Table 1.

Traffic demand does not exactly follow the patterns created from equation (3). There is an additional short term fluctuation, which could be described by some random components. This random fluctuation could either be treated as additive or multiplicative with normal distribution \( \phi \). Based on field observations, multiplicative treatment was adopted for the purpose of this research.

Demand values for each 5-minute interval \( D_{5 \text{ min}} \) were estimated from hourly demands considering short term stochastic variation of demand:

\[
D_{5 \text{ min}} = \varphi \times \frac{HD_{\text{th}}}{12} \tag{4}
\]

where \( \varphi \) is a multiplicative random term with expected value of 1. In order to find distribution parameters of \( \varphi \), the relationship between 5-minute aggregated traffic counts and hourly traffic volumes during uncongested hours of the year 2003 was analyzed. Distribution parameters for \( \varphi \) and goodness of fit indicators are summarized in Table 2.

Since there are on/off ramps on the test bed, demand variations might not be the same on segment A and segment B. Thus demand variations on each segment were modeled separately by analyzing the detector data corresponding to each segment. If the number of vehicles entering or leaving the test bed from on/off ramps were known, demand variations on segment B could alternatively be modeled as the function of traffic demand on segment A. However, because such data were not available, demand variations were modeled separately for each segment.

(2) Capacity

a) Stochastic concept of capacity

Empirical capacity distribution function for a roadway under specific prevailing conditions can be estimated by using mathematical methods for lifetime data analysis \(^{12}\). Empirical studies revealed that the Weibull distribution is the function that best fits the capacity distribution function on freeway segments \(^{12}\):

\[
F_c(q) = 1 - \left(\frac{q}{\beta}\right)^\alpha \tag{5}
\]

where \( \alpha \) and \( \beta \) are the shape and scale parameters of the distribution function and \( F_c(q) \) is the capacity distribution function.

Applying the same methodology, Inano, et al. \(^{13}\) investigated the breakdown phenomena on several segments of intercity expressways in Japan and estimated shape and scale parameters of the capacity distribution function of several bottleneck sections. There are 4 bottleneck sections on the test bed of this study which were investigated by Inano, et al. \(^{13}\). The parameters of capacity distribution function for each of these bottlenecks are shown in Table 3. The scale parameter of the bottleneck section in 322.38 KP (Kilopost (km)) is 379.2 (veh/5 minute·2ln), which is the lowest value compared with other bottlenecks. Thus, for the same traffic volume, the probability of having a breakdown is higher in 322.38 KP. Fig.4 represents the empirical fundamental diagram in 322.38 KP which includes considerable number of congested intervals. The main reason for traffic breakdown in 314.27 KP and 322.38 KP was the existence of the sag sections.

### Table 1
Model parameters to estimate daily traffic demand ratio \( (DD_d) \) from equation (3).

<table>
<thead>
<tr>
<th>Category</th>
<th>Model Parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Segment A</td>
</tr>
<tr>
<td>January</td>
<td>-0.0609</td>
</tr>
<tr>
<td>February</td>
<td>-0.0231</td>
</tr>
<tr>
<td>March</td>
<td>0.0613</td>
</tr>
<tr>
<td>April</td>
<td>-0.0155</td>
</tr>
<tr>
<td>May</td>
<td>-0.0336</td>
</tr>
<tr>
<td>June</td>
<td>-0.0371</td>
</tr>
<tr>
<td>July</td>
<td>0.0138</td>
</tr>
<tr>
<td>August</td>
<td>0.1230</td>
</tr>
<tr>
<td>September</td>
<td>0.0129</td>
</tr>
<tr>
<td>October</td>
<td>-0.0154</td>
</tr>
<tr>
<td>November</td>
<td>0.0024</td>
</tr>
<tr>
<td>December</td>
<td>-0.0348</td>
</tr>
<tr>
<td>Sunday/holiday</td>
<td>-0.1436</td>
</tr>
<tr>
<td>Monday</td>
<td>-0.0004</td>
</tr>
<tr>
<td>Tuesday</td>
<td>0.0286</td>
</tr>
<tr>
<td>Wednesday</td>
<td>0.0411</td>
</tr>
<tr>
<td>Thursday</td>
<td>0.0465</td>
</tr>
<tr>
<td>Friday</td>
<td>0.0699</td>
</tr>
<tr>
<td>Saturday</td>
<td>-0.0847</td>
</tr>
<tr>
<td>Consecutive holiday a</td>
<td>-0.0183</td>
</tr>
<tr>
<td>Peak Period b</td>
<td>-0.0668</td>
</tr>
<tr>
<td>0 mm/day</td>
<td>0.0108</td>
</tr>
<tr>
<td>1-30 mm/day</td>
<td>-0.0208</td>
</tr>
<tr>
<td>31-90 mm/day</td>
<td>-0.0413</td>
</tr>
<tr>
<td>More than 90 mm/day</td>
<td>-0.1769</td>
</tr>
<tr>
<td>Constant</td>
<td>1.0156</td>
</tr>
<tr>
<td>Multiple R square</td>
<td>0.7744</td>
</tr>
</tbody>
</table>

\( a \) When a holiday comes after Sun. or before Sat.  
\( b \) Jan. 1-4, Apr. 29-May 5, Aug. 10-16, Dec. 29-31

### Table 2
Distribution parameters for \( \varphi \) in equation (4).

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>1.00</td>
</tr>
<tr>
<td>Standard deviation</td>
<td>0.13</td>
</tr>
<tr>
<td>Kolmogorov-Smirnov statistic</td>
<td>0.03919</td>
</tr>
<tr>
<td>Anderson-Darling statistic</td>
<td>17.382</td>
</tr>
<tr>
<td>Chi-Squared statistic</td>
<td>107.76</td>
</tr>
</tbody>
</table>

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However in other bottleneck sections the reason was not recognizable. Since there are several bottleneck sections on the test bed, breakdown of traffic flow may occur in different locations on each segment. In this study, breakdown probability is considered for each segment rather than a single bottleneck section. Capacity distribution function was estimated for each segment by incorporating the capacity distribution function of all bottleneck sections on each segment. Considering the independency of different breakdown events, the probability of breakdown on a segment with $n$ bottlenecks can be estimated from equation (6) that is one minus the product of the probability of non-breakdown of each bottleneck section:

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

where $F_{c,i}(q_i)$ and $F_c(q)$ are the capacity distribution function of the bottleneck $i$ and that of a segment with $n$ bottlenecks, respectively.

For segment A, considering all three bottleneck sections, estimations from equation (6) delivered a Weibull distribution with shape and scale parameters of 14.5 and 383 (veh/5min·2ln). However, since there is only one bottleneck section on segment B, capacity distribution function of 314.27 KP was used for modeling capacity on segment B. Capacity of each segment is generated using the inverse of the Weibull distribution function:

$$C = \beta \left(-\ln(u)\right)^{\frac{1}{\alpha}}$$

where $C$ is the segment capacity and $u$ is a uniform distributed random term between 0 and 1.

b) Capacity adjustments
Chung, et al. [14] investigated the impacts of rain on the capacity of several highly congested segments of Tokyo Metropolitan Expressway. Results of their study are implemented to adjust simulated capacities according 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 rainfalls, 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 approach [15] is adopted to estimate adjustment factors (which is also similar to HCM [16] methodology).

c) Capacity drop and queue discharge flow
Existence of different capacity values under flowing and congested traffic conditions has been proven by a number of studies. When breakdown occurs, the queue will form upstream of the bottleneck. The resulting queue will dissipate at the rate equal to the capacity after breakdown. Thus, to estimate the queue length, speed of queuing vehicles and the required time for complete dissipation of queue, it is necessary to know the amount of capacity drop after breakdown. Using the distribution of breakdown flow rates (observed immediately prior to breakdown) and the distribution of queue discharge flow, Inano, et al. [13] investigated the capacity drop phenomena on several intercity expressway segments in Japan. They measured an average of 10% reduction in capacity after breakdown. Since the test bed of our study is also an intercity expressway segment, average capacity drop of 10% is adopted for the purpose of this research.

(3) Speed-flow relationship
Demand and capacity are compared at each

<table>
<thead>
<tr>
<th>Kilopost (km)</th>
<th>Cause of Congestion</th>
<th>Slope</th>
<th>Scale Parameter</th>
<th>Shape Parameter</th>
</tr>
</thead>
<tbody>
<tr>
<td>314.27</td>
<td>Sag</td>
<td>-1.0% → +1.0%</td>
<td>450.6</td>
<td>10.7</td>
</tr>
<tr>
<td>318.35</td>
<td>Unknown</td>
<td>-0.4% → +1.1%</td>
<td>526.7</td>
<td>10.9</td>
</tr>
<tr>
<td>320.37</td>
<td>Unknown</td>
<td>+1.6%</td>
<td>443.2</td>
<td>13.3</td>
</tr>
<tr>
<td>322.38</td>
<td>Sag</td>
<td>-2.7% → +1.1%</td>
<td>379.2</td>
<td>22.1</td>
</tr>
</tbody>
</table>
5-minute interval. Once demand exceeds capacity, traffic conditions turn into congested. To estimate the duration of congestion, knowing the queue discharge flow, shockwave analysis is used to estimate the number of queuing vehicles. Traffic density is the key parameter of the shockwave analysis and given the traffic volume, density can be estimated if speed is known. Hence, it is necessary to estimate the average speed at congested and uncongested time intervals.

**a) Uncongested conditions**

Speed-flow relationships calibrated by Hong and Oguchi\(^\text{17}\) are used to estimate 85\(^{th}\) percentile speeds during uncongested conditions. Using their models, first, distribution of the vehicles through different lanes is defined regarding the pavement surface conditions (dry/wet) and number of lanes. Then the 85\(^{th}\) percentile speed for each lane is estimated by using the calibrated speed-flow relationships. As in this study it is preferable to estimate average speeds rather than 85\(^{th}\) percentiles, in order to define required adjustments, we obtained average speeds (\(v_d\)) relative to each traffic volume category, from detector data on each segment of the test bed and compared the values with estimated 85\(^{th}\) percentile speeds (\(v_m\)) derived from Hong and Oguchi\(^\text{17}\) models. Regarding Fig.4, only samples with average speed of above 80 km/h were considered for the analysis. After examining several functional forms, the second order polynomial function found to be the best fit function regarding higher \(R^2\) values. Appropriate second order polynomial functions were fitted to both data sets for each segment.

As shown in Fig.5a) and Fig.5b), the difference between observed average speeds and estimated 85\(^{th}\) percentile speeds increases as traffic flow approaches capacity area. This difference (\(\Delta v\)) is described by equation (8) and equation (9) for segment A and segment B, respectively. These equations are applied to modify estimated 85\(^{th}\) percentile speeds (\(v_m\)) and convert them into average values (\(v_d\)) according to traffic volume on each segment:

**b) Congested conditions**

To estimate the average speed of the congested flow, site specific speed-flow relationships were developed through investigation of 5-minutes aggregated speeds and traffic volumes of the congested flow on each segment of the test bed in the year 2003. It is assumed that weather conditions and proportion of heavy vehicles do not affect the speed-flow relationship during congested conditions. Regarding Fig.4, speed threshold of 60 km/h was set for congested conditions. It should be noted that intervals with average speeds around 60 km/h may also include transient flow intervals during which traffic flow conditions change from congested to uncongested and vice versa. Since inclusion of such samples may result in a biased speed-flow relationship they should be excluded from the analysis beforehand. Fig.6a) and Fig.6b) show the average speed of congested flow corresponding to traffic volume categories after excluding transient state observations on segment A and segment B. There are 5 detectors installed on segment A while on segment B there are only 2 detectors. Each point in Fig.6a) and Fig.6b) represents the average speed of corresponding congested flow, derived from an individual detector. After trying different functional forms, the second order polynomial function was found satisfactory to represent speed-flow relationship during congestion on each segment. In addition to significant statistical fitness, the function meets the fundamental traffic flow theory requirements since it pass through the origin when traffic flow is zero. Developed equations for speed-flow relationships during congested periods are presented in Fig.6a) and Fig.6b) for segment A.

<table>
<thead>
<tr>
<th>Segment</th>
<th>Equation</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>(\Delta v = v_d - v_m = -0.0128q - 4.0)</td>
</tr>
<tr>
<td>B</td>
<td>(\Delta v = v_d - v_m = -0.0235q - 2.88)</td>
</tr>
</tbody>
</table>

Fig.5 Speed-flow relationships for uncongested conditions.

<table>
<thead>
<tr>
<th>Traffic volume (q) (Veh/5min-2in)</th>
<th>Speed (v) (km/h)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>100</td>
</tr>
<tr>
<td>100</td>
<td>120</td>
</tr>
<tr>
<td>200</td>
<td>140</td>
</tr>
<tr>
<td>300</td>
<td>160</td>
</tr>
<tr>
<td>400</td>
<td>180</td>
</tr>
</tbody>
</table>

Table 1: Speed-volume relationships for uncongested conditions.
(4) Accidents

The relationship between accidents and traffic conditions was investigated by many studies. Zhou and Sisiopiku\(^{18}\) found that the correlation between \(v/c\) ratio and accident rate follows a general U-shape pattern on the freeways of the United States. Chang, \textit{et al.}\(^{19}\) as well as Hikosaka and Nakamura\(^{20}\) observed the same tendency on Korean freeways and Japanese expressways, respectively. Lord, \textit{et al.}\(^{21}\) developed predictive models to estimate accident rate as a function of traffic volume, \(v/c\) and traffic density based on the data collected on Canadian freeways. The results showed that predictive models that incorporate \(v/c\) and traffic density perform better compared with the models that use traffic volume as the only explanatory variable. Most of the researches in this respect emphasize that as traffic condition becomes congested, the risk of certain types of accidents (e.g. rear-end) increases. However, the shape of such relationship is the function of road characteristics and drivers' behavior which might be different for each location.

Hikosaka and Nakamura\(^{20}\) investigated the relationship between accident rate and traffic flow conditions on various segments of Tomei Expressway and developed separate models to estimate accident rate relative to traffic density in congested and uncongested conditions. These models are used in this study to generate accidents according to traffic conditions. Since density is known at each time interval, congested and uncongested time intervals are separately categorized based on their density level. For each category, accident rate is estimated according to traffic conditions and density level by using equation (10) and equation (11). Then, number of accidents is estimated from equation (12) relative to section length \(l\) and traffic throughput \(q_i\) corresponding to density category \(i\):

\[
AR_i = 0.0488k_i^2 - 2.983k_i + 60.456 \quad (10)
\]

\[
AR_i = 0.0416k_i^2 - 2.716k_i + 97.142 \quad (11)
\]

\[
AN_i = \frac{AR_i \times l \times \sum q_i}{10^4} \quad (12)
\]

where \(AR_i\) (\(AN_i\times10^8\)/veh·km) is the accident rate, \(k_i\) is density and \(AN_i\) is the number of accidents corresponding to density category \(i\). Estimated numbers of accidents for each category of density and traffic conditions are generated randomly at corresponding time intervals. It should be noted that these models were developed by using average values of accident rate and traffic density. Therefore to avoid over- or underestimation, an appropriate adjustment factor was applied to the models for each segment.

\textbf{a) Clearance time and capacity reduction}

Duration of an accident is directly related to accident clearance time which is defined as the time period between the occurrence and removal of an accident. To define accident duration, clearance time of 268 accidents occurred on Tomei Expressway in 2003 was analyzed and the distribution of the clearance times was investigated. For modeling purpose, several functional forms were considered and finally 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.

Depending on the lane at which the accident occurs, the remaining available capacity might be different. To estimate the available capacity after accidents, considering the number of lanes, adjustment factors of 0.81 and 0.35 are adopted from...
for accidents occurring on the shoulder or the main lanes, respectively.

(5) Measurement of queuing vehicles

As demand exceeds available capacity, since density is known, number of queued vehicles can be estimated through shockwave analysis. As presented in Fig.7, speed of the shockwave $w$ is estimated from equation (13) and queue propagation rate $Q$ (veh/5 minute) is estimated from equation (14):

$$w = \frac{q_1 - QDF}{k_1 - k_2}$$  \hspace{1cm} (13)  

$$Q = (q_1 - QDF) - k_1w$$  \hspace{1cm} (14)

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. $QDF$ for congested intervals can be estimated considering the capacity distribution function and the capacity drop.

(6) Travel time and reliability estimation

To estimate buffer time as a measure of travel time reliability, travel times should be estimated at each 5-minute interval during the analysis period. Travel times are first estimated at each time interval for segment A and segment B considering the interactions between them. Afterwards, for the whole test bed travel times are estimated by summing the corresponding travel times on segment A and segment B at any time interval. For uncongested conditions, traffic condition is assumed to be uniform along each segment of the test bed, so travel times for each segment could simply be estimated through dividing the segment length by the average speed of traffic flow. Since there might be more than one bottleneck section on each segment, the impacts of several bottlenecks are modeled through a single virtual bottleneck. The location of the virtual bottleneck plays a significant role in estimating travel times during the congested periods. As shown in Fig.7, during congested conditions the following areas are defined with different operating speeds on each segment: i) upstream of queuing vehicles; ii) queuing vehicles and iii) downstream of queuing vehicles. Different speeds on these areas should be considered to estimate travel times during congested conditions on each segment. Regarding Fig.7, equation (15) is proposed to estimate travel times ($TT$) during congested conditions on each segment:

$$TT = \frac{\delta x l - Q/k_2}{v_1} + \frac{Q/k_2}{v_2} + \frac{l - \delta x l}{v_3}$$  \hspace{1cm} (15)

Given $Q$ as the number of queuing vehicles and $k_2$ as the density of congested flow, $Q/k_2$ yields queue length in kilometer. $\delta$ is an adjustment factor ($0 < \delta \leq 1$) that is multiplied to the segment length ($l$) to define the location of the virtual bottleneck.

To estimate travel times from equation (15), the only unknown parameter is $\delta$ which defines the location of the virtual bottleneck. Since the ultimate
The goal of the model is to estimate buffer time index, $\delta$ can be defined through an iterative procedure by minimizing the RMSE of estimated buffer time index from the model and measured values from empirical data. The following steps describe the procedure to define $\delta$ for each segment of the test bed: 
Step 1: Set $\delta = 0.1$; Step 2: Run the simulation model for 5 times for each segment and estimate travel times and buffer time index at each 5-minute interval for the whole analysis period; Step 3: Compare estimated buffer time index with measured values from empirical data and calculate RMSE for each trial of simulation; Step 4: Set $\delta = \delta + 0.1$; if $\delta < 1$ then go to Step 5, else go to Step 2; Step 5: Plot $\delta$ versus RMSE and select the $\delta$ value corresponding to the minimum RMSE. As shown in Fig. 8 for segment A, following the steps above, $\delta$ for weekdays/non-holidays and weekends/holidays were estimated equal to 0.65 and 0.76, respectively. For segment B, the $\delta$ values were estimate equal to 1.0 and 0.3 for weekdays/non-holidays and weekends/holidays, respectively.

(7) Interaction between segments

Segment A is located in the upstream of segment B. Therefore, interactions between segments should be considered when estimating travel times for each segment. Two conditions are considered for this purpose: i) Congested conditions on segment A and ii) Queue spillback from segment B.

When traffic condition is congested on segment A, the arriving traffic volume to segment B is equal to the queue discharge flow from segment A plus/minus the vehicles entering or leaving the test bed from on/off ramps. As discussed earlier, the queue discharge flow was assumed to be 10% lower than the capacity before breakdown. Thus, estimated demand for segment B is reduced by 10% during the time intervals when traffic condition is congested on segment A.

If traffic condition is congested on segment B, the resulting queue may extend to segment A and affect travel times at corresponding time intervals. The queue length and the position of the back of queue are estimated dynamically at each time interval during the congested periods on segment B. If the resulting queue from segment B extends to segment A and traffic condition on segment A is uncongested, the portion of segment A which is occupied by the queue from downstream is estimated. Since speed of queuing vehicles is known, travel time on segment A is adjusted consequently. Occasionally traffic condition on segment A might be congested when there is queue spillback from segment B. In this case, if extended queue from segment B reaches the existing queue in segment A, both queues are combined together. The speed of queuing vehicles is estimated from the speed-flow relationship of segment B for congested conditions and travel time on segment A is adjusted according to the position of the back of queue in such time intervals.

6. RESULTS AND VALIDATION

Analysis of traffic flow data on the test bed points out that generally on weekends the overall traffic flow is lower than that on weekdays. On daily basis, traffic flow is low during midnight and early morning hours. However, the proportion of heavy vehicles in traffic stream is significantly high during the period. The peak period on weekdays starts around 7 am and continues until about 1 pm. Traffic flow is relatively high until the evening where it gradually starts to decrease again. Such variations in traffic flow results in unstable travel conditions on segment A due to the existence of several bottleneck sections. But for segment B, since it is located downstream of bottleneck sections, travel conditions are relatively stable.

A sample output of simulated demand, capacity and resulting queues over a week are shown for segment A in Fig. 9. In addition to random variations of capacity which is due to stochastic nature of traffic flow breakdown, systematic variations are also conspicuous. Capacity during the nighttime is considerably lower than daytime values, mostly because of the high proportion of heavy vehicles in traffic stream that surges beyond 60% time by time. Conversely, on the weekends where heavy vehicles are not much prevalent, capacity is marginally higher compared with weekdays. Sometimes demand exceeds available capacity during peak periods and recurring congestion occurs as a result of capacity drop and accumulation of unmet demand. Queues propagate in the upstream of the bottleneck.
with a rate relative to the speed of the resulting shockwaves. However, the magnitude and duration of recurring congestion is much smaller than that of non-recurring congestion which occurs occasionally due to accidents. Duration of non-recurring congestion is defined depending on the available capacity after accident, demand variations and clearance time of the accident.

The simulation model was run for 5 times for the test bed. Travel times, buffer time index and predicted number of accidents were estimated for segment A, segment B and the whole test bed in the year 2003. The buffer time index was estimated using the methodology described in section 3 for all days, weekdays/non-holidays, and weekends/holidays. Estimated buffer time index was compared with previously measured values from empirical data and the RMSE was estimated for each trial of simulation. The results are presented in Fig.10, Fig.11 and Fig.12 for segment A, segment B and the whole test bed, respectively. Since the model is stochastic, estimated buffer time index may vary at each time interval every time the simulation is run. Hence, to make an intuitive evaluation, the mean buffer time index derived from all trials of simulation was also estimated for each category of days and compared with measured values from empirical data.

As buffer time index is strongly dependent on average travel time at each time interval, the average of simulated travel times were estimated for each time interval and compared with measured values from empirical data. The comparison results and estimated RMSE for segment A, segment B and the whole test bed is presented in Fig.13 for all day categories.

According to Fig.10, travel time unreliability varies from 40% to 70% on all days and weekdays/non-holidays during the morning peak periods on segment A. The model could reasonably predict the beginning and the end of daily unreliable travel periods. The buffer time index is estimated with RMSE of 4.6% and 5.3% for all days and weekdays/non-holidays, respectively. On weekends/holidays, estimated buffer time index from all simulation trials follows the same tendency as measured values from empirical data. However the RMSE is about 6.8% that is higher compared with weekdays/non-holidays. Considering the smaller number of samples for each time interval (130 samples), buffer time index varies more irregularly on weekends/holidays for each simulation trial. Moreover, holidays and weekends were considered to be in the same category of days. Yet, characteristics of demand and capacity might be different on holidays and weekends. Inaccuracies in modeling demand and capacity may contribute in elevated dispersion for estimated buffer time index on weekends/holidays.

As shown in Fig.13 for segment A, estimated average travel times in all categories of days is close to measured values from empirical data in most time intervals with some over- and underestimations especially in the beginning of the peak period. The possible reasons for such estimation errors will be discussed here. As mentioned in section 5, speed-flow relationships were defined only for congested and uncongested conditions. However, in the beginning of the peak period, traffic flow might be in transient conditions, which is not considered in the proposed methodology. Another source of estimation errors is the demand estimation model. The accuracy of demand estimation model is lower during congested periods since traffic volume during congested periods does not represent the real demand.

For segment B, travel times are fairly reliable on all days and weekdays/non-holidays. The simulation model could estimate buffer time index with RMSE about 3.4% and 2.8% for all days and weekdays/non-holidays, respectively whereas on weekends/holidays estimation error is 4.9%. As presented in Fig.13, average travel times were estimated reasonably with low error on all day cate-
Such results could be interpreted as superior performance of the simulation method on less congested segments. Travel time reliability on the whole test bed (Fig.12) follows the same tendency as segment A. The buffer time index on all days and weekdays/non-holidays was estimated with RMSE equal to 3.5% and 3.0%, respectively. The RMSE in case of weekends/holidays is equal to 7.3% which is higher than that of weekdays/holidays.

According to available accident records, 80 accidents occurred on segment A in 2003 from which 61 accidents took place on weekdays/non-holidays and 19 accidents happened on weekends/holidays. The simulation model predicts 60 accidents for weekdays/non-holidays and 21 accidents for weekends/holidays in average. For segment B, there were 19 accidents reported in 2003, from which 12 accidents were on weekdays/non-holidays and 7 accidents were on weekends/holidays. The model estimates 12 accidents on weekdays/non-holidays and 8 accidents on weekends/holidays. It is worthwhile to note that in this study accidents are modeled merely based on traffic conditions (traffic density) without considering other influencing factors such as road geometry, weather conditions, speed variance between different lanes and other external factors.
Overall, the estimation errors for buffer time index are less than 8.0% for both segments as well as the whole test bed in all day categories. On the other hand, the model could reasonably estimate the number of expected accidents on the test bed. Considering the variety of models incorporated in the proposed methodology, estimation errors are not very significant, as far as planning applications are considered. Thus, the methodology might be used for evaluating the impact of congestion improvement schemes on travel time reliability and safety prior to implementing them in real conditions, at least for the test bed of this study.

**7. CONCLUSIONS**

A methodology was proposed to estimate travel time reliability and frequency of accidents, as the function of demand, capacity and weather conditions on intercity expressway segments. Since the methodology is applicable without requiring travel time data, knowing the impact of congestion improvement schemes on demand and capacity, road factors.

Overall, the estimation errors for buffer time index are less than 8.0% for both segments as well as the whole test bed in all day categories. On the other hand, the model could reasonably estimate the number of expected accidents on the test bed. Considering the variety of models incorporated in the proposed methodology, estimation errors are not very significant, as far as planning applications are considered. Thus, the methodology might be used for evaluating the impact of congestion improvement schemes on travel time reliability and safety prior to implementing them in real conditions, at least for the test bed of this study.
authorities may use this methodology to investigate impact of congestion improvement schemes (e.g., hard shoulder utilization) on congestion levels, reliability of travel times and accident frequency. The methodology has also some implications for ITS applications on expressways.

As shown in Fig. 2 for the test bed of this study, travel conditions are relatively unreliable during the morning peak periods on weekdays likewise in the morning and evening of weekends/holidays. One may suggest opening the hard shoulder to traffic during the peak periods of weekdays and congested hours of holidays in order to improve reliability of travel times and mitigation of congestion levels. Benefits or disadvantages of such dynamic lane operation schemes on travel time reliability and their impact on safety can be measured in advance through this methodology.

Most of the models used in the proposed methodology are based on empirical data collected on expressways in Japan. Yet, the framework is applicable in other locations as well. If required data are available, capacity distribution functions, demand variations, speed-flow relationships and the rela-

![Fig. 12 Comparing simulated buffer time index with measured values from detector data (Segment A + Segment B).](image-url)
The relationship between accidents and traffic conditions can be modeled for any other expressway segments. If generalized models are available for capacity distribution functions, demand patterns and speed-flow relationships, the methodology would be applicable even for the segments where detector data are not available.

The results of this study are valid based on the analysis of limited number of intercity expressway segments. However, development of a more generalized methodology calls for extra investigations of various expressway segments.

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REFERENCES

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