Analyzing Travel Time Reliability and Its Influential Factors of Emergency Vehicles with Generalized Extreme Value Theory

Zhenhua Zhang

Department of Civil, Structural and Environmental Engineering
The State University of New York, Buffalo, NY 14260
Email: zhenhuaz@buffalo.edu
Tel: +1(716)208-0637

Qing He[1]

Department of Civil, Structural and Environmental Engineering
Department of Industrial and Systems Engineering
The State University of New York, Buffalo, NY 14260
Email: qinghe@buffalo.edu
Tel: +1(716)645-3470

Jizhan Gou

Serco Inc.
Reston VA 20190
Email: Jizhan.Gou@serco-na.com
Tel: +1(703)259-3355

Xiaoling Li

Northern Region Operations,
Virginia Department of Transportation, Fairfax, VA 22030
Email: Ling.li@vdot.virginia.gov
Tel: +1(571)350-2020

[1] Corresponding author
Abstract

Travel time reliability is very critical for emergency vehicle (EV) service and operation. The travel time characteristics of EVs are quite different from those of ordinary vehicles (OVs). Although EVs own highest road privilege, they may still experience unexpected delay that results in massive loss to the society. In this study, we employ the generalized extreme value (GEV) theory to measure extremely prolonged travel time and analyze the potential influential factors. First, among three GEV distributions, Weibull distributions are found to be the best distribution model according to several goodness-of-fit tests; a new reliability index is derived to measure travel time reliability. Numerical examples demonstrate the advantages of GEV-based reliability index over variance and percentile value in the applications of EV. This index will be of great practicability in the EV operation performance and reliable route choices. Second, we further investigate the potentially influential factors of EV travel time reliability. Results show that link length and left-turn traffic volume may have an adverse impact on the link reliability while more left-turn lanes may increase the travel time reliability. The influential factor study will help us understand the causes of the EV travel time delay and the differences of travel time reliability between OVs and EVs.

Keywords: travel time reliability; emergency vehicle; generalized extreme value distributions; influential factors

1 Introduction

Travel time reliability is a critical component of on-route travel time analysis and the study has attracted increasing attention in recent years. Federal Highway Administration (FHA) [1] defines the travel time reliability as the consistency or dependability in travel times, as measured from day-to-day and/or across different times of the day. This concept comes from the idea that on-route travel time may deviate from the expected travel time (mean of travel time), and this deviation may cause an unexpected delay for the driver; thus, the measures of travel time reliability should be consistent and stable over a time period between a given pair of origin and destination.
Previous studies of travel time reliability concentrate on ordinary vehicles (OVs), and the measures of travel time reliability include but not limited to: percent variance (standard deviation over average travel time), misery index (length of delay of only the worst trips) and buffer time (the difference between the average travel time and the 95th percentile travel time) [2]. These measures consider two important aspects of travel time reliability: the quantitative values and variation values of travel time. They serve well as good references for daily commuters, transit operators, commercial drivers. One question may be whether they are still valid as an effective measure for emergency vehicles (EVs).

EV is a general term for police cars, fire trucks or ambulances and is designated and authorized to respond to emergencies. The study of travel time reliability and its influential factors for unreliable travel time are very critical to the emergency vehicles. Compared with OVs, the EV is provided with certain road privileges and its operation is mission-oriented instead of fixed scheduled. Thus, the reliability studies on EV travel time should fully consider the uniqueness:

- First, EVs are treated with emergency vehicle preemption (EVP) when passing the signalized intersections. EVP is the signal control logic providing priority for specific users, and this requires higher priority consideration than transit signal priority [3]. Also, the effects of time-of-day traffic congestion, which usually influence OVS [4], may be partially neutralized for EVs because OVs move over and make way for EVs as soon as it is notified by EV sirens. Both the EVP and make-way behavior will increase the EV speed, and thus reduce the quantitative values of travel time and variance [5].

- Second, EV operation runs for the special task and the route is also not fixed. The EV travel time is much more random than that of OVs both in mission start time and locations. Thus, the corresponding travel time reliability studies cannot build on the daily travel experience but on some discrete and occasional scenarios. This means the methodology in evaluating the EV travel time should also be different from that of OVs.

- Third, the variance or expected delay of travel time is more severe for EVs than for OVs because EVs usually run on much more urgent missions; the EV is required to arrive as soon as possible and the travel time delay hurt EVs more than OVs. Thus, the reliability
studies for EV should place more attention on the extremely prolonged travel time and corresponding measures can be of great practicability in EV operations.

Our study tries to close the gap in the study of travel time reliability between OVs and EVs by two major contributions: First, we propose a measure of the EV travel time reliability which addresses the extremely prolonged travel time. Empirical studies show that the Generalized Extreme Value (GEV) theory and corresponding distributions can unveil the characteristics of extreme EV travel time. A new reliability index is proposed to measure and quantify the reliability of extremely prolonged travel time. Second, we identify and prove the major influential factors on the EV travel time reliability. A study is conducted on potential influential factors including time, distance, intersection capacity utilization, and occupancy. The results provide insights in answering how EV travel time is influenced and how EV operation is delayed.

Overall, fully considering the uniqueness of the EV operations, the reliability of EV travel time in this paper does not focus on the expected travel time that refers to the quantitative values of travel time and variance but on the extremity degree of extremely prolonged travel time. The rest of this paper is organized deliver our research purposes: Section 2 conducts a literature review on travel time studies of OV and EV and the applications of GEV distributions. Section 3 describes the raw data of travel time and the methods of extracting travel time. Section 4 introduces the background of the GEV distributions. In Section 5, a reliability index is derived to quantify both the travel time and link reliability. In Section 6, an influential factor analysis on travel time reliability is conducted. In Section 7, we conclude by several important findings and contributions.

2 Literature review

Travel time reliability is viewed regarding the consistency of operation of the route under investigation [6]. One common approach is to unveil and explore the statistical properties of the travel time distribution, especially standard deviation and skewness [7]. A few findings have identified the distribution features of OV travel time. For example, some researchers [8] empirically proved that travel time follows a right-skewed distribution. A better understanding of the distributions of travel time is needed for the development of improved metrics for reliability [9]. Several different kinds of distributions have been employed to describe the shape of (OV)
travel time including Burr distribution [9], lognormal distribution [10, 11], Weibull distribution [12], etc. Correspondingly, important measures of travel time reliability are derived from these distributions. Besides, the proposed index should consider the deviation of the actual travel time from the expected travel time. There are newly emerged techniques borrowing the same idea as buffer time or percentile values to access the travel time reliability. Most of them are innovative models by including the expected delay when defining the travel time reliability.

As compared to studying all travel time observations, one approach is more direct and meaningful which only study and model the travel time on the tail of the distribution that is the extremely large. For example, Xu et al. [13] propose the mean-excess total travel time (METTT) as an alternative network-wide risk measure to more cost-effectively capture the distribution tail. The “tail” travel time can be taken as a kind of “extreme events” and the “extreme” features are important for EV travel time study.

Rare in transportation-related studies, the studies on the extreme events are pervasive in mechanism [14], finance [15], hydrology [16], climate [17], oil market [18] etc. To model the extreme events, there is a family of distributions including Gumbel, Fréchet, and Weibull distributions [19]. As Extreme value theory is considered to provide the basis for the statistical modeling of extremes [15], it potentially provides insights in the extremely prolonged travel time. Our study combines the generalized extreme value theory with the travel time analysis and selects the family of GEV distributions to model the travel time reliability. An index based on GEV distributions is generated to measure the travel time reliability over different time periods and in different road links.

Most of the previous travel time reliability studies focus on the OVs. This may be partially due to the difficulties of data acquisition, and most traffic operators are more interested in the OVs' travel time studies. Even though, travel time studies for EVs are still of great practical significance as they deal with the emergent situations. For instance, Westgate et al. [20] estimate the travel time (service time) for ambulances with Bayesian data augmentation; Zhang et al. [5] study the routing problems of EVs with reliable travel time. There are also studies focusing the Emergency Vehicle Preemption (EVP) [21], vehicle communications [22], etc. which are closely related to the EV operations. In comparison, this study has two unique interests that distinguish from the previous
studies. First, this paper only evaluates and investigates the performance of extremely prolonged travel time which can severely affect the EV operation; the Extreme Value Theory is applied to serve this specific purpose. Second, this paper conducts two influential factor studies separately on link reliability and travel time reliability; current influential factor studies for OVs generalized several influential factors including signal delay [23], departure time [24], time-of-day features [25], etc. This paper will justify how effectively these potentially influential factors contribute to EVs’ travel time.

3 Data description

The study area is located in the urban network of North Virginia (NOVA) as a part of Washington D.C. Metropolitan Area. There are more than 400 signalized intersections in this area, shown in Figure 1. The study area provides a good test bed for the study of EV travel time: there are hundreds of police stations, hospitals and fire stations located in this area constituting the potential origins and destinations for EV; also, the network is ranked as the fourth greatest congested metropolitan area in the United States [26] and the traffic patterns show different time-of-day features [27]. The variety of traffic conditions and road designs help understand the influential factors of EV travel time.

The process of extracting travel time is illustrated in Figure 2. For each intersection (noted as Central intersection in the figure), we pair two adjacent signalized intersections (Adjacent intersections 1 and 2 in the figure) along the major road. EV will send a priority request to the signalized intersections once it is going to pass by. Once the priority request is validated by EVP system on the intersection, an electrical relay in the traffic signal cabinet is closed. It allows the controller to service the call [28] and the corresponding time stamps are recorded. Preemption time stamps of along signalized intersections can be paired to extract the link travel time of EVs just as the travel time from Adjacent intersection 1 to the Central intersection shown in Figure 2. As we mainly study the travel time between two consecutive intersections, we define this travel time as “intersection-based link travel time” that is shown in Figure 2. From October 2012 to January 2013, we finally obtained about 5,500 pieces of EV travel time. To make the travel time on different links comparable, we mainly study the unit travel time by dividing the travel time by the
corresponding link length (s/m). Summary statistics reveal that the average unit travel time of EVs is 0.084 (i.e. 26.8 mph) and median unit travel time 0.067 s/m (i.e. 33.8 mph). One can see that the distribution of unit travel time (s/m) is heavy-tailed.

As the link-based travel time is derived from EVP records, the mechanism of data acquisition is quite different from that of OVs. The travel time reliability studies on OVs usually quantify the continuous daily travel time on a designated route or consecutive links. In comparison, the routes of EVs are random and highly mission-oriented; and the data sample size is also limited. This makes the EV travel time link-based instead of route-based. The methodology in the following sections is intentionally designed to quantify the EV travel time reliability.

Together with travel time, there are other traffic-related variables including traffic flow, occupancy, and geographic information. The traffic flow and occupancy are collected by the lane-based loop detectors at a frequency of 15 minutes. Because of the malfunction of the detector, we rule out the extremely large traffic flow data. Also, there are geographic-related variables including the number of directional lanes and link length. The information is summarized in Table 2.

Table 2 Raw data collected in our study area

4 Background

4.1 GEV distributions

GEV theory deals with the distributions of data of abnormally low or high value in the tails of some data-generating distribution [29]. It emphasizes to assess the probability of rare events, especially those events that are in the right tail of the distribution. Its advantage mainly lies in the ability to measure extreme deviations from the median of a probability distribution. These GEV distributions have three types: Gumbel distribution (Type I), Frechet distribution (Type II) and Weibull distribution (Type III) [30].

The general form of GEV distributions can be expressed as:

\[ F(x) = e^{-t(\phi(x))} \] (1)
Where $F(x)$ is the cumulative distribution function; $t(\phi(x))$ is a function composition, whose possible function parameters include $\xi, \gamma$ and $\nu$; $\phi(x)$ has an empirical function form as $\frac{x-\nu}{\gamma}$; $\nu$ is taken as the location parameter; $\gamma$ is the scale parameter and $\xi$ is the shape parameter.

Gumbel distribution assumes that $\xi = 0$, while the other two distributions assume $\xi > 0$. The cumulative distribution functions show right skewed characteristics with long tails. This shape is mainly determined by the shape parameter $\xi$. The probability density functions and cumulative probability functions for Gumbel, Frechet and Weibull distributions are:

$$f(x) = \begin{cases} \frac{1}{\gamma} \exp\left(-\phi(x) - \exp(-\phi(x))\right) & \text{for Gumbel} \\ \frac{\xi}{\gamma} \left(\phi(x)\right)^{-\xi-1} \exp\left(-\left(\phi(x)\right)^{-\xi}\right) & \text{for Frechet} \\ \frac{\xi}{\gamma} \left(\phi(x)\right)^{-\xi-1} \exp\left(-\left(\phi(x)\right)^{-\xi}\right) & \text{for Weibull} \end{cases}$$

$$F(x) = \begin{cases} \exp\left(-\exp(-\phi(x))\right) & \text{for Gumbel} \\ \exp\left(-\left(\phi(x)\right)^{-\xi}\right) & \text{for Frechet} \\ 1 - \exp\left(-\left(\phi(x)\right)^{-\xi}\right) & \text{for Weibull} \end{cases}$$

### 4.2 Selection of proper GEV distributions

In this subsection, we extract the extremely prolonged travel time for our study and then select the most suitable GEV distribution to model these travel time.

To find the extremely prolonged travel time, one approach exists for practical extreme analysis that is called “Peak Over Threshold (POT)” [17]. This method relies on extracting, from a continuous record, the peak values that exceed a certain threshold. The selection of threshold is either based on the physical criteria, or mathematical and statistical considerations. From the view of National Highway Traffic Safety Administration (NHTSA) [31], low-speed vehicles should be those operating in the 20-25 mph speed range that equals to 0.089-0.112 s/m. Even though this criterion is intended for OVs, there still exist some inspirations for EVs. EVs may operate at a higher average speed than OVs because of the EVP and make-way behavior. Also, low-speed EVs may cause more losses than OVs. The selected threshold speed should be low enough to show the
EVs operates at extreme conditions. From the view of extremity, the percentage of extreme events in total records is not strictly decided. For instance, flood peaks [32] takes the maximum value in a period; extreme events in applications such as financial risk measuring in [15] account for around 5% of the total events. Thus, we use the threshold of unit travel time to be 0.15 s/m. Under this criterion, 229 of our total unit travel times are extracted. These take about 5% of the total observations.

We employ the maximum likelihood estimation (MLE) to estimate the parameters of the distributions. The maximization method has been studied thoroughly over the past few decades, and one may refer to Newton-Raphson for Maximum Likelihood Estimation [33]. To judge the goodness-of-fit, we conduct three tests including Kolmogorov-Smirnov test (KS test) [34], Anderson-Darling test [35] and Chi-square test [36]. All these tests can calculate a corresponding statistic measuring the differences between the estimated and observed distributions. KS-test calculates the maximum probability difference between the estimated distribution and the real data distribution; while the other two tests calculate the overall differences between the estimated data and the real data. The lower the metrics are, the better the goodness-of-fit is. The estimated $\xi$, $\gamma$, $\delta$ and the test results are shown in Table 3.

<table>
<thead>
<tr>
<th>Table 3 Goodness-of-fit test results and parameters for three GEV distributions</th>
</tr>
</thead>
<tbody>
<tr>
<td>From the statistics of test results shown in Table 3, the best probability density distribution should be Weibull distribution. Probability density and cumulative density plots for both empirical data and theoretical data are illustrated in Figure 3.</td>
</tr>
</tbody>
</table>

One can see that in this study, due to the small sample size in our study area, the parameters of Weibull distributions are derived based on the extremely prolonged travel time in all links. Even though, combining the travel time observations from multiple links are expected to reduce the bias of observations in different links, this will also overlook the unique distribution features in each link. If there are more sample sizes per link over a longer observation period, the results are expected to be more accurate.
5 Link travel time reliability

5.1 Model the travel time reliability

In this section, we will quantify the travel time reliability of EVs based on the Weibull distribution in Section 4.2. A reliability index derived from the distribution will be employed to measure reliability level of those extremely prolonged travel time. The index for reliable travel time possesses two important features: first, it should have a small deviation; second, the travel time value should be small. Thus, for each observed extreme value, its reliability level can be quantified as:

\[ R(x) = 1 - F(x | \xi, \varphi, \theta) \]  

(3)

Where \( R(x) \) is the reliability index of unit travel time in our study; \( F \) is the cumulative distribution function; \( \xi, \varphi, \theta \) are the function parameters obtained by MLE. One can see that the larger the travel time is, the lower the reliability index and thus the worse the travel time reliability should be.

To measure the link travel time reliability, we can calculate the weighted average of the travel time reliability index of the historical unit travel time data on that link. The larger the unit travel time is, the higher the weight should be to reflect its extremity level. The weight for each travel time reliability index is the difference between the unit travel time and the extremity threshold. The link reliability index is defined as:

\[ R(L) = \frac{\sum_{(x_i - \tau) \cdot R(x_i)} \in \Gamma_L}{\sum_{(x_i - \tau)} \in \Gamma_L} \]  

(4)

Where \( L \) is the link ID; \( R(L) \) is the link reliability index; \( \Gamma_L \) is the set of all extreme travel time in this link; \( x_i \) is the \( i \)th unit travel time value; \( \tau \) is the extremity threshold equal to 0.15 s/m in our study. One can see that the link reliability also ranges from 0 to 1. Figure 4 shows link reliability index for all links in our region. It is worth mentioning that for display purpose, we take the maximum link reliability for each link. The link reliability indices are set to be 1 for those links with no field observation.
5.2 Comparisons with other reliability indices

Theoretically, the link reliability index proposed in Section 5.1 has its own advantages:

First, it only studies the “extreme events” of travel time and ignores those lower than the extremity threshold. The extremely large travel time is the major concern of EV operators, and the larger the values are, the worse the travel time reliability should be. Second, our method unveils the distribution features of the tail travel time in the whole region and employs the cumulative density probability of the fitted distribution to derive a measure of reliability. This method is capable of eliminating the effects of data deficiencies in some links and deleting some noises.

An example of comparison among reliability index, percentile value, and variance is shown in Figure 5. We create two datasets and apply those indices to measure their reliability levels. Figure 5 displays their probability density plots of these two datasets. The sample size for both datasets is 43. The ranges for two datasets are [0.01, 0.09] and [0.135, 0.158], respectively. One can see that Dataset 1 has higher variance than Dataset 2, but part of Dataset 2 exceeds the extremity threshold. Although Dataset 1 shows much higher variance, it is still reliable for EV because all of the observations in Dataset 1 lie within the threshold. As compared, Dataset 2 may be worse because there are some data observations higher than the threshold.

**Figure 5 Probability density plots for two datasets.**

Table 4 compares proposed reliability index with other reliability indices for both Dataset 1 and Dataset 2. Note that only the proposed reliability index indicates that the higher the value is, the more reliable the travel time should be. Thus, others are usually taken as the disutility. Under this setting, the variance cannot give good comparison results between the two datasets because it did not consider the magnitude of travel time. For Dataset 2, the 90th percentile value of indicates a referenced unit travel time value lower than 0.15 s/m while 95th percentile shows travel time value higher than 0.15 s/m; this means that the percentile values may not be robust and usually overestimates the reliability level. Besides, buffer Index also gives a worse evaluation of Dataset 1 than Dataset 2. We also compare the proposed reliability index with the travel time acceptability defined by Watling [37]. As one can see, both indices value the lateness part of the travel time which is higher than 0.15 and take into account the distribution features of travel time. Designed
for different research purposes, both studies consider the travel time reliability as a reasonable combination of average and variance while ours only focuses on the extremely prolonged travel time.

**Table 4 Comparisons of proposed reliability index with other measures**

In sum, the proposed reliability index can distinguish the reliability levels between two datasets and quantify the reliability degree of the dataset which potentially has an extremely prolonged travel time, while the percentile values or variance may overlook the extreme cases for EV travel time. Besides, because the route of EV is random, the available travel time data are the data collection from a set of links instead of continuous records of individual links. Thus, the proposed index is applicable in monitoring the extremity level of travel time in an area than the other indices.

### 6 Influential factor analysis

#### 6.1 Influential factors on link reliability

In this subsection, we focus on the links whose link reliability is lower than 1. Some studies discovered the possible relationship between travel time and traffic patterns (speed over time) and length, direction, lane width, etc. [38] and the exogenous factors may impact on the travel time distribution of OVs [39]. In comparison, travel time, which is a major component of the traffic pattern, may also have some relationships with the link length and number of lanes. In Figure 6(a), the link length bears a negative power relationship with the link reliability which means longer links may be more probable to decrease the link reliability and thus cause unexpected delays for EV. In Figure 6(b), one can see that most of the links with bad travel time reliability have 3-5 lanes. For links with 1, 2 and 6 lanes, the performance is also bad given that the samples in these cases are limited. We can say that the number of lanes is a probable influential factor on the link reliability.

**Figure 6 Relationship between link reliability index with (a) link length and (b) number of lanes on that link**
6.2 Influential factors on travel time reliability

In this subsection, we will find the significant influential factors on travel time reliability. The influential factors are classified into three broad categories: factors that are related to the time, related to traffic conditions and related to the link features. Time-related factors include six time periods; link-related factors include the length of road link and the number of lanes; traffic-related factors include 15-minute link occupancy and flow, 15-minute intersection capacity utilization (ICU). ICU is a good indicator to describe the jam situation of a signalized intersection. When ICU is 1, the capacity of intersection is fully allocated to accommodate traffic demand. The calculation of ICU requires the data of traffic volume, and the number of lanes in all approaches of the signalized intersections and the methods employed to calculate it strictly follow that in [40].

We do not predict the travel time reliability but to investigate several potential influential factors available at hand and analyze their impacts. In Section 4.2, Weibull distribution is proved to be the most suitable distribution for extremely prolonged travel time. Therefore, we conduct a Weibull regression analysis on the potentially influential factors on the travel time reliability. We can write the response variable in a log-linear form:

\[
\log(E(y_i)) = \beta \cdot X_i + \alpha + e_i
\]

\[
\log(E(Y)) = \beta \cdot X + \alpha + e
\]  

(5)

Where \(E(y_i)\) is the \(i\)th expected travel time; \(E(Y)\) is the vector of expected travel time, \(\alpha = (\alpha, \alpha, ... \alpha, ... , \alpha)^T\) is the vector of intercepts; \(\beta\) is the set of the coefficients of the variables; \(e\) is the set of residue errors that follow Weibull distribution.

The mean of GEV distributions can be written as:

\[
\mu = v + \gamma \varphi(\xi)
\]  

(6)

Where \(\varphi_W = \int_0^\infty x^{\frac{1}{\xi}} e^{-x} dx\) for Weibul distribution.

For each observation:

\[
\log(E(y_i)) = \beta \cdot X_i + \alpha = v + \gamma \varphi(\xi)
\]  

(7)
Thus the probability functions of GEV distributions are given by:

\[ f(y_i) = \xi \left( \frac{y_i - u}{\gamma} \right)^\xi - 1 \exp \left( - \left( \frac{y_i - u}{\gamma} \right)^\xi \right) \]

\[ = \frac{\xi}{\xi} \left( \frac{y_i - \exp(\beta X_i + \alpha) + \gamma \varphi(\xi)}{\gamma} \right)^\xi - 1 \exp \left( - \left( \frac{y_i - \exp(\beta X_i + \alpha) + \gamma \varphi(\xi)}{\gamma} \right)^\xi \right) \] (8)

The likelihood functions are:

\[ L(\xi, \gamma, \beta|Y, X) = \left( \frac{\xi}{\gamma} \right)^n \prod_{i=1}^{n} \left( \frac{y_i - \exp(\beta X_i + \alpha) + \gamma \varphi(\xi)}{\gamma} \right)^{1+\xi} \exp \left( - \left( \frac{y_i - \exp(\beta X_i + \alpha) + \gamma \varphi(\xi)}{\gamma} \right)^\xi \right) \] (9)

The results of \( \xi, \sigma, \beta \) can be obtained by maximizing the log likelihood function. The problem can be solved by Newton-Raphson for Maximum Likelihood Estimation [33] and will not be detailed in this paper. Further, \( \beta \) is assumed to be unbiased. The standard deviations of the variable coefficients can be obtained by:

\[ sd_{j} = \frac{1}{n-N} \frac{\sum_{i=1}^{n} (y_i - \hat{\beta})^2}{\sum_{i=1}^{n} (X_j - \bar{X}_j)^2} \] (10)

Where \( sd_{j} \) is the standard deviation of \( \beta_j \); \( n \) is the number of observations and \( N \) is the number of coefficients to be estimated. Further, we assume that \( \frac{\beta}{sd} \) follows a t distribution with degree of freedom equal to \( n - N - 1 \):

\[ t_i = \frac{\hat{\beta}_i}{sd_i} \sim t(n - N - 1) \] (11)

The significance level of each variable can be calculated by \( Prob(t > |t_i|) \). The lower the significance level, the more statistically significant the variables should be. Table 5 shows the relations and significance levels of the potential influential factors on the travel time reliability values.

Table 5 Relations and significance levels of influential factors to travel time reliability

The value of Estimate identifies the positive versus negative relation of the factors while the significance levels (Pr(|t|)) tell the credibility of their relations. We mainly concern the covariates whose Pr(|t|) are small because the travel time reliability may be partially or even
wholly be accounted by the influential factors with high significance levels. One can see only the
link length, the number of left turn lanes, and the left-turn volume have $\text{Pr}(>|t|) < 5\%$. Longer links may diminish the travel time reliability that coincides with our observations in
Section 6.1. The left-turn volume can negatively impact the EV travel time reliability, whereas the
number of left-turn lanes has a positive impact. One reason could be that the travel time reliability
is impacted when there is not enough space in the left turn lane for OV to pull over. Comparatively,
the road conditions and other geometry design can seldom influential the travel time reliability:
The results also indicate that EV travel time is not quite sensitive to the jammed road conditions
and also does not show a clear time-of-day pattern. Unlike OV, which is usually delayed by
signalized intersections, the service level of intersection is not a significant influential factor for
EV travel time reliability. This is mainly due to the fact that EVP provides preferential treatments
to EV despite the congestion level at intersections.

Influential factors such as the median, roadside clearance, sight distance, etc. are not
included in our study due to the lack of field data. The factorization of the road conditions and
their corresponding influences on EV travel time can be conducted in future studies.

7 Conclusions

This study focuses on the travel time reliability of emergency vehicles (EV), which draws little
attention in the previous literature. Our major findings can be summarized as:

First, a reliability index, derived from GEV distributions, is proposed to measure both
travel time and link reliability of EV. It is found that the extremely prolonged EV travel time
follows Weibull distribution and the features of these extreme EV unit travel time are revealed to
be right-skewed with a long-tail. Numerical studies even show the reliability index is more
adaptive in describing the EV travel time reliability than variance or percentile value:

- First, the index considers the magnitude of the EV travel time and higher travel time
reliability indicates a better travel time saving.

- Second, the index fully considers the deviation of the extremely prolonged travel time and
higher travel time reliability should have less variance.
Second, we unveil that the longer link length has a negative impact on the link reliability. It is also found that most extremely prolonged travel times are recorded on major arterials or the links with a large number of lanes.

Third, the influential factors of travel time reliability are statistically investigated by a Weibull regression model. The left-turn lanes may have a positive impact on the travel time reliability with proved high significance level while link length and left-turn volume may do the opposite. Other factors such as jammed on-road conditions, time-of-day and intersection capacity utilization (ICU) are not significant influential factors that make EV travel time quite different from that of OV.

The reliability index in this paper is of great practicability in evaluating the EV operation performance and reliable route choices. Even though, one may also see that the driver’s perceptions towards the road conditions are inherently variable, the distributions of extremely prolonged travel time should also be different by links. Thus, the result can be improved and more accurate by deriving separate distributions on each link when there are larger sample size and longer observation period. In future studies, we will focus on how to increase the operational performance of EV towards accidents which include less response time, better route choice, etc. What's more, the route or path travel time will be an interesting topic in the future studies and influential factors associated with path travel time can be further examined. One other potential topic is to study the driving behavior of EV operators during emergency responses. The relevant studies are expected to enhance our understanding of EV travel time features and practically increase the travel time reliability in future.
Appendix: EVP Data Description and Raw data Processing

The EVP process has been elaborately illustrated in [5]. When an EV approaches the intersection, the strobe device on EV is sensed, and EVP is activated at the intersection when an “Alert” event is recorded. The signal phase is then preempted to be green for EV. Once the EV passes the intersection and the strobe signal is no longer received, the EVP is deactivated when an “OK” event is recorded. The time difference between the two “OK” events from two adjacent intersections can be regarded as the link travel time.

The existing challenge in this dataset is that no vehicle ID is recorded during EVP process. Therefore, we need to pair two “OK” events in order to obtain the travel time between two intersections. As EV does not appear as frequently as OV, the situation that two or more EV appear in the same location at the same time is rare and we can guarantee the quality of extracted travel time. Also we make the following assumptions to make the extraction more reasonable:

- **Assumption 1:** In urban streets, EV travels within a range of speed because the speed of the EV should obey certain rules [41]. In this study, we assume the highest speed is $V_{\text{max}}$ and lowest is $V_{\text{min}}$. Given the distance between two consecutive intersections, we can obtain the reasonable travel time range. For an “OK” event at a given intersection, the matched “OK” event in adjacent intersections should occur within the reasonable travel time range.

- **Assumption 2:** For one “OK” event recorded by a given intersection, there are only one reasonable “OK” event in the total records of its nearest four intersections. If not, the “OK” event is abandoned.

- **Assumption 3:** It is rare for multiple EVs to pass the same intersection at the same time. Therefore, in order to ensure the unique matching, we delete all “OK” events of the same intersection that matched the same “OK” event of an adjacent intersection.

Assumption 1 helps calculate the bounds of the travel time between the two consecutive signalized intersections and filter unreasonable travel times. Assumption 2 ensures that there are no multiple pairs of “OK” events in adjacent intersections that match the same “OK” event in a given intersection. Assumption 3 ensures that there are no multiple pairs of “OK” events in a given intersection that matches an “OK” event in any adjacent intersection.
Figure 1 Selected intersections and road networks in NOVA
Figure 2 Illustration of intersection-based link travel time

- Case 1: travel time measure from intersection 1
- Case 2: travel time measure from intersection 2

Figure 3 (a) Probability density distribution plots of observed unit travel time (s/m) and fitted Weibull distribution; (b) Cumulative density distribution plot for fitted Weibull distribution.
Figure 4 Link reliability of all links in the region.

Figure 5 Probability density plots for two datasets.
Figure 6 Relationship between link reliability index with (a) link length and (b) number of lanes on that link.
Table 1 The equations of three travel time reliability measures and their compositions

<table>
<thead>
<tr>
<th>Author and year</th>
<th>Name of Index</th>
<th>Composition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean-excess travel time (^{(1)}) in Chen and Zhou [42]</td>
<td>(\eta_p^{rs}(\alpha) = E[T_p^{rs} \mid T_p^{rs} \geq E(T_p^{rs})] + \gamma_p^{rs}(\alpha))</td>
<td>Expected</td>
</tr>
<tr>
<td>Travel time utility (^{(2)}) in Fosgerau [4]</td>
<td>(U(D, T) = \alpha T + \gamma(T - D)^{+} + \beta(T - D)^{-})</td>
<td></td>
</tr>
<tr>
<td>Travel time acceptability (^{(3)}) in Watling [37]</td>
<td>(\mu_r = \theta_0 d_r + \theta_2 \max(0, c_r - \tau_k))</td>
<td></td>
</tr>
</tbody>
</table>

1 \(r\) and \(s\) are origin and destination respectively; \(p\) is the route; \(\alpha\) is the confidence level.

2 \((2) T\) is stochastic travel time and \(D\) is the scheduled travel time. \(\alpha, \beta,\) and \(\gamma\) are weights.

3 \((3) r\) is the path; \(d_r\) is composite of attributes; \(\tau_k\) is the \(k\)th acceptable arrival time; \(\theta_0, \theta_1,\) and \(\theta_2\) are weights.

Table 2 Raw data collected in our study area

<table>
<thead>
<tr>
<th>Raw data</th>
<th>Description</th>
<th>Sample</th>
</tr>
</thead>
<tbody>
<tr>
<td>Preemption records</td>
<td>Date and time information left by the emergency vehicles when they pass the signalized intersection</td>
<td>2012-11-23 12:23</td>
</tr>
<tr>
<td>Traffic flow</td>
<td>Lane-based hourly traffic flow every 15 minutes</td>
<td>0 ~ 1500 vph</td>
</tr>
<tr>
<td>Traffic occupancy</td>
<td>Lane-based occupancy within every 15 minutes</td>
<td>0 ~ 100 %</td>
</tr>
<tr>
<td>Lane information</td>
<td>Number of lanes in each direction on a link. The storage left and right turn lanes are included.</td>
<td>0 ~ 5</td>
</tr>
<tr>
<td>Link length</td>
<td>Distance between the central intersection and an adjacent intersection</td>
<td>0 ~ 400 m</td>
</tr>
</tbody>
</table>
Table 3 Goodness-of-fit test results and parameters for three GEV distributions

<table>
<thead>
<tr>
<th>Types</th>
<th>$\nu$</th>
<th>$\gamma$</th>
<th>$\xi$</th>
<th>Kolmogorov-Smirnov test</th>
<th>Anderson Darling test</th>
<th>Chi-square test</th>
</tr>
</thead>
<tbody>
<tr>
<td>Type I: Gumbel</td>
<td>0.19788</td>
<td>0.0474</td>
<td>\</td>
<td>0.13186</td>
<td>4.466</td>
<td>34.503</td>
</tr>
<tr>
<td>Type II: Frechet</td>
<td>0.02126</td>
<td>0.17028</td>
<td>4.1695</td>
<td>0.08781</td>
<td>3.371</td>
<td>37.636</td>
</tr>
<tr>
<td>Type III: Weibull</td>
<td>0.15001</td>
<td>0.07608</td>
<td>1.0333</td>
<td>0.07948</td>
<td>2.957</td>
<td>25.461</td>
</tr>
</tbody>
</table>

Table 4 Comparisons of proposed reliability index with other measures

<table>
<thead>
<tr>
<th>Reliability index</th>
<th>Variance</th>
<th>90th percentile</th>
<th>95th percentile</th>
<th>Buffer Index</th>
<th>Travel time acceptability (Watling [37])$^1$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dataset 1</td>
<td>1</td>
<td>0.023</td>
<td>0.08</td>
<td>0.089</td>
<td>0.039</td>
</tr>
<tr>
<td>Dataset 2</td>
<td>0.96</td>
<td>0.006</td>
<td>0.148</td>
<td>0.152</td>
<td>0.011</td>
</tr>
</tbody>
</table>

(1) the weight parameters $\theta_1$ and $\theta_2$ are set to be 1.
Table 5 Relations and significance levels of influential factors to travel time reliability

| Influential factor                       | Estimate | Sd  | t value | Pr(>|t|) |
|-----------------------------------------|----------|-----|---------|---------|
| Link features                           |          |     |         |         |
| Link length                             | -0.0007  | 0.001 | -5.49   | 0.000   |
| Number of left turn lanes               | 0.1693   | 0.0926 | 1.829   | 0.067   |
| Number of through lanes                 | -0.0216  | 0.0888 | -0.243  | 0.808   |
| Number of right turn lanes              | 0.2114   | 0.1617 | 1.307   | 0.191   |
| Traffic features                        |          |     |         |         |
| Occupancy on left turn lanes*           | -0.0004  | 0.0019 | -0.187  | 0.852   |
| Occupancy on through lanes              | 0.002    | 0.0021 | 0.94    | 0.347   |
| Occupancy on right turn lanes           | -0.0051  | 0.0035 | -1.469  | 0.142   |
| Volume on left turn lanes               | -0.0007  | 0.0004 | -1.827  | 0.068   |
| Volume on through lanes                 | 0.0001   | 0.0001 | 0.811   | 0.417   |
| Volume on right turn lanes              | 0.0008   | 0.0006 | 1.482   | 0.138   |
| Intersection capacity utilization (ICU) | -0.0968  | 0.256 | -0.378  | 0.705   |
| Time features                           |          |     |         |         |
| AMpeak_weekday                          | -0.089   | 0.1804 | -0.493  | 0.622   |
| PMpeak_weekday                          | -0.0813  | 0.1106 | -0.735  | 0.463   |
| Noon_weekday                            | 0.0954   | 0.1667 | 0.572   | 0.567   |
| AMpeak_weekend                          | -0.5102  | 0.5954 | -0.857  | 0.392   |
| PMpeak_weekend                          | 0.137    | 0.2356 | 0.581   | 0.561   |
| Noon_weekend                            | 0.0454   | 0.2238 | 0.203   | 0.839   |
There are more than one directional lanes on a link. The occupancy and volume in our analysis refer to the average value.
References:

1. Taylor, R., Travel Time Reliability: Making It There on Time, All the Time. Us Department of Transportation, Federal Highway Administration’, (U.S. Department of Transportation Federal Highway Administration, 2010)


