Incorporating the standstill distance and time headway distributions into freeway car-following models and an application to estimating freeway travel time reliability

Chaoru Lu
Norwegian University of Science and Technology

Jing Dong
Iowa State University, jingdong@iastate.edu

Andrew Houchin
Snyder & Associates, Inc.

See next page for additional authors
Incorporating the standstill distance and time headway distributions into freeway car-following models and an application to estimating freeway travel time reliability

Abstract
Standstill distances and following time headways are two important microsimulation model parameters associated with driver aggression. This paper investigates the distributions of standstill distances and time headways and incorporates these distributions into car-following models to estimate travel time reliability. By incorporating standstill distance and following headway into car-following models as stochastic parameters, a speed-density region can be generated, based on which various travel-time-reliability measures can be calculated. Key findings of this study are as follows: (1) Both standstill distances and time headways follow fairly dispersed distributions. Therefore, it is suggested that microsimulation models should include the option of allowing standstill distances and time headways to follow distributions as well as to be specified separately for different vehicle classes. (2) By incorporating stochastic standstill distance and time headway parameters in car-following models, travel-time-reliability measures can be estimated more precisely and faster compared with using VISSIM.

Keywords
car-following model, standstill distance distribution, time headway distribution, travel time reliability

Disciplines
Civil Engineering | Transportation Engineering

Comments
This article is published as Lu, Chaoru, Jing Dong, Andrew Houchin, and Chenhui Liu. “Incorporating the standstill distance and time headway distributions into freeway car-following models and an application to estimating freeway travel time reliability.” Journal of Intelligent Transportation Systems 25, no. 1 (2021): 21-40. DOI: 10.1080/15472450.2019.1683450.

Authors
Chaoru Lu, Jing Dong, Andrew Houchin, and Chenhui Liu

This article is available at Iowa State University Digital Repository: https://lib.dr.iastate.edu/ccee_pubs/260
Incorporating the standstill distance and time headway distributions into freeway car-following models and an application to estimating freeway travel time reliability

Chaoru Lu, Jing Dong, Andrew Houchin & Chenhui Liu

To cite this article: Chaoru Lu, Jing Dong, Andrew Houchin & Chenhui Liu (2019): Incorporating the standstill distance and time headway distributions into freeway car-following models and an application to estimating freeway travel time reliability, Journal of Intelligent Transportation Systems, DOI: 10.1080/15472450.2019.1683450

To link to this article: https://doi.org/10.1080/15472450.2019.1683450
Incorporating the standstill distance and time headway distributions into freeway car-following models and an application to estimating freeway travel time reliability

Chaoru Lu\textsuperscript{a}, Jing Dong\textsuperscript{b}, Andrew Houchin\textsuperscript{c}, and Chenhui Liu\textsuperscript{d}

\textsuperscript{a}Department of Civil and Environmental Engineering, Norwegian University of Science and Technology (NTNU), Trondheim, Norway; \textsuperscript{b}Department of Civil, Construction and Environmental Engineering, Iowa State University, Ames, IA, USA; \textsuperscript{c}Snyder & Associates, Inc, Des Moines, IA, USA; \textsuperscript{d}National Research Council/Turner-Fairbank Highway Research Center, McLean, VA, USA

ABSTRACT

Standstill distances and following time headways are two important microsimulation model parameters associated with driver aggression. This paper investigates the distributions of standstill distances and time headways and incorporates these distributions into car-following models to estimate travel time reliability. By incorporating standstill distance and following headway into car-following models as stochastic parameters, a speed-density region can be generated, based on which various travel-time-reliability measures can be calculated. Key findings of this study are as follows: (1) Both standstill distances and time headways follow fairly dispersed distributions. Therefore, it is suggested that microsimulation models should include the option of allowing standstill distances and time headways to follow distributions as well as to be specified separately for different vehicle classes. (2) By incorporating stochastic standstill distance and time headways in car-following models, travel-time-reliability measures can be estimated more precisely and faster compared with using VISSIM.

Introduction

Microscopic simulation models have been widely used in transportation studies. The core of microsimulation is the car-following model, which describes the interaction of a vehicle and the preceding vehicle traveling in the same lane. Standstill distance (i.e., the distance between stopped vehicles) and following time headway (i.e., the time between successive vehicles when following) are two of the important parameters in many car-following models, including Wiedemann 99 (implemented in VISSIM), the Van Aerde model (implemented in INTEGRATION), and the Pitt model (implemented in FRESIM). Following time headway has been demonstrated associated with aggressive driver behavior (Filev, Lu, Prakah-Asante, & Tseng, 2009). Dijker, Bovy, and Vermijs (1998) and Houchin, Dong, Hawkins, and Knickerbocker (2015) have pointed out that the distributions for time headway and standstill distance should be introduced into car-following models. However, existing microsimulation tools only allow time headway and standstill distance to be specified as constants.

The calibration of car-following models concerns both steady-state and non-steady-state behavior (Rakha & Crowther, 2003). The calibration of steady-state behavior influences estimates of road capacity, speed, and jam density. Non-steady-state behavior determines how traffic conditions move from one steady state to another. In this paper, Pipes and Van Aerde models were used to represent the steady-state car following logic and derive macroscopic traffic flow properties.

Literature review

Following time headways and standstill distances vary from driver to driver and by vehicle type (Durrani et al., 2016; Hoogendoorn & Bovy, 1998; Houchin et al., 2015; Ye & Zhang, 2009). Various probability distributions, such as the gamma, normal, lognormal, and Weibull distributions, have been used to describe this heterogeneity in relation to time headways (Zang, 2009; Zhang, Wang, Wei, & Chen, 2007). In particular, Ye and Zhang (2009) have analyzed headway in terms of four different lead-follow vehicle types—that is, car-car, car-truck, truck-car, and truck-truck—and...
have found that vehicle-type-specific and mixed-vehicle-type distributions are statistically different. Standstill distance distributions, on the other hand, have not been well studied in the context of freeway traffic, probably due to the difficulty of data collection. For this paper, both time headway and standstill distance data were collected and have been used to fit corresponding probability distributions.

Various car-following models have been developed over the past decades, including Gazis-Herman-Rothery (GHR) models, safety distance models, linear models, psychophysical models, and fuzzy-logic-based models (Brackstone & McDonald, 1999). Among these models, some have been implemented in microscopic traffic simulation software such as VISSIM and CORSIM. To the best of the authors’ knowledge, none of the existing microscopic traffic simulation software allows input of the headway and standstill distance parameters as distributions. Nevertheless, randomly distributed driver behavior parameters have been considered in a few car-following models. For example, based on data obtained by videotaping traffic, Ahn, Cassidy, and Laval (2004) verified that the variation in driver behavior parameters in Newell’s car-following model, that is, time displacement and space displacement, are well described by a bivariate normal joint distribution. Later, to assure that the driver behavior parameters in Newell’s car-following model, that is, time displacement and space displacement, are well described by a bivariate normal joint distribution.

One of the potential applications of stochastic traffic simulation models is estimating travel time reliability. Various approaches have been developed to estimate travel time reliability (e.g., Al-Deck & Emam, 2006; Higatani et al., 2009; Kwon, Barkley, Hranac, Petty, & Compin, 2011; Noland & Polak, 2002; Oh & Chung, 2006; Zheng et al., 2018; Zhang, He, Gou, & Li, 2019). In particular, based on existing traffic simulation models, Kim, Mahmassani, Vovsha, Stogios, and Dong (2013) and Schroeder, Rouphail, and Aghdash (2013) have proposed as estimated travel-time-reliability measures scenario-based approaches able to capture exogenous sources of variation in travel time. However, stochastic driver behavior in terms of following headway and standstill distance have not been considered in previous studies (though recently, Abdulsattar, Mostafizi, and Siam [2019] investigated the impact of connected vehicles on travel time reliability in a work zone environment via agent-based simulation).

In order to quantify travel time reliability, several performance measures have been proposed, such as the standard deviation for the travel time, buffer time, difference between the 90th and 10th percentiles for the travel time distribution, and probability that a trip can be successfully completed within a specified time interval (Dong et al., 2006; Higatani et al., 2009; Kaparias, Bell, & Belzner, 2008; Tu et al., 2007; Van Lint, Van Zuylen, & Tu, 2008). Among these reliability measures, buffer time, 95th percentile travel times, the buffer index, the planning time index and the frequency with which congestion exceeds some expected threshold have been recommended for use by practitioners because of their technical merit and ease of understanding (Texas Transportation Institute and Cambridge System Inc., 2006). In this paper, travel-time-reliability measures are estimated using car-following models that include both stochastic time headway and standstill distance parameters.

**Objective**

The objective of this paper is to investigate the standstill distance and travel time headway parameters and incorporate these distributions into car-following models to estimate travel time reliability. In particular, car-following models implemented in VISSIM, INTEGRATION, and FRESIM are considered. Steady-state speed–density relationships were generated using four different input modes: deterministic overall headway and standstill distance parameters, deterministic headway and standstill distance parameters for various lead-follow vehicle types, overall headway and standstill distance distributions, and headway and standstill distance distributions for various lead-follow vehicle types. The resulting speed–density plots are compared with VISSIM simulation output under various parameter assumptions as well as with real-world observations. In addition, the proposed car-following model with stochastic standstill distance and time headway parameters is used to estimate travel-time-reliability measures. These reliability measures are compared with those calculated based on VISSIM simulation output and field data.

The main contributions of this paper include: (1) demonstrating user heterogeneity in terms of following headway and standstill distance based on field-collected data; (2) proposing a method for
estimating travel time reliability that incorporates stochastic time headways and standstill distances in existing car-following models; (3) showing the necessity of considering random driver behavior parameters in microscopic traffic simulation tools in order to better match field observations.

The remainder of this paper is organized as follows. The next section describes the time headway and standstill distance distributions, derives the steady-state speed-density relationships for different car-following models, and estimates travel time index based on the Pipes car-following model. Section 3 presents estimated travel-time-reliability measures and different input modes' speed-density relationships. Section 4 presents discussion and conclusions.

Methodology

This section presents the approach to incorporating the stochastic headway and standstill distributions into car-following models and estimating travel time reliability.

Our modeling approach consists of three parts. First, we propose a two-component travel time distribution to derive travel-time-reliability measures. Second, we derive from the Pipes car-following model a mathematical formulation of travel time under the congested state. Third, we use the Monte Carlo simulation method to generate travel time estimates that reflect the congested state's stochastic time headways and standstill distances.

Multistate models have been used to fit travel time distributions that contain multiple component distributions (Guo, Rakha, & Park, 2010; Park, Rakha, & Guo, 2011). The normal, gamma, and lognormal distributions have been considered as component distributions of various multistate models. In particular, Guo et al. (2010) have proposed a two-component travel time distribution model containing a free-flow state and congested state. The mixture normal, mixture lognormal, and mixture Weibull distributions can be used to describe this two-component travel time distribution. Since the variations in free-flow travel times are generally small, the distribution's reliability measures are mostly determined by congested travel times. Therefore, to simplify reliability measure calculation, this two-component model ignores free-flow travel time variation, treating travel times in a free-flow state as a Dirac delta function.

For example, based on travel time data collected on I-235 in Des Moines, IA, a pair of two-component travel time distributions is shown in Figure 1. In Figure 1(a), the probability density function (PDF) of travel times can be viewed as a mixture Gaussian distribution consisting of a free-flow travel time distribution and a congested travel time distribution. As the travel time variation is small under free-flow conditions, the PDF of the free-flow state can be appropriately simplified as a Dirac delta function, as shown in Figure 1(b).

To calculate travel-time-reliability measures, such as planning index and buffer time, the 95th percentile and mean travel times are needed. The cumulative density function of this simplified two-component travel time distribution can be written as

\[
F(x) = \alpha F_F(x) + (1 - \alpha) F_C(x)
\]

where \(F_F(x)\) is the cumulative density function of the Dirac delta distribution; \(F_C(x)\) is the cumulative density function of the congested state; \(\alpha\) is the mixture proportion.

For the Dirac delta distribution, the cumulative distribution function is the Heaviside step function in which:

\[
F_F(x) = \begin{cases} 
1, & x \geq t_0 \\
0, & x < t_0
\end{cases}
\]

where \(t_0\) is the free-flow travel time.

As a result, the 95th percentile travel time can be calculated as follows:

\[
TT_{95} = \begin{cases} 
F_C^{-1}(0.95 - \alpha), & 0 \leq \alpha < 0.95 \\
t_0, & \alpha \geq 0.95
\end{cases}
\]

The mean travel time for this two-component model can be calculated as:

\[
\mu = \alpha t_0 + (1 - \alpha) \mu_C
\]

where \(\mu_C\) is the mean travel time in the congested state.

Based on the 95th percentile travel time, free-flow travel time, and mean travel time, reliability measures can be derived, including the following:

- Planning time – The 95th percentile travel time
- Planning time index – The ratio of 95th percentile travel time to ideal or free-flow travel time

\[
Planning\ time\ index = \frac{TT_{95}}{t_0}
\]

- Buffer time – The difference between the 95th percentile travel time and the average travel time

\[
Buffer\ time = TT_{95} - \mu
\]

- Buffer index – The size of the buffer as a percentage of the average, calculated as the 95th percentile
Our proposed travel-time-reliability estimation framework is shown in Figure 2. First, real-world traffic data are clustered into either the free-flow state or congested state based on the level of service criteria for urban freeways defined in the Highway Capacity Manual (HCM, 2016). That is, the congested state is defined as when the density is greater than 26 veh/mi/ln. On this basis, the free-flow travel time can be calculated. Second, a stochastic car-following model can be used to generate the congested state's travel time distribution. Finally, based on the previously described simplified two-component travel time distribution, reliability measures can be calculated.
Historical traffic data (Regarding density and free-flow speed)

Select data with the same timestamp, \( t[n] \)

Free-flow state

Yes

Corridor-level free-flow travel time

No

Density of any link > 26 veh/mi/ln

Congested state

No

Is \( t[n] \) the last timestamp?

Yes

Link-level density distributions for the congested condition

\( \alpha \), Corridor-level free-flow travel time

Stochastic car-following model

Travel-time-reliability measures

Corridor-level travel times for the congested state

Figure 2. Proposed estimation framework for corridor-level travel-time-reliability measures.

Table 1. Plausible function forms of time headway and standstill distance distributions.

<table>
<thead>
<tr>
<th>Probability density function</th>
<th>Parameters</th>
<th>Mean</th>
<th>Mode</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gamma ( p(x) = \frac{c}{a^\alpha} x^{\alpha-1} e^{-\frac{x}{a}} )</td>
<td>( \alpha &gt; 0 ) - shape ( \beta &gt; 0 ) - rate</td>
<td>( \frac{\alpha}{\beta} )</td>
<td>( \frac{\alpha-1}{\beta} ) for ( \alpha \geq 1 )</td>
</tr>
<tr>
<td>Weibull ( p(x) = \frac{k}{\theta} \left( \frac{x}{\theta} \right)^{k-1} e^{-\left( x/\theta \right)^k} )</td>
<td>( k &gt; 0 ) - shape ( \theta &gt; 0 ) - scale</td>
<td>( \theta \cdot \Gamma(1 + \frac{1}{k}) )</td>
<td>( \theta \left( \frac{k}{k+1} \right)^{1/k} ) for ( k &gt; 1 )</td>
</tr>
<tr>
<td>Lognormal ( p(x) = \frac{1}{\sigma \sqrt{2\pi}} e^{-\frac{(\ln x - \mu)^2}{2\sigma^2}} )</td>
<td>( \sigma^2 &gt; 0 ) - shape ( \mu \in R ) - log scale</td>
<td>( e^{\mu - \frac{\sigma^2}{2}} )</td>
<td>( e^{\mu + \sigma^2/2} )</td>
</tr>
<tr>
<td>Normal ( p(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(x - \mu)^2}{2\sigma^2}} )</td>
<td>( \sigma^2 &gt; 0 ) - variance ( \mu \in R ) - mean</td>
<td>( \mu )</td>
<td></td>
</tr>
</tbody>
</table>

\( \Gamma(\cdot) \) - Gamma function.

Stochastic headways and standstill distances

In this study, four statistical distributions were considered to fit the time headway and standstill distance data. In order to determine how well these distributions fit the observations, log-likelihood values were compared (Table 1).

The likelihood ratio test was used to compare vehicle-type-specific models (i.e., car following car, car following truck, truck following car, and truck following truck) with the overall model. This test statistic, which is chi-square distributed, is shown in Equation (8).

\[
\chi^2 = -2(LL_R - LL_U) \tag{8}
\]

where \( LL_R \) is the log-likelihood value for the overall model; \( LL_U \) is the sum of the log-likelihood values for the vehicle-type-specific models

Steady-state car-following models

Steady-state car-following models describe the relationship between the desired speed of following vehicles, the speed of lead vehicles and the spacing between lead and following vehicles. The macroscopic speed-density relationship can be derived from steady-state car-following behavior, as described in this section.

Car-following model in FRESIM

The Pitt car-following model, developed by the University of Pittsburgh, has been implemented in FRESIM (Halati, Lieu, & Walker, 1997). According to Aydin and Benekohal (2001), the basic model can be described as follows:

\[
S[m] = S[m] + c_6[m]u[m] + bc_6[m]\Delta u[m] \tag{9}
\]
where $S[m]$ is the spacing between the lead and the following vehicles $m - 1$ and $m$ (miles); $S_j[m]$ is the congested spacing when vehicles are completely stopped in a queue (miles); $c_3[m]$ is the car-following sensitivity factor for vehicle $m$; $u[m]$ is the speed of the following vehicle $m$ (miles per hour); $b$ is the calibration constant equal to 0.1 if the speed of the following vehicle exceeds the speed of the leading vehicle; otherwise, $b$ is 0; $\Delta u[m]$ is the difference in speed between the lead and following vehicles $m - 1$ and $m$ (miles per hour).

The spacing when vehicles are completely stopped is the summation of the standstill distance and the vehicle length, as shown in Equation (10).

$$S_j[m] = d_j[m] + l,[m - 1]$$

where $d_j[m]$ is the standstill distance (miles) between lead vehicle $m - 1$ and following vehicle $m$; $l,[m - 1]$ is the length of vehicle $m - 1$ (miles).

Since the steady state assumes equal and constant speeds, the car-following model in FRESIM can be simplified as follows:

$$S[m] = S_j[m] + c_3[m]u[m]$$

$$u[m] = \min\left(\frac{S[m] - S_j[m]}{c_3[m]}, \frac{1}{u_f}\right)$$

In fact, FRESIM's steady-state car-following behavior can be described using the Pipes model (1953) (Rakha & Crowther, 2003). The speed–density relationship according to the Pipes car-following model is as follows:

$$U = \frac{n(1 - k \times S_j)}{k \times \sum_{m=1}^{n} c_3[m]}, U \in [0, u_f]$$

where $k$ is the density (vehicles per mile per lane); $U$ is the speed (miles per hour); $S_j$ is the average jam spacing, that is, $S_j = \sum_{m=1}^{n} S[m] / n$. Rakha and Crowther (2003) have shown that the driver sensitivity factor can be expressed as

$$c_3 = \frac{1}{q_c} \left(\frac{1}{k u_f}\right)$$

where $q_c$ is the roadway capacity (vehicles per hour per lane); $k$ is the jam density (vehicles per mile per lane); $u_f$ is the free-flow speed (miles per hour).

The relationship between flow rate and headway and the relationship between jam density and congested spacing are thus represented by Equations (15) and (16), respectively:

$$q[m] = \frac{1}{h_a[m]}$$

$$k_j[m] = \frac{1}{S_j[m]}$$

where $h_a[m]$ is the average time headway between lead vehicle $m - 1$ and following vehicle $m$.

By substituting Equations (15) and (16) into Equation (14), we have

$$c_3[m] = h_a[m] - \frac{S_j[m]}{u_f}$$

Car-following model in INTEGRATION

By combining the Pipes model and Greenshields model, Van Aerde and Rakha (1995) proposed a car-following model that has been implemented in INTEGRATION (Van Aerde & Assoc., 2005a, 2005b). The Van Aerde model (Rakha & Crowther, 2003) is calculated as

$$S[m] = a_1[m] + \frac{a_2[m]}{u_f - u[m]} + a_3[m]u[m]$$

where $a_1[m]$ is the fixed-distance headway between the lead and following vehicles, $m - 1$ and $m$ (miles); $a_2[m]$ is the first variable-distance headway between the lead and following vehicles, $m - 1$ and $m$ (miles$^2$ per hour); $a_3[m]$ is the second variable-distance headway between the lead and following vehicles, $m - 1$ and $m$ (hour).

The Van Aerde model’s speed–density relationship can be derived as

$$k = \frac{1}{a_1 + \frac{a_2}{u - u_f} + a_3 u}$$

Its model parameters $a_1$, $a_2$, and $a_3$ can be computed as follows (Demarchi, 2002):

$$a_1 = \frac{u_f}{k_j u_c^2} (2u_c - u_f)$$

$$a_2 = \frac{u_f}{k_j u_c^2} (u_f - u_c)^2$$

$$a_3 = \frac{1}{u_c} - \frac{u_f}{k_j u_c^2}$$

where $u_c$ is the speed at capacity (miles per hour).

By substituting Equations (15) and (16) into Equations (20)–(22), the model parameters for each vehicle pair can be derived as follows:

$$a_1[m] = \frac{S_j[m] u_f}{u_c^2} (2u_c - u_f)$$

$$a_2[m] = \frac{S_j[m] u_f}{u_c^2} (u_f - u_c)^2$$

$$a_3[m] = h_a[m] - \frac{S_j[m] u_f}{u_c^2}$$
Based on Equation (19), Equations (23)–(25), speed can therefore be calculated as follows:

$$U = \frac{\bar{a}_1 u_1 + \bar{a}_1^2 \sigma_{a_1} + \sqrt{\bar{a}_1^2 u_1^2 - \frac{1}{2} \bar{a}_1^2 \sigma_{a_1}^2 + 4 \bar{a}_1 \bar{a}_1' u_1}}{2 \bar{a}_1}, \quad U \in [0, u_f]$$

(26)

where $\bar{a}_1$ is the average of $a_i[m]$, that is, $\bar{a}_1 = \frac{\sum_{i=1}^{n} a_i[m]}{n}$

**Car-following model in VISSIM**

The Weidemann 74 and Weidemann 99 car-following models, which are psychophysical or action-point models (Gao, 2008), have been implemented in VISSIM. These models have been developed from Pipes car-following logic and consider other factors, such as the spacing in which a following vehicle reacts to a lead vehicle's speed change as well as the following vehicle driver's perception of this speed change. Under steady-state conditions, the car-following model in VISSIM reverts to the Pipes model (as shown in Equation (12)) (Rakha & Crowther, 2002).

**Travel time reliability based on steady-state car-following models**

By incorporating standstill distance and time headway distributions into the abovementioned car-following models, travel-time-reliability measures can be estimated using Monte Carlo simulation. In each simulation run, a realization of the stochastic parameters leads to a realization of the speed–density point. Collectively, the speed–density region can therefore be estimated. A sufficient number of simulations can provide a good representation of the speed–density region under uncertainty. Given the standstill distances and time headway distributions, the following procedure can be implemented through Monte Carlo simulation to estimate the speed–density region. Accordingly, travel times under the congested condition can be generated. The 95th percentile and mean travel time can be calculated based on Equations (3) and (4). The reliability measures can be derived from Equations (5)–(7). The detailed procedure is as follows:

**Input:**
- Free-flow speed, $u_f$
- Truck percentage, $P$
- Number of links = $X$
- Link length, $L_x, x \in [1, X]$
- Density distribution under the congested condition for link $x$, $k_x, x \in [1, X]$

**Output:** Speed-density range/Travel times under congested conditions

Truncated vehicle-type-specific standstill distance distributions (see Section "Standstill distance"), $S_j \in (0, \text{Upper Bound})$; Truncated vehicle-type-specific headway distributions (see Section "Time headway distribution"), $H \in [\text{Lower Bound}, \text{Upper Bound}]$; Number of simulations = $Z$

For $z=1$ to $Z$,
- For $x=1$ to $X$,
  1: Generate a set of random samples for vehicles, say $M$ vehicles, with $P$ percent of trucks.
  2: Randomly generate density values for link $x$ from the density distribution.
  3: Determine the vehicle following type between the leading vehicle ($m-1$) and the following vehicle ($m$) in the vehicle set.
  4: According to the truncated vehicle-type-specific standstill distance and headway distributions, generate the standstill distances and time headways for the vehicle pair based on the corresponding probability distributions.
  5: Calculate $S_j$ for each vehicle pair using Equation (10)
  6: **FRESIM:** Calculate $c_3$ for following vehicle ($m$) using Equation (17).
    **INTEGRATION:** Calculate $a_1$, $a_2$, and $a_3$ for the following vehicle ($m$) using Equations (23)–(25).

End For

7: Select first $n$ observations, where $\max \sum_{m=2}^{\infty} \text{headway}[m] \leq \text{time interval}$.

The time interval of 1 minute was used in this study.

8: **FRESIM:** Use Equation (13) to calculate the speed on the target link for the density point.

**INTEGRATION:** Use Equation (26) to calculate the speed on the target link for the density point.

9: Calculate travel time on the target link by using the link length divided by the speed from step 8.

End For

10: Calculate corridor-level travel time by adding the travel times for all links

End For
In order to estimate the accuracy and efficiency of the proposed framework, this FRESIM car-following model was compared with VISSIM simulation results. Note that the car-following logic of both FRESIM and VISSIM under the steady-state condition reverts to the Pipes car-following model (Rakha & Crowther, 2002).

**Travel time reliability based on VISSIM**

Corridor-level travel time can also be obtained through PTV VISSIM. VISSIM is a popular piece of microscopic traffic simulation software that adopts the psychophysical car-following model developed by Wiedemann (PTV AG, 2014). Because VISSIM can simulate the behavior of individual vehicles and produce diverse evaluation parameters, it has been widely used in transportation engineering for modeling various traffic scenarios. There are two car-following models available in VISSIM, Wiedemann 74, and Wiedemann 99, which are used to model urban traffic and freeway traffic, respectively. In this study, the Wiedemann 99 car-following model was used.

Driver behavior parameters were calibrated as in Dong et al. (2015) using locally collected data. Three car-following model parameters, including standstill distance (CC0), time headway (CC1), and “following” variation (CC2), have been found to have a significant influence on traffic capacity. Traffic volume for the study corridor was balanced based on the method proposed by Shaw and Noyce (2014). The congested and free-flow conditions were simulated separately. The travel time distribution measures were calculated by sampling travel times from the VISSIM output based on the percentage of congested versus free-flow conditions in the real world.

**Data collection**

The time headways and standstill distances used in this study were collected from various freeway segments throughout Iowa. In order to collect the time headway data, side-fired radar detectors with video cameras were installed temporarily at several locations. These radar detectors collected the length, speed, lane detected, and time detected for each vehicle. Vehicle classification was determined based on vehicle length. Vehicles with a length greater than 40 feet were considered trucks. Other vehicles were counted as cars. Time headway is calculated as the time difference between two vehicles’ arrival at the same location. By examining the relationship between leading and following vehicles’ speed correlations and headways (Vogel, 2002) and consistent with Wasielewski (1979), a threshold of 4 seconds was selected, below which the vehicles were considered as follows.

Standstill distances were measured based on these videos whenever vehicles on the freeway stopped in a queue. In addition, videos of incidents causing stop-and-go traffic were downloaded after the fact from Iowa Department of Transportation closed-circuit cameras (CCTV) for processing. Screen captures of these video sources were taken whenever vehicles were stopped within the frame. These stopped vehicles were identified and the distances between them were measured using an Adobe Photoshop tool capable of measuring distances on a plane distorted by perspective. Painted lane lines (10 feet long) were used as the control measurement on which the software based the rest of its measurements. The length of these lane lines was confirmed using Google Earth. Thus, standstill distances were measured between every pair of stopped vehicles. The accuracy of measuring standstill distance via Photoshop was tested by taking photos of a grid with known dimensions from several angles and comparing the measurements of the software to the actual dimensions. The average of the absolute relative error of these measurements was 1.2 percent (Houchin et al., 2015).

In this study, probe vehicle travel time data were queried from the Regional Integrated Transportation Information System (RITIS, 2016), which archives INRIX probe vehicle data at 1-minute aggregation intervals (Lu & Dong, 2018). This dataset provides time-stamped segment-based speeds, travel times, historical average speed, free-flow speed, and confidence scores. As stated in the INRIX Interface Guide (2014), the record represents real-time data only when the confidence score equals 30; otherwise, the value is estimated from historical data. Consequently, all travel times used in this study are those with a confidence score of 30 (Table 2).

<table>
<thead>
<tr>
<th>Table 2. Travel time summary statistics.</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
</tr>
<tr>
<td>Travel time</td>
</tr>
<tr>
<td>Mean (min)</td>
</tr>
<tr>
<td>Minimum (min)</td>
</tr>
<tr>
<td>Maximum (min)</td>
</tr>
<tr>
<td>Standard deviation</td>
</tr>
</tbody>
</table>

**Results**

**Time headway and standstill distance distributions**

In this subsection, four statistical distributions are considered to fit the time headway and standstill distance data collected for Iowa freeways.
Figure 3. Histogram of vehicle-type-specific and all-vehicle-type time headways.

Table 3. Time headway summary statistics.

<table>
<thead>
<tr>
<th></th>
<th>Overall</th>
<th>Car-Car</th>
<th>Car-Truck</th>
<th>Truck-Car</th>
<th>Truck-Truck</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of observations</td>
<td>26,0415</td>
<td>200,994</td>
<td>22,324</td>
<td>30,467</td>
<td>6630</td>
</tr>
<tr>
<td>Mean (sec)</td>
<td>1.8997</td>
<td>1.8010</td>
<td>2.3990</td>
<td>1.8412</td>
<td>2.4133</td>
</tr>
<tr>
<td>Minimum (sec)</td>
<td>0.4</td>
<td>0.4</td>
<td>0.402</td>
<td>0.4</td>
<td>0.401</td>
</tr>
<tr>
<td>Maximum (sec)</td>
<td>4</td>
<td>4</td>
<td>4</td>
<td>4</td>
<td>4</td>
</tr>
<tr>
<td>Standard deviation</td>
<td>0.9644</td>
<td>0.9671</td>
<td>0.8719</td>
<td>0.8958</td>
<td>0.8751</td>
</tr>
</tbody>
</table>

Table 4. Log-likelihood ratio test statistic for headway models.

<table>
<thead>
<tr>
<th>Distribution</th>
<th>Goodness of fit</th>
<th>Overall</th>
<th>Car-Car</th>
<th>Car-Truck</th>
<th>Truck-Car</th>
<th>Truck-Truck</th>
<th>( \chi^2 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lognormal</td>
<td>Log-likelihood</td>
<td>-365935</td>
<td>-273963</td>
<td>-43161</td>
<td>-32813</td>
<td>-10243</td>
<td>11511</td>
</tr>
<tr>
<td></td>
<td>AIC</td>
<td>731014</td>
<td>542821</td>
<td>86676</td>
<td>63132</td>
<td>20490</td>
<td>-</td>
</tr>
<tr>
<td>Gamma</td>
<td>Log-likelihood</td>
<td>-349881</td>
<td>-264511</td>
<td>-40681</td>
<td>-29884</td>
<td>-9127</td>
<td>11356</td>
</tr>
<tr>
<td></td>
<td>AIC</td>
<td>700289</td>
<td>531923</td>
<td>81342</td>
<td>60721</td>
<td>18594</td>
<td>11172</td>
</tr>
<tr>
<td>Weibull</td>
<td>Log-likelihood</td>
<td>-346687</td>
<td>-263588</td>
<td>-40303</td>
<td>-28605</td>
<td>-8605</td>
<td>9741</td>
</tr>
<tr>
<td></td>
<td>AIC</td>
<td>699693</td>
<td>521073</td>
<td>80867</td>
<td>57212</td>
<td>17287</td>
<td>17044</td>
</tr>
<tr>
<td>Normal</td>
<td>Log-likelihood</td>
<td>-360322</td>
<td>-276102</td>
<td>-42211</td>
<td>-28617</td>
<td>-8522</td>
<td>9741</td>
</tr>
<tr>
<td></td>
<td>AIC</td>
<td>720644</td>
<td>552204</td>
<td>84422</td>
<td>57234</td>
<td>17044</td>
<td>-</td>
</tr>
</tbody>
</table>

Time headway distribution

Figure 3 shows the histogram of time headways by different lead-follow vehicle types and for the overall data. As Figure 3 illustrates, all distributions are right-skewed. Table 3 summarizes the time headway statistics. It should be noted that the estimated distributions were truncated in order to constrain the time headway values within a reasonable range. In particular, the lower bound of the time headway distributions was set as 0 seconds. The upper bound of the following time headways was set as 4 seconds (Dong et al., 2015; Wasielewski, 1979).

As might be expected, the mean time headways when a car is following (i.e., Car-Car and Truck-Car) are significantly different from those when a truck is following (i.e., Car-Truck and Truck-Truck). In addition, large standard deviations are associated with all lead-follow vehicle types, as well as with the pooled dataset, indicating fairly dispersed distributions.

The lognormal, gamma, normal, and Weibull distributions were used to fit the vehicle-type-specific and overall time headways. Table 4 lists the Akaike information criterion (AIC) values, log-likelihood values, and log-likelihood ratio test statistics. It will be noted that the \( \chi^2 \) test statistics are all greater than the critical value of the chi-square distribution at the 5% significance level, indicating that the vehicle-type-specific headway models are significantly different from the overall headway model. In addition, based on the log-likelihood and
AIC values, the Weibull distribution was the best fitting model for the Car-Car, Truck-Car, Truck-Truck, and Overall time headways. For the Truck-Truck time headways, the best fitting model was the normal distribution, although the Weibull distribution provided a similar fit. The best fitting models are considered as input in the car-following models for which results are summarized in the subsequent sections. Table 5 lists all models' estimated parameters.

**Standstill distance**

Figure 4 shows the histogram of vehicle-type-specific and overall standstill distances. The Car-Car and Truck-Truck distances follow a similar shape and are slightly right-skewed. The Car-Truck and Truck-Car plots both follow a bimodal distribution. The two peaks in these plots correspond to medium and large trucks, both of which in this paper are considered "Trucks." The sample size for Truck-Truck pairs was too small to draw any firm conclusion and thus the associated standstill distances are not included in Figure 4.

Table 6 lists the standstill distance statistics. It should be noted that the estimated distributions were truncated in order to constrain the standstill distance values within a reasonable range. In particular, the lower and upper bounds of the standstill distance distributions are set as 0 and 25 feet, respectively (Dong et al., 2015).

Table 5. Estimated parameters for time headway distributions.

<table>
<thead>
<tr>
<th>Lead-follow vehicle type</th>
<th>Overall</th>
<th>Car-Car</th>
<th>Car-Truck</th>
<th>Truck-Car</th>
<th>Truck-Truck</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model</td>
<td>Weibull</td>
<td>Weibull</td>
<td>Weibull</td>
<td>Weibull</td>
<td>Normal</td>
</tr>
<tr>
<td>Parameters</td>
<td>Shape</td>
<td>Scale</td>
<td>Shape</td>
<td>Scale</td>
<td>Mean</td>
</tr>
<tr>
<td></td>
<td>2.082</td>
<td>2.148</td>
<td>3.042</td>
<td>2.040</td>
<td>2.399</td>
</tr>
<tr>
<td></td>
<td>Scale</td>
<td>2.150</td>
<td>2.033</td>
<td>2.699</td>
<td>Standard deviation</td>
</tr>
<tr>
<td></td>
<td>2.083</td>
<td>0.875</td>
<td>5.778</td>
<td>3.691</td>
<td></td>
</tr>
</tbody>
</table>

Figure 4. Histogram of vehicle-type-specific and mixed-vehicle-type standstill distances.

Table 6. Standstill distance summary statistics.

<table>
<thead>
<tr>
<th></th>
<th>Overall</th>
<th>Car-Car</th>
<th>Car-Truck</th>
<th>Truck-Car</th>
<th>Truck-Truck</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of observations</td>
<td>1,238</td>
<td>1,140</td>
<td>40</td>
<td>48</td>
<td>10</td>
</tr>
<tr>
<td>Minimum (ft)</td>
<td>1.03</td>
<td>1.03</td>
<td>3.75</td>
<td>2.45</td>
<td>5.77</td>
</tr>
<tr>
<td>Maximum (ft)</td>
<td>24.72</td>
<td>24.72</td>
<td>23.53</td>
<td>24.45</td>
<td>17.72</td>
</tr>
<tr>
<td>Standard deviation</td>
<td>4.539</td>
<td>6.322</td>
<td>4.733</td>
<td>5.778</td>
<td>3.691</td>
</tr>
</tbody>
</table>
Table 7. Log-likelihood ratio test statistic for standstill distance models.

<table>
<thead>
<tr>
<th>Distribution</th>
<th>Goodness of fit</th>
<th>Overall</th>
<th>Car-Car</th>
<th>Truck</th>
<th>$\chi^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lognormal</td>
<td>Log-likelihood</td>
<td>3674.64</td>
<td>3220.06</td>
<td>313.76</td>
<td>27.64</td>
</tr>
<tr>
<td></td>
<td>AIC</td>
<td>7287</td>
<td>6494</td>
<td>631</td>
<td>—</td>
</tr>
<tr>
<td>Gamma</td>
<td>Log-likelihood</td>
<td>3604.40</td>
<td>3277.99</td>
<td>309.36</td>
<td>34.1</td>
</tr>
<tr>
<td></td>
<td>AIC</td>
<td>7211</td>
<td>6559</td>
<td>622</td>
<td>—</td>
</tr>
<tr>
<td>Weibull</td>
<td>Log-likelihood</td>
<td>3611.13</td>
<td>3282.28</td>
<td>307.80</td>
<td>42.1</td>
</tr>
<tr>
<td></td>
<td>AIC</td>
<td>7224</td>
<td>6568</td>
<td>619</td>
<td>—</td>
</tr>
<tr>
<td>Normal</td>
<td>Log-likelihood</td>
<td>3680.66</td>
<td>3341.68</td>
<td>312.36</td>
<td>55.24</td>
</tr>
<tr>
<td></td>
<td>AIC</td>
<td>7361</td>
<td>6683</td>
<td>624</td>
<td>—</td>
</tr>
</tbody>
</table>

Table 8. Estimated parameters for standstill distance distributions.

<table>
<thead>
<tr>
<th>Lead-follow vehicle type</th>
<th>Model</th>
<th>Parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>Overall</td>
<td>Gamma</td>
<td>Shape 3.95</td>
</tr>
<tr>
<td>Car-Car</td>
<td>Lognormal</td>
<td>Log scale 2.11</td>
</tr>
<tr>
<td>Truck</td>
<td>Weibull</td>
<td>Shape 14.29</td>
</tr>
</tbody>
</table>

Distance is not a reliable estimate. Therefore, the Truck-Truck group was excluded from subsequent analysis. In addition, the Car-Truck and Truck-Car groups were combined in subsequent analysis into one group named "Truck.

Table 7 lists the log-likelihood values of using the lognormal, gamma, normal, and Weibull distributions to fit the standstill distances of the overall, Car-Car, and Truck data. It will be noted that the $\chi^2$ test statistics are all greater than the critical value of the chi-square distribution at the 5% significance level. This indicates that the Car-Car and Truck standstill distance distributions are significantly different from the overall standstill distance distribution. Based on the log-likelihood and AIC values, the lognormal distribution was the best fitting model for the Car-Car data, the gamma distribution was the best fitting model for the Overall data, and the Weibull distribution was the best fitting model for the Truck data. However, note that the differences between alternative distributions for all groups’ standstill distances are small. The best fitting models were used as input in the subsequent analysis. Estimated parameters for the best fitting distributions are listed in Table 8.

**Speed–density relationship**

Four different input modes were used to derive different car-following models’ speed–density relationships:

1. Using the overall mean time headway and mean standstill distance as deterministic parameters. (This is the typical input method for traffic simulation software.)

2. Using the means for the four lead-follow vehicle-type-specific time headways as a deterministic time headway parameter along with the mean standstill distances of the Car-Car and Truck groups as a deterministic standstill distance parameter.

3. Using the overall time headway and standstill distance distributions as random parameters.

4. Using the distributions for the four lead-follow vehicle-type-specific time headways as a random time headway parameter along with the Car-Car and Truck standstill distance distributions as a random standstill distance parameter.

Speed–density relationships for the congested regime can be generated using the FRESIM car-following model. Figure 5(a) plots speed–density curves thus generated using deterministic parameters. On the left, four speed–density curves considering the vehicle-type-specific time headways and standstill distances are plotted, corresponding to different lead-follow vehicle types. It will be noted that these vehicle-type-specific speed-density curves are fairly close to the overall speed-density curve. Figure 5(b), in contrast, plots the speed–density region generated using stochastic parameters. By changing the time headway and standstill distance parameters from constants to distributions, the speed–density relationship changes from a curve to a region. Use of randomly distributed parameters results in a wide speed-density plot region. It will be noted that the speed–density region generated by the vehicle-type-specific distributions is slightly larger than the one generated by the overall distribution.

Speed–density relationships for the congested regime can also be generated using the steady-state INTEGRATION car-following model. As shown in Figure 6(a), with deterministic time headway and standstill distance parameters, the speed–density curve generated using the Car-Car parameters is significantly different from the one associated with the Car-Truck parameters. Figure 6(b) shows that, as with
the FRESIM car-following model, the use of the
lead-follow vehicle-type-specific distributions with the
INTEGRATION car-following model results in the
largest speed-density plot region.

By comparing Figures 5 and 6, it can be seen
that the INTEGRATION car-following model gen-
erates a larger speed–density region than the
FRESIM model when using the vehicle-type-

Figure 5. Speed-density ranges generated using the FRESIM car-following model. (a) Speed-density curves generated using deter-
ministic parameters. (b) Speed-density regions generated using stochastic parameters.
specific time headway and standstill distance distributions. In addition, the vehicle-type-specific distribution input mode results in the largest speed-density region, as this input mode considers both systematic and random heterogeneity in drivers' behavior. Therefore, the vehicle-type-specific distribution input mode of the steady-state FRESIM car-following model is compared with VISSIM simulation output and field measurements in the next subsections.

Figure 6. Speed-density ranges generated using the INTEGRATION car-following model. (a) Speed-density curves generated using deterministic parameters. (b) Speed-density regions generated using stochastic parameters.
Comparison of results for the vehicle-type-specific distribution input mode and VISSIM simulation

In this subsection, we investigate the necessity of using the vehicle-type-specific distribution as input in microsimulation software.

The default values for North America (PTV Group, 2014) as well as the measured time headway and standstill distance values’ mean, 5th percentile, and 95th percentile were used as input to run the VISSIM simulations. Time headway was converted to VISSIM’s CCI parameter based on the following equation:

\[
CCI = \frac{\text{Time Headway} - \text{CC0} + \text{Lead Vehicle Length}}{\text{Speed}}
\]

(28)

where CC = the standstill distance between two vehicles

By varying only the standstill distance in VISSIM and keeping other parameters default, scatterplots for the simulated speed and density data are shown in Figure 7. (The speed–density region generated from the stochastic FRESIM car-following model was used as reference.) It can be seen that the VISSIM simulation tends to predict lower speeds when the density is low.

By changing the CCI in VISSIM and keeping other parameters default, scatterplots for the simulated speed and density data are shown in Figure 8. As with Figure 7, it can be seen that compared to the proposed method VISSIM again tends to overestimate the congestion effect.

Comparison of vehicle-type-specific distribution input mode results and field data

In this subsection, real-world traffic data are used to evaluate the performance of the proposed stochastic car-following model that incorporates the lead-follow vehicle-type-specific time headway and standstill distance distributions.

In recent years, the Iowa Department of Transportation (DOT) has been placing Wavetronix radar sensors along interstates and major highways in the state. The majority of sensors have been installed in the major metropolitan areas and provide information relevant to incident management, traffic operations, and planning. The existing Iowa DOT Wavetronix sensors cover the Des Moines metropolitan area’s highway network. These sensors count vehicles by lane and classification as well as register vehicle speeds. Aggregated traffic flow and speed data for I-235, one of the busiest freeways in West Des Moines, Iowa, were obtained through an online data portal maintained by TransSuite. Data from four selected I-235 sensors were compared with the speed-density regions generated using the stochastic FRESIM car-following model. The data used for this analysis were collected during peak hours (either 7:00–9:00 a.m. or 4:00–7:00 p.m.) on weekdays from January 1 to December 31, 2015.
Figure 8. Speed-density plots simulated using VISSIM with varying CC1 parameters, compared with the speed-density region generated using the stochastic FRESIM car-following model.

Figure 9. Field data compared with the speed-density regions generated using the stochastic FRESIM car-following model.

Figure 9 plots the resulting speed–density data for congested traffic conditions that occurred during these peak hours. It will be noticed that most of the field-collected data points fall within the region generated by the stochastic FRESIM car-following model that incorporates the vehicle-type-specific time headway and standstill distance distributions. By comparing Figures 7–9, we can see that the speed–density region generated by the proposed method can better represent real-world observations than VISSIM simulation output.

**Travel time index and travel time reliability**

One potential application of the proposed stochastic car-following model is to predict travel time reliability. A Monte Carlo simulation was performed to generate travel times under congested conditions. The weight of the free-flow state was calculated according to the framework shown in Figure 2. Travel-time-reliability measures were calculated according to Equations (3)–(7).
Multiple VISSIM simulation runs were executed to generate predicted travel times. CC0 and CC1 were set as 9.7 feet and 1.3 seconds, respectively, based on the measured mean time headway and standstill distance values. All other parameters were kept default. Ten replications were performed for each scenario. The planning horizon for each simulation was set at 5,400 seconds, including an 1,800-second warm-up period. The travel time for every vehicle's travel from the starting point to the ending point was collected, excluding data from the warm-up period.

Figure 10 shows the study's 13-mile I-235 freeway corridor where all radar sensor and INRIX data were collected and it notes all radar sensor locations along this corridor. Probe vehicle travel time data were queried from the Regional Integrated Transportation Information System (RITIS, 2016) that archives INRIX probe vehicle data at 1-minute aggregation intervals. This dataset provides timestamped segment-based speeds, travel times, historical average speed, free-flow speeds, and confidence scores.

Actual traffic volumes associated with each segment/on-ramp/off-ramp that were collected from these radar sensor and INRIX data sources for both the congested and free-flow scenarios are shown in Table 9.

Travel-time-reliability measures calculated using the INRIX travel time data were compared with the reliability measures obtained from the proposed model and VISSIM. As shown in Table 10, both the proposed model and VISSIM overestimated the mean travel time and underestimated the travel time reliability for the freeway segment investigated in this study. However, compared with the INRIX data's actual travel-time-reliability measures, the proposed model generated more accurate reliability measures than VISSIM with less computational time.

Conclusion

This paper presents a method of estimating travel-time-reliability measures by incorporating following time headway and standstill distance distributions into car-following models.

First, the following time headway and standstill distance distributions were estimated based on data collected from various locations within the state of Iowa in the USA. In terms of following time headway distributions, five distributions were estimated for different lead-follow vehicle types, namely the Car-Car, Truck-Truck, Car-Truck, Truck-Car, and Overall groups. In terms of standstill distance distributions, the Car-Car standstill distances were significantly different from the Car-Truck and Truck-Car standstill distances, but the Car-Truck and Truck-Car standstill distance distributions did not differ significantly from each other. Therefore, the Car-Truck and Truck-Car groups were combined into one group labeled "Truck." Standstill distance distributions were estimated for the resulting three Car-Car, Truck, and Overall groups, respectively.

Second, the estimated following time headway and standstill distance distributions were incorporated into the steady-state FRESIM and INTEGRATION car-following models to generate predicted speed–density relationships. Results showed that vehicle-type-specific distribution input can result in speed–density regions that better replicate real-world observations compared to speed–density curves generated using the mean following time headway and standstill distance parameters typically input into traffic simulation software. In
Table 9. Actual traffic volumes in congested and uncongested conditions.

<table>
<thead>
<tr>
<th>ID</th>
<th>Segment description</th>
<th>Type</th>
<th>Lanes</th>
<th>Congested</th>
<th>Uncongested</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1-235 EB to VALLEY WEST-EB</td>
<td>Mainline</td>
<td>3</td>
<td>5727</td>
<td>1733</td>
</tr>
<tr>
<td>2</td>
<td>1-235 EB to VALLEY WEST-EB-R</td>
<td>Off-ramp</td>
<td>1</td>
<td>340</td>
<td>108</td>
</tr>
<tr>
<td>3</td>
<td>Ramp 1</td>
<td>On-ramp</td>
<td>1</td>
<td>285</td>
<td>438</td>
</tr>
<tr>
<td>4</td>
<td>1-235 EB from Vly West Dr-EB</td>
<td>Mainline</td>
<td>3</td>
<td>5672</td>
<td>2063</td>
</tr>
<tr>
<td>5</td>
<td>1-235 EB from Vly West Dr-EB-R</td>
<td>On-ramp</td>
<td>1</td>
<td>230</td>
<td>580</td>
</tr>
<tr>
<td>6</td>
<td>Ramp 2</td>
<td>Off-ramp</td>
<td>1</td>
<td>146</td>
<td>114</td>
</tr>
<tr>
<td>7</td>
<td>1-235 WB E of 22nd STREET-EB</td>
<td>Mainline</td>
<td>3</td>
<td>576</td>
<td>2529</td>
</tr>
<tr>
<td>8</td>
<td>1-235 WB E of 22nd STREET-EB-R</td>
<td>On-ramp</td>
<td>1</td>
<td>874</td>
<td>308</td>
</tr>
<tr>
<td>9</td>
<td>Ramp 3</td>
<td>Off-ramp</td>
<td>1</td>
<td>470</td>
<td>455</td>
</tr>
<tr>
<td>10</td>
<td>1-235 @ 8th Street Loop-EB</td>
<td>Mainline</td>
<td>3</td>
<td>6160</td>
<td>2382</td>
</tr>
<tr>
<td>11</td>
<td>1-235 EB to 8th Street Loop-EB-R</td>
<td>On-ramp</td>
<td>1</td>
<td>408</td>
<td>307</td>
</tr>
<tr>
<td>12</td>
<td>Ramp 4</td>
<td>Off-ramp</td>
<td>1</td>
<td>176</td>
<td>52</td>
</tr>
<tr>
<td>13</td>
<td>1-235 EB EAST OF 63RD-EB</td>
<td>Mainline</td>
<td>3</td>
<td>6392</td>
<td>2637</td>
</tr>
<tr>
<td>14</td>
<td>1-235 EB EAST OF 63RD-EB-R</td>
<td>On-ramp</td>
<td>1</td>
<td>644</td>
<td>360</td>
</tr>
<tr>
<td>15</td>
<td>Ramp 5</td>
<td>On-ramp</td>
<td>1</td>
<td>127</td>
<td>127</td>
</tr>
<tr>
<td>16</td>
<td>Ramp 6</td>
<td>Off-ramp</td>
<td>1</td>
<td>982</td>
<td>665</td>
</tr>
<tr>
<td>17</td>
<td>1-235 at 42nd STREET EB-EB</td>
<td>Mainline</td>
<td>4</td>
<td>6181</td>
<td>2459</td>
</tr>
<tr>
<td>18</td>
<td>Ramp 7</td>
<td>On-ramp</td>
<td>1</td>
<td>12</td>
<td>380</td>
</tr>
<tr>
<td>19</td>
<td>Ramp 8</td>
<td>Off-ramp</td>
<td>1</td>
<td>39</td>
<td>172</td>
</tr>
<tr>
<td>20</td>
<td>1-235 EB 28th STREET-EB</td>
<td>Mainline</td>
<td>4</td>
<td>6232</td>
<td>3011</td>
</tr>
<tr>
<td>21</td>
<td>Ramp 9</td>
<td>Off-ramp</td>
<td>1</td>
<td>751</td>
<td>385</td>
</tr>
<tr>
<td>22</td>
<td>Ramp 10</td>
<td>On-ramp</td>
<td>1</td>
<td>35</td>
<td>35</td>
</tr>
<tr>
<td>23</td>
<td>1-235 EB to MLK-EB</td>
<td>Mainline</td>
<td>4</td>
<td>5516</td>
<td>2661</td>
</tr>
<tr>
<td>24</td>
<td>Ramp 11</td>
<td>Off-ramp</td>
<td>1</td>
<td>278</td>
<td>346</td>
</tr>
<tr>
<td>25</td>
<td>Ramp 12</td>
<td>Off-ramp</td>
<td>1</td>
<td>171</td>
<td>214</td>
</tr>
<tr>
<td>26</td>
<td>Ramp 13</td>
<td>Off-ramp</td>
<td>1</td>
<td>310</td>
<td>387</td>
</tr>
<tr>
<td>27</td>
<td>Ramp 14</td>
<td>On-ramp</td>
<td>1</td>
<td>120</td>
<td>120</td>
</tr>
<tr>
<td>28</td>
<td>Ramp 15</td>
<td>On-ramp</td>
<td>1</td>
<td>15</td>
<td>15</td>
</tr>
<tr>
<td>29</td>
<td>1-235 WB WEST END of BRIDGE-EB</td>
<td>Mainline</td>
<td>4</td>
<td>4892</td>
<td>1848</td>
</tr>
<tr>
<td>30</td>
<td>Ramp 16</td>
<td>On-ramp</td>
<td>1</td>
<td>247</td>
<td>462</td>
</tr>
<tr>
<td>31</td>
<td>1-235 EB at WALKWAY-EB</td>
<td>Mainline</td>
<td>4</td>
<td>5139</td>
<td>2318</td>
</tr>
<tr>
<td>32</td>
<td>1-235 EB at WALKWAY-EB-R</td>
<td>Off-ramp</td>
<td>1</td>
<td>375</td>
<td>108</td>
</tr>
<tr>
<td>33</td>
<td>1-235 EB 9th STREET WALL-EB</td>
<td>Mainline</td>
<td>3</td>
<td>4764</td>
<td>1460</td>
</tr>
<tr>
<td>34</td>
<td>1-235 EB 9th STREET WALL EB-EB-R</td>
<td>Off-ramp</td>
<td>1</td>
<td>460</td>
<td>42</td>
</tr>
<tr>
<td>35</td>
<td>Ramp 17</td>
<td>On-ramp</td>
<td>1</td>
<td>46</td>
<td>524</td>
</tr>
<tr>
<td>36</td>
<td>Ramp 18</td>
<td>Off-ramp</td>
<td>1</td>
<td>373</td>
<td>273</td>
</tr>
<tr>
<td>37</td>
<td>Ramp 19</td>
<td>On-ramp</td>
<td>1</td>
<td>2</td>
<td>46</td>
</tr>
<tr>
<td>38</td>
<td>Ramp 20</td>
<td>Off-ramp</td>
<td>1</td>
<td>59</td>
<td>59</td>
</tr>
<tr>
<td>39</td>
<td>1-235 EB at E 21st St-EB</td>
<td>Mainline</td>
<td>3</td>
<td>3920</td>
<td>1656</td>
</tr>
<tr>
<td>40</td>
<td>1-235 WB at Washington-EB</td>
<td>Mainline</td>
<td>3</td>
<td>3920</td>
<td>1656</td>
</tr>
<tr>
<td>41</td>
<td>1-235 WB at Washington-EB-R</td>
<td>On-ramp</td>
<td>1</td>
<td>374</td>
<td>192</td>
</tr>
<tr>
<td>42</td>
<td>Ramp 21</td>
<td>Off-ramp</td>
<td>1</td>
<td>20</td>
<td>164</td>
</tr>
<tr>
<td>43</td>
<td>Ramp 22</td>
<td>On-ramp</td>
<td>1</td>
<td>57</td>
<td>107</td>
</tr>
<tr>
<td>44</td>
<td>Ramp 23</td>
<td>Off-ramp</td>
<td>1</td>
<td>642</td>
<td>317</td>
</tr>
<tr>
<td>45</td>
<td>1-235 NB EUCLID LOOP-EB</td>
<td>Mainline</td>
<td>3</td>
<td>3689</td>
<td>1474</td>
</tr>
<tr>
<td>46</td>
<td>1-235 NB EUCLID LOOP-EB-R</td>
<td>On-ramp</td>
<td>1</td>
<td>216</td>
<td>52</td>
</tr>
<tr>
<td>47</td>
<td>Ramp 24</td>
<td>On-ramp</td>
<td>1</td>
<td>201</td>
<td>10</td>
</tr>
<tr>
<td>48</td>
<td>1-235 NB from EUCLID-EB</td>
<td>Mainline</td>
<td>3</td>
<td>4106</td>
<td>1536</td>
</tr>
<tr>
<td>49</td>
<td>1-235 NB from EUCLID-EB-R</td>
<td>On-ramp</td>
<td>1</td>
<td>425</td>
<td>144</td>
</tr>
</tbody>
</table>

Table 10. Travel-time-reliability measures.

<table>
<thead>
<tr>
<th>Mean 95th percentile travel time</th>
<th>Planning time index</th>
<th>Buffer time</th>
<th>Buffer time index</th>
<th>CPU time (sec)</th>
</tr>
</thead>
<tbody>
<tr>
<td>INRIX</td>
<td>17.26</td>
<td>24.69</td>
<td>1.90</td>
<td>7.43</td>
</tr>
<tr>
<td>Model-based</td>
<td>17.78</td>
<td>23.90</td>
<td>1.84</td>
<td>6.12</td>
</tr>
<tr>
<td>VISSIM</td>
<td>17.26</td>
<td>24.30</td>
<td>1.87</td>
<td>6.78</td>
</tr>
</tbody>
</table>

Finally, travel times under congested conditions were generated using the steady-state FRESIM car-following model with stochastic following time headway and standstill distance parameters. This simplified two-component model was applied to estimate travel-time-reliability measures. The travel-time-reliability measures generated using the proposed model, VISSIM, and actual INRIX data were then compared. Both the proposed method and VISSIM...
slightly overestimated the travel time reliability for the freeway segment investigated in this study. However, the proposed method provided better estimates in less time compared to VISSIM simulation.

The findings of this study indicate the importance of calibrating driver behavior parameters to local conditions when using microsimulation models. It is recommended that microsimulation models be modified to include the option of allowing standstill distances and time headways to follow distributions as well as be set separately for different vehicle classes. The proposed model has been demonstrated to provide an accurate and fast way to estimate corridor-level travel time reliability that considers the heterogeneity in driver behavior in terms of following time headways and standstill distances. This study therefore helps traffic engineers gain deep insight into the stochastic nature of driver behavior parameters. Considering the limitations of probe data discussed by Ahsani, Amin-Naseri, Knickerbocker, and Sharma (2018) as well as the ready availability of data from the radar sensors widely deployed on freeways, the proposed method can be used to estimate corridor travel time reliability even where probe vehicles are limited.

It should be noted that the present paper does have limitations. First, because of the limited sample size for truck-related standstill distances, the Car-Truck and Truck-Car standstill distances were grouped and the Truck-Truck standstill distances were excluded. In future research, more truck-related standstill distance data need to be collected and analyzed. Second, only steady-state car-following models were considered for this study. In future research, other factors, such as the weather, special events, and work zone impacts should be incorporated to further improve the accuracy of the proposed model.

Disclosure statement
No potential conflict of interest was reported by the authors.

ORCID
Jing Dong http://orcid.org/0000-0002-7304-8430

References


Schroeder, B. J., Roupahl, N. M., & Aghdashi, S. (2013). Deterministic framework and methodology for evaluating travel time reliability on freeway facilities. Transportation Research Record: Journal of the Transportation Research Board, 2396(1), 61–70. doi:10.3141/2396-08


Conference on Computational Intelligence and Software Engineering. Wuhan, China: IEEE

