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Calibrating the Wiedemann's vehicle-following model using mixed vehicle-pair interactions ☆

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ABSTRACT

Microscopic traffic simulation models require the calibration of car-following (or vehicle-following) models. The parameters of vehicle-following models control individual driver's spacing, time gap, speed variation and acceleration during different driving conditions. In recent studies, these parameters have been determined for different vehicle classes separately since heavy vehicles generally keep longer spacing and time gap than light vehicles. These parameters have been commonly estimated based on the observed macroscopic traffic flow data such as average volume and speed. However, these data cannot reflect actual vehicle-following behavior of individual vehicles. Also, the effect of the lead vehicle class on the following vehicle's behavior has been neglected in the parameter estimation. Thus, this study estimates the driving behavior parameters for cars and heavy vehicles in the Wiedemann 99 vehicle-following model. For the estimation, 2169 vehicle trajectories were obtained from a 640-m segment of US-101 in Los Angeles, California during the morning peak hours. Separate parameters were estimated for three vehicle classes (cars, heavy vehicles, and motorcycles) and three vehicle-following cases (car following car, car following heavy vehicle, and heavy vehicle following car). From the comparison of the driving behavior parameters between cars and heavy vehicles, it was found that heavy vehicles keep longer spacing and time gap with the lead vehicle, are less sensitive to the lead car behavior, and apply smaller acceleration when they start from stationary position compared to cars. It was also found that the parameters significantly varied across different vehicle pairs even for the same vehicle class and the same vehicle-following case. The estimated parameters were also validated as the VISSIM simulation with the estimated parameters better reflected the observed cumulative average speed and acceleration distributions than the simulation with the default parameters. The results indicate that differences in the parameters among different vehicle-following cases and the variability of parameters for different vehicle pairs must be considered in the fixed parameters for each vehicle class currently used in the Wiedemann's model.

1. Introduction

The capacity of freeways depends on the composition of traffic flow which affects mutual interaction between light vehicles (cars, motorcycles) and heavy vehicles (trucks and buses). According to the Highway Capacity Manual 2010 (TRB, 2010),

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freeway capacity decreases in the presence of heavy vehicles. This is because heavy vehicles are bigger and slower than cars. Low acceleration and deceleration rates of these vehicles make car drivers more cautious and hence decrease overall speeds along roadways. Consequently, the capacity is more likely to decrease as truck traffic grows.

According to the U.S. Department of Transportation, there has been about 110% increase in vehicle-kilometers travelled (VKT) by trucks between 1960 and 2011 (Bureau of Transportation Statistics, 2012). Similarly, medium and heavy trucks travelled about 9% of total VKT in Canada in 2009 although they were only 4% of the total number of vehicles (Natural Resources Canada, 2014). Annual growth rate in VKT of medium and heavy trucks were 3.8% and 0.4%, respectively (Natural Resources Canada, 2014).

Trucking activity is vital for domestic and international trades but high truck volume creates traffic problems including congestion, air pollution and safety. To alleviate these problems, traffic analysts and transport planners today have developed various traffic control strategies to harmonize the movements of light and heavy vehicles (e.g., truck differential speed limit, truck-only lanes). However, these strategies cannot be implemented directly in the field due to their high costs and safety issues. Fortunately, microscopic traffic simulation modeling can be used as a substitute to evaluate the effects of potential traffic control strategies in regulated environments.

The fundamental component of a microscopic traffic simulation model is a car-following (or vehicle-following) model which predicts the behavior of the following vehicles based on the behavior of the lead vehicles. To reflect actual driver behavior in the simulation, driver behavior parameters in the vehicle following model need to be calibrated using observed data. While efforts to calibrate vehicle-following models can be found in past studies, few limitations are worth noting.

First, calibration efforts in previous studies were based on macroscopic traffic flow parameters such as average speed, network capacity, travel time and delay. However, different vehicle trajectories can result in the same traffic flow parameters. This suggests that conventional calibration methods cannot ensure that the properties of the observed and simulated vehicle trajectories will be similar (Jie et al., 2013).

Second, most vehicle-following simulation models have been calibrated for passenger cars only. As such, these models fail to account for the differences in vehicle-following behavior among different types of mixed vehicles – e.g. cars, light trucks, heavy trucks, motorcycles, etc. To realistically replicate actual traffic flow, particularly car–truck mixed flow, separate vehicle-following models should be calibrated for different types of mixed-vehicle-interactions.

Third, although some studies calibrated vehicle-following models for different types of following vehicle (e.g., Manjunatha et al., 2013), they did not consider the effect of the lead vehicle type on the vehicle-following behavior. For instance, car drivers are more likely to maintain longer spacing with a preceding large truck than a preceding car. Thus, the utilized vehicle-following model in the simulation program should be calibrated for different combinations of the lead and following vehicle types (Ossen and Hoogendoorn, 2011).

The objectives of this paper are to estimate the parameters of a vehicle-following model for cars and heavy vehicles separately using the observed trajectories of both lead and following vehicles (vehicle-pair trajectory), and to analyze the behavioral differences in the way cars and heavy vehicles follow each other based on the estimated parameters. To our knowledge, such work has not been conducted in previous studies.

The remainder of our study is organized as follows. Section 2 provides a succinct overview of the literature found on vehicle-following models. Next, Section 3 describes the general characteristics of the data used to perform the analysis. This is followed by Section 4 that discusses the details of the Wiedemann's vehicle-following model used in the study. Section 5 presents the calibration results and provides a detailed discussion on them, while Section 6 provides some conclusions and recommendations for future research.

2. Literature review

Analysts compared traffic flow to fluid streams and developed some fundamental relationships among traffic density, flow and mean speed (Lighthill and Whitham, 1955). These macroscopic relationships describe how different parameters of traffic flow vary over time and space which help determine the capacity of a roadway (Ni, 2013). In addition to the external influences on traffic flow, (e.g., stop or yield controls and traffic signals), there are some individual vehicle factors within traffic which affect the capacity and safety. These factors include individual speeds, braking capabilities and driver behavior such as driving skill, perception of safety and visual alertness (Rothery, 2014).

Pipes (1953) is a pioneer who studied velocities and accelerations of vehicles following a leading vehicle in a line of traffic. He assumed that the movement of vehicles in a line of traffic is always based on a ''law of separation'' called California Vehicle Code. The law articulates that ''a good rule for following another vehicle at a safe distance is to allow yourself the length of a car (about fifteen feet) for every ten miles per hour you are traveling''.

Following Pipe's work, researchers at General Motors developed series of models which estimated the response of the following vehicle in reaction to the actions of the lead vehicle (Siuhi and Kaseko, 2010). These models predict the response in terms of acceleration or deceleration of the following vehicle based on a stimulus, i.e., difference in speeds (namely relative speed) between the lead and following vehicles. This relationship was controlled by sensitivity parameter(s). The main limitations of the above models were: (1) the distributions of driver reaction time lags were assumed to be the same for all vehicles and drivers, (2) following vehicle's driver could detect even a very small stimulus, and (3) all other parameters used in the models were assumed to be the same for all vehicle types and drivers.

Gipps (1981) proposed a new model which relies on the desired braking and acceleration rates of the following vehicle to maintain a perceived safety distance behind the lead vehicle. The safety distance has three components: (1) the distances travelled in perception–reaction process, (2) the braking distance, and (3) a buffer for additional safety. The safety distance is described in a function of maximum desired braking rates of both lead and following vehicles (Brackstone and McDonald, 1999). Gipps developed separate models for the two regimes of car-following and free flow, and suggested to use the lower speed value of the two models at any point in time during driving (Ni, 2013). The limitation of this model is that a driver may perceive the deceleration rate of the lead vehicle by considering the conditions of several cars downstream. Therefore, the additional safety distance considered in the model might be significantly different from reality. The Intelligent Driver Model (IDM) is one of the simple models that estimates the following vehicle acceleration as a function of its own speed, gap, and relative velocity in each time step (Treiber, 2000). The model acceleration was divided into two components: a desired acceleration that occurs when the vehicle is not following any vehicle and a braking deceleration that occurs due to the influence of a lead vehicle. In the free-driving condition, as the vehicle approaches the desired speed, the acceleration approaches zero. In the car-following condition, the actual gap between vehicles is compared to the desired gap. The acceleration is zero when the actual gap is equal to the desired gap. However, the deceleration increases with lower actual gap, higher own speed and higher relative velocity.

Recently, Papathanasopoulou and Antoniou (2015) predicted the following vehicle speed based on the speeds and spacing of the following and lead vehicles using the locally weighted regression (loess) method. The data were collected from the instrumented vehicles in Naples, Italy. The results show that the loess method can better predict car following behavior than the calibrated Gipps model. Zheng et al. (2015) developed a vehicle type dependent model for analyzing car following dynamics in mixed vehicle environment using the NGSIM trajectory data. This model used the lead vehicle's image size and its rate of change as stimuli to the following vehicle's driver who accelerated/decelerated to keep a desired image size and zero speed difference during close following conditions. He et al. (2015) developed a nonparametric car-following model which does not require the assumed driver behavior parameters. They demonstrated the nonparametric model could replicate the observed individual vehicle trajectories and traffic dynamics in the NGSIM data.

Wiedemann and Reiter (1992) developed different perception thresholds and four different driving regimes: (1) free flow, (2) approaching, (3) following and (4) decelerating. They defined the relative speed between the lead and following vehicles as the action point which leads to the reaction of the following vehicle (e.g., acceleration or deceleration). Perception thresholds of large and small relative speeds control the behavior of the following driver. In the 'following' state, the driver is sensitive to actions of the lead vehicle and unconsciously react by increasing or decreasing speed. Two vehicle-following models were developed based on this concept: (1) the Wiedemann 74 model for urban roads (Wiedemann, 1974; Wiedemann, 1991) and (2) the Wiedemann 99 model for freeways (Aghabayk et al., 2013b). These models have been adapted in the VISSIM microscopic traffic simulation software (PTV AG, 2011). To simulate driver behavior, ten "driving behavior parameters" (CC0–CC9) must be specified in VISSIM (PTV AG, 2011). A complete discussion of these parameters is provided in Section 4 of this paper.

CC0 (spacing between stationary vehicles) and CC1 (time gap) have been found as significant parameters which not only affect the capacity of a roadway, but also interact with other parameters – namely CC8 (acceleration from stationary position) and CC4/CC5 (sensitivity to accelerations/decelerations of lead vehicle) (Lownes and Machemehl, 2006a). Therefore, it is important to calibrate all ten parameters using field data since default values might not be appropriate especially if they interact with others.

Following current practice, these parameters are typically calibrated such that only a single parameter is specified for all vehicle types or passenger cars only. For instance, the driving behavior parameters were calibrated for all vehicle types in VISSIM (Saccomanno et al., 2009; Lu et al., 2014; Kan et al., 2014). Menneni et al. (2009) calibrated CC1, CC2, CC3, CC4 and CC5 for all vehicle types using vehicle-pair trajectory data collected from US-101 and I-80 freeways. Jie et al. (2013) also calibrated CC1, CC2, CC3, CC7 and CC8 for passenger cars only using vehicle-pair trajectory data collected from an intersection in The Netherlands. However, a single parameter for all vehicle types is not a valid assumption since driver behavior of a car and a heavy vehicle is different on freeways (Ossen and Hoogendoorn, 2011; Sarvi and Ejtemai, 2011).

Ossen and Hoogendoorn (2011) demonstrated that driving styles (whether the following driver react to a stimulus of relative speed or difference in desired headway and actual spacing) significantly vary among different passenger car drivers. They also found that the vehicle-following behavior is different between car and truck drivers – e.g., variation in speeds during following is lower for trucks than cars. Finally, it was also observed that drivers of following cars keep smaller time headway when they follow trucks compared to when they follow cars. This is because car drivers expect that trucks require longer breaking distances and longer time to completely stop in an emergency situation. For the same reason, Sarvi and Ejtemai (2011) observed that the following trucks keep longer headways and spacing than following cars from vehicle-pair trajectory data for Tokyo and Melbourne freeways.

Furthermore, Aghabayk et al. (2012) found that vehicle-following behavior of passenger cars and heavy vehicles vary with the type of the lead vehicle and speed using vehicle-pair trajectory data for the I-80 freeway in the United States. They classified vehicle following into the following four cases: (1) car following car (CC), (2) car following heavy vehicle (CH), (3) heavy vehicle following car (HC), and (4) heavy vehicle following heavy vehicle (HH). It was found that spacing and time headway were the highest for the HH case and the shortest for the CC case. They also found that for speeds lower than 30 km/h, both headway and spacing were higher for the CH case than the HC case. However, the opposite was observed for speeds greater than 30 km/h. Similarly, Higgs et al. (2011) found that truck driver behavior is different at different speed levels using naturalistic driving data collected from cameras and sensors. These studies suggest that separate driving behavior parameters need to be estimated for different speed levels.

Due to this difference in vehicle-following behavior between cars and heavy vehicles, Manjunatha et al. (2013) estimated the ten driving behavior parameters of the Wiedemann's model in VISSIM for 5 different vehicle classes in the case of India. However, their study did not consider the type of the lead vehicle in the estimation. Furthermore, some researchers have developed new car-following models for mixed traffic flow considering behavioral difference among vehicle types. For instance, Ravishankar and Mathew (2011) modified Gipp's car-following model using different parameters for cars and heavy vehicles. Aghabayk et al. (2013a) presented a new car-following model which incorporates the effect of the lead vehicle type. This model used an artificial intelligence approach called "local linear model tree" to predict the following vehicle's speed based on the relative speed and spacing. They confirmed that the type of lead vehicle affects the behavior of the following vehicle. However, their models have not been implemented in a microscopic traffic simulation program.

3. Data

The datasets used in this study were obtained from the Next Generation Simulation (NGSIM) project's community website (http://ngsim-community.org/). The NGSIM project was an initiative taken by the United States Department of Transportation, Federal Highway Administration (FHWA) (FHWA, 2006). The purpose of the project was to develop behavioral algorithms for effective microscopic modeling and understanding of vehicle interactions.

The utilized data contain 2169 vehicle trajectories on a 640-m segment of US-101 (Hollywood Freeway) in Los Angeles, California as shown in Fig. 1. This highway section consists of five lanes in the mainline and an auxiliary lane between the on-ramp at Ventura Boulevard and the off-ramp at Cahuenga Boulevard.

The video of southbound vehicle movements on June 15, 2005 at 7:50–8:35 AM was recorded using eight synchronized cameras on a 36-storey building adjacent to the study area (Cambridge Systematics, 2005). Vehicle trajectory data were extracted from the recorded videos using the customized software, NG-VIDEO. This study used the data for the first 15-min period or Period 1 (7:50–8:05 AM) for the estimation of the driving behavior parameters in VISSIM. The study also used the data for the second 15-min period or Period 2 (8:05–8:20 AM) for the validation of the estimated parameters. The data contain information on vehicle position, velocity, acceleration, lengths, widths, occupied lane, spacing, headway, and vehicle

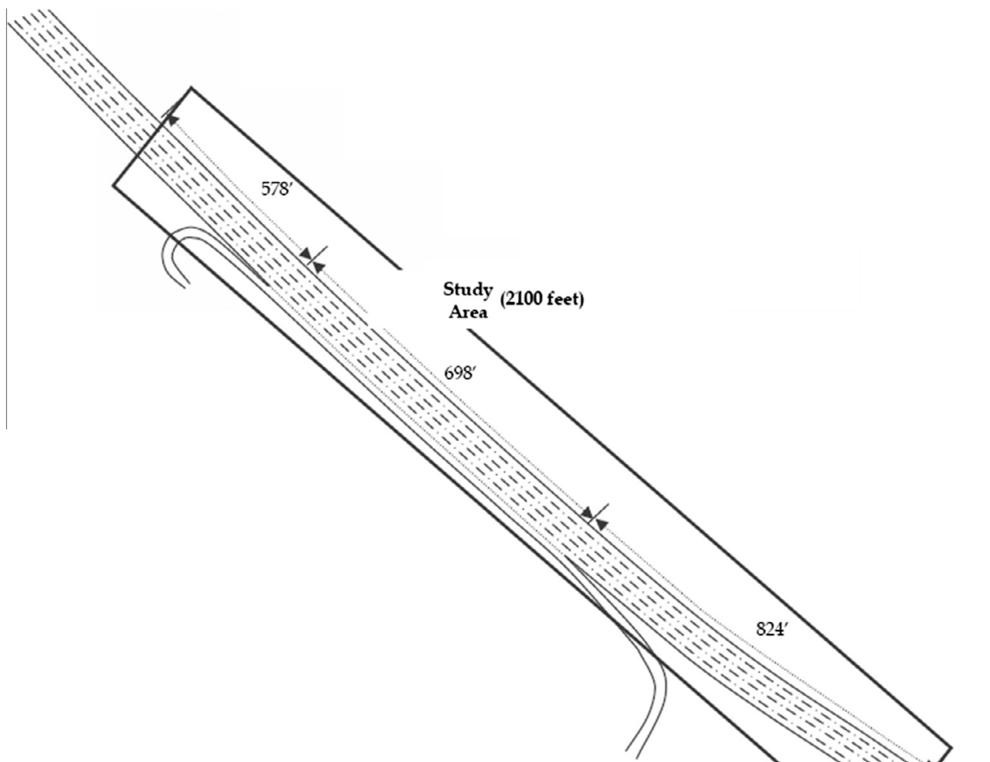

Fig. 1. Schematic drawing of US-101. (Source: Cambridge Systematics, 2005)

class (passenger car, heavy vehicle and motor cycle) at every one-tenth of a second. The data also identify the lead and following vehicles.

For the analysis of vehicle following behavior in the mainline freeway only, the data points on the ramps and auxiliary lane were removed. About 3600 unique vehicle pairs in the mainline were extracted. Proportions of cars, heavy vehicles (trucks and buses) and motorcycles were 96.1%, 2.6%, and 1.3%, respectively. Although there were only three vehicle classes, the lengths of vehicles significantly varied as shown in Fig. 2. Average lengths of cars, heavy vehicles and motorcycles were 14 ft (4 m), 40 ft (12 m), and 8 ft (2.5 m) respectively. The vehicle pairs were divided into the following four cases:

Car following car (CC) – 3129 pairs
Car following heavy vehicle (CH) – 99 pairs
Heavy vehicle following car (HC) – 154 pairs
Heavy vehicle following heavy vehicle (HH) – 7 pairs

The HH case and motorcycle-involved vehicle-following cases were ignored in the comparison because their sample sizes were relatively smaller.

Smoothing of the data records was required since our preliminary analysis showed a large fluctuation of speed and acceleration in the raw trajectory profiles. Traditionally, the simple moving average technique has been used to smooth noisy data. However, this technique is not suitable in our case because it either takes the full weights of neighboring data points in the smoothing window or completely drops them. An alternative would have been the Kalman filtering technique, which is one of the most well-known and used data fusion algorithms (Faragher, 2012). However, this method would complicate the process by introducing more smoothing parameters in addition to smoothing window width. Therefore, we opted for the Symmetric Exponential Moving Average (SEMA) method to smooth the data in this study. As noted by Thiemann et al. (2008), SEMA ensures that the weights of data points decrease as the distance from the center of smoothing window increases. First, speed and acceleration were calculated based on the change in observed vehicle positions over time. Next, the calculated speed and acceleration were smoothed using SEMA.

4. Methods of analysis

In this study, vehicle-following behavior was analyzed based on the parameters of the Wiedemann's 99 vehicle-following model (Aghabayk et al., 2013b). This model was selected because it has been adapted by and continuously improved in the VISSIM microscopic traffic simulation model (PTV AG, 2011). Wiedemann's model is a psycho-physical vehicle following model which determines the following driver's reactions (acceleration/deceleration) based on his/her perceptions of changes

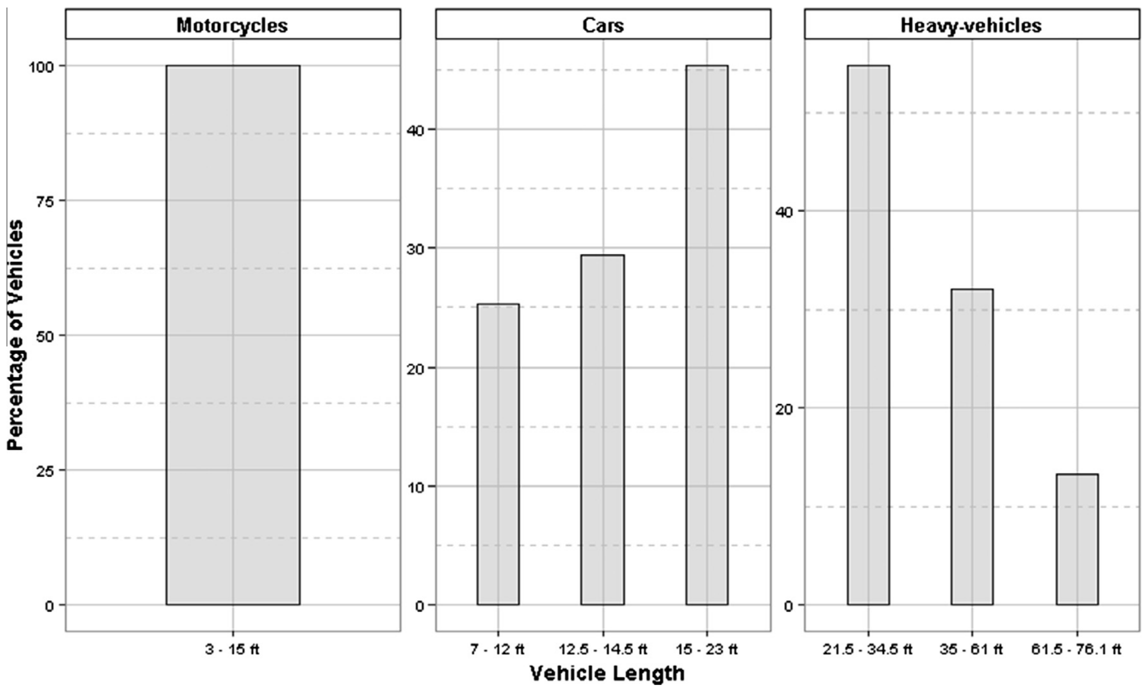

Fig. 2. Distribution of vehicle lengths.

in relative position and relative speed (Wiedemann and Reiter, 1992; Brackstone and McDonald, 1999). Relative position (ΔX) is the front-to-rear spacing between the following and lead vehicles whereas relative velocity (ΔV) is defined as the following vehicle's velocity minus the lead vehicle's velocity. The changes in ΔX and ΔV are perceived only when the physical impulse of the size of the lead vehicle exceeds certain thresholds (Wiedemann and Reiter, 1992). These perception thresholds and their associated reactions affect the vehicle following behavior. Vehicle following is classified into four exclusive processes, as illustrated in Fig. 3. In each of these driving processes, the model outputs the acceleration or deceleration of following vehicle. However, the details of the theoretical models in VISSIM describing the vehicle acceleration as a function of vehicle velocity, relative velocity, time/space gap, etc. and their differences from original Wiedemann's model are not available to public (Song et al., 2015).

When the spacing (or time gap) is large, the following driver is not influenced by the lead vehicle's acceleration and tries to move at desired speed. If there is no significant change in the lead vehicle's speed, ΔX continues decreasing. At a certain distance, *SDV*, the following driver perceives that he/she is closing to a slower vehicle ahead. At this moment, the driver starts decelerating to the lead vehicle's speed. *CLDV* can be defined as the lower limit of perception of closing.

Upon reaching the zero ΔV, the driver tries to maintain an ideal gap behind the lead vehicle by continuing traveling at the current speed. Rates of acceleration and deceleration are low during this *unconscious* vehicle-following process. The minimum spacing during the vehicle-following process is defined as Minimum Safety Distance. Due to imperfect throttle control, the following vehicle's speed oscillates continuously. When the driver perceives that he/she is falling behind the lead vehicle (i.e., the gap with the lead vehicle is increasing), he/she consciously accelerates to reach the lead vehicle's velocity (zero ΔV) again.

Similarly, when the driver recognizes that he/she is moving faster and might get too close to the lead vehicle, he/she consciously decelerates. The perceptions of speed differences at these two occasions are termed as *OPDV* and *CLDV*, respectively. In a rare occasion when the lead vehicle suddenly decelerates, the following driver has to apply hard deceleration to avoid crashing. This is defined as emergency braking which occurs when the spacing is less than the safety distance and a little more than the ΔX at stationary position (critical situation in Fig. 3). If the following vehicle moves at a *lower spacing*, a collision occurs (Wiedemann and Reiter, 1992).

The following contains the description of different driving behavior parameters (CC0–CC9) used in VISSIM 5.40 to calibrate vehicle-following model. These parameters are the measures of the vehicle-following perception thresholds described above. The relationship between these parameters and Wiedemann's 99 model thresholds can be found in Aghabayk et al. (2013b). The definitions of these parameters were used to investigate the qualitative vehicle-following behavior in the observed data. The means, standard deviations and distributions of each parameter are described in the results section.

4.1. Spacing between stopped vehicles (CC0)

CC0 is the desired distance that the following vehicle keeps behind the lead vehicle when both are at stationary positions. The distance was taken as the spacing between the front of the following vehicle and the rear of the lead vehicle (i.e., $AX - L$ in Fig. 4(e)). The average front-to-rear spacing of the following vehicle was considered as CC0 for each vehicle class.

4.2. Time gap (CC1)

CC1 is the time gap that the following vehicle wants to keep (i.e., *BX* in Fig. 4(d)). Safety distance for the following vehicle behind the lead vehicle at a given time is estimated as the sum of CC0 and CC1 $\times$ following vehicle speed. At a given time frame, the time required by the following vehicle to traverse CC0 and the length of the lead vehicle was subtracted from the front-to-front time headway. CC1 was estimated as a weighted mean of these gaps for different speed intervals by the class of the following vehicle.

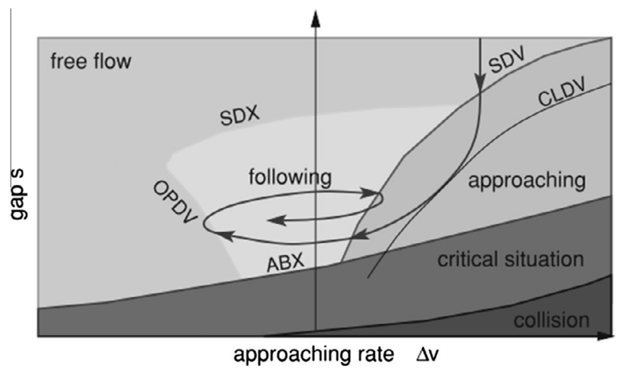

Fig. 3. Wiedemann's car-following model. (Source: Treiber and Kesting, 2013)

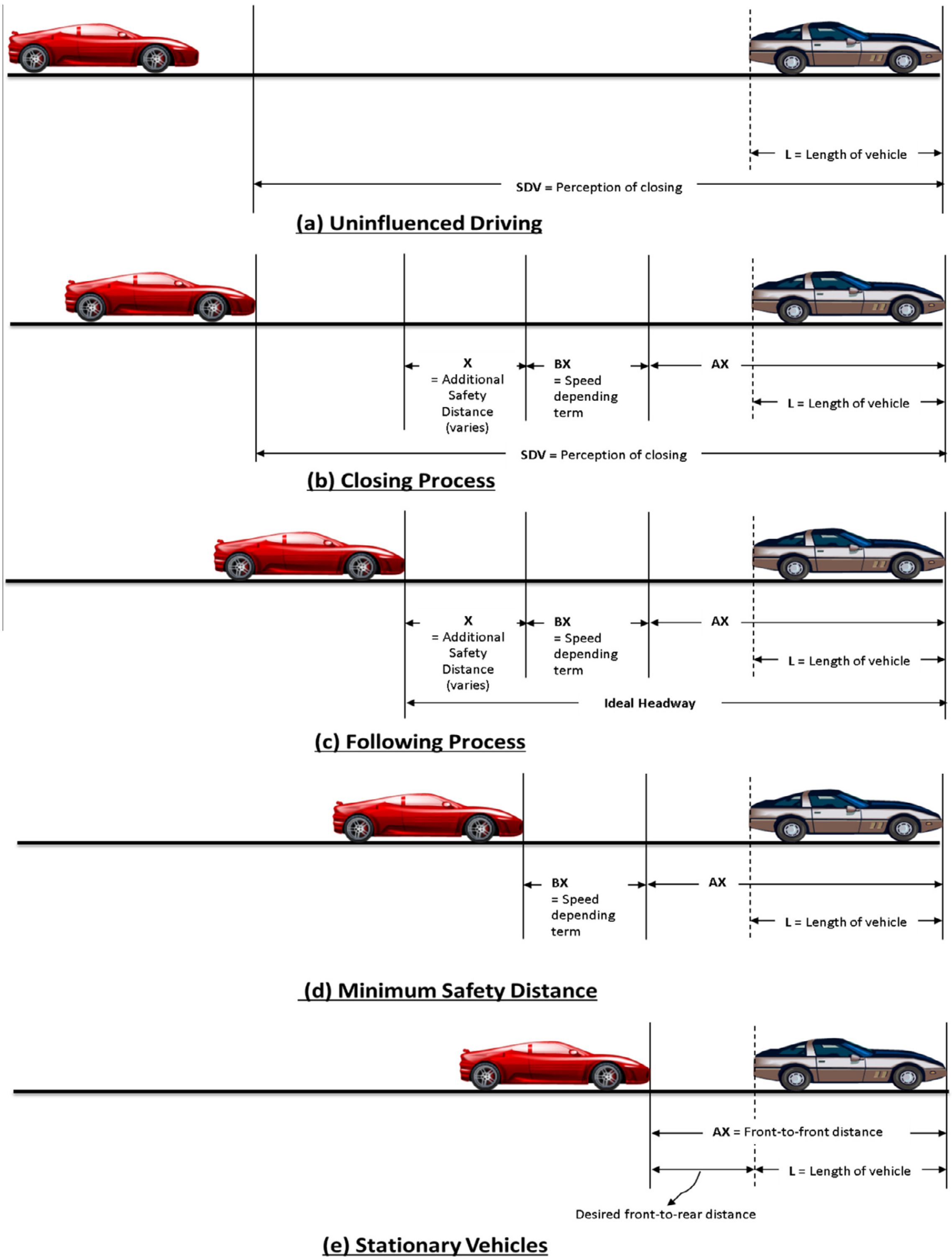

Fig. 4. Vehicle following phases.

4.3. Variation in following distance (CC2)

To estimate the parameters CC2–CC7, the time periods during which a vehicle approaches and unconsciously follows the lead vehicle should be identified. Fig. 5 illustrates the behavior of a car following another car in a relative velocity–spacing plot.

As the following vehicle approaches to the lead vehicle, it continuously decelerates until zero relative velocity (i.e., the speeds of the lead and following vehicles are the same) reaches. This is when the relative velocity changes from a positive value to a negative value. The data points corresponding to the following vehicle's deceleration to the lead vehicle's velocity were labelled as 'closing'.

During the unconscious following process, the following vehicle's driver tries to maintain an ideal gap behind the lead vehicle. The rates of acceleration/deceleration are generally low and the relative velocity varies around zero. The data points around the zero relative velocity corresponding to low acceleration/deceleration were labelled as 'unconscious following'. Individual vehicle pairs were manually reviewed in this manner to identify the unconscious following process.

CC2 is the additional safety distance that the driver wants to keep during the unconscious following process (i.e., *X* in Fig. 4(c)). The parameter was estimated as a mean of the differences in the maximum and minimum spacing (minimum safety distance) during the unconscious following process for all vehicle pairs as shown in Fig. 5 (Menneni et al., 2009).

4.4. Time to decelerate to enter following (CC3)

At the start of the closing process, the following driver recognizes a slower vehicle ahead. After some perception and reaction time, the driver decelerates to maintain the desired gap with the lead vehicle (Fig. 4(b)). CC3 is the time elapsed from the beginning of deceleration to the beginning of the unconscious following process. It was estimated as a mean of the durations of the closing process for all vehicle pairs.

4.5. Sensitivity to accelerations of lead vehicle (CC4 and CC5)

CC4 and CC5 mark the maximum negative relative velocity and maximum positive relative velocity, respectively, during the unconscious following process as shown in Fig. 5 (Menneni et al., 2009). Higher values of these parameters indicate that drivers are less sensitive to the lead vehicle's acceleration/deceleration rates and their speeds vary more significantly during the unconscious following process. CC4 and CC5 were estimated as a mean of the absolute maximum relative velocity in the unconscious following condition for all vehicle pairs. The units of these parameters are meters per second regardless of length unit (feet or meters) used for the other parameters.

4.6. Influence of spacing on speed oscillation (CC6)

CC6 represents how the following vehicle's speed oscillation varies as the distance to the lead vehicle changes. However, although CC6 is used to estimate *CLDV* and *OPDV* in a mathematical function (Aghabayk et al., 2013b), no study has clearly

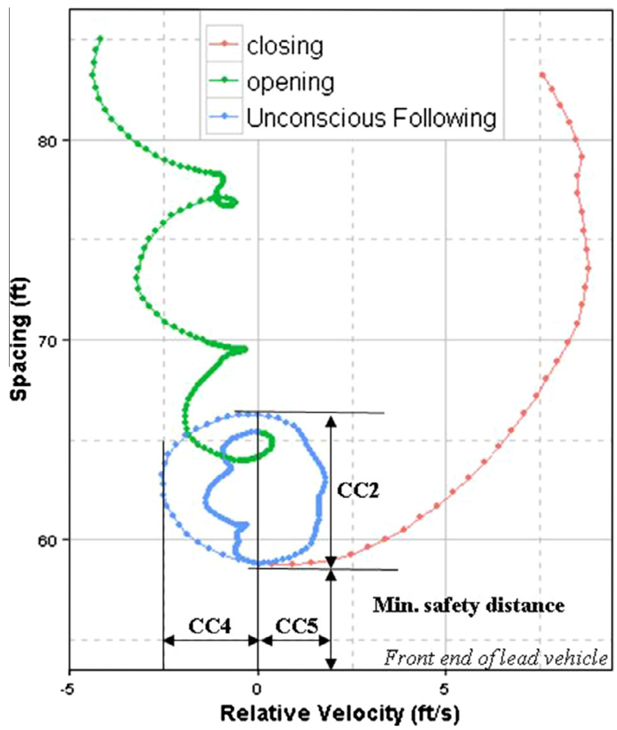

Fig. 5. Estimation of CC2, CC4 and CC5 parameters from vehicle trajectory data. (Source: Menneni et al., 2009)

explained how to estimate CC6. In fact, the effect of changing the value of CC6 on the capacity was not significant in past studies (e.g., Woody, 2006; Lownes and Machemehl, 2006b). This is because the impact of larger speed oscillation with longer spacing (i.e., higher CC6) is not likely to be significant in congested conditions (Lownes and Machemehl, 2006b). Therefore, CC6 was not estimated in this study and the default value of 11.44 was used for the validation of the VISSIM simulation.

4.7. Acceleration during speed oscillation (CC7)

CC7 is a mean of the accelerations during the unconscious following process for each vehicle-following case.

4.8. Standstill acceleration (CC8) and acceleration at 80 km/h (CC9)

CC8 is the desired acceleration when the vehicle starts moving again from stationary position It was estimated as the mean of the maximum acceleration observed by all the slow moving vehicles i.e. vehicles moving at a velocity of 22 ft/s or less. The selection of 22 ft/s was based on the observation that for lower speeds the observed accelerations were also very low.

CC9 is the acceleration of vehicle at speed of 80 km/h. It was estimated as a mean of the maximum acceleration rates of vehicles moving at 66 ft/s or higher velocity.

4.9. Validation of driving behavior parameters

After the above driving behavior parameters were estimated using the observed data for Period 1, the VISSIM simulations were run for Period 2 using the estimated parameters (except for CC6) for Period 1 and the default parameters. In the VISSIM simulations, the desired speed distributions and acceleration/deceleration functions were calibrated using the observed data for Period 2. Then, the cumulative distributions of average speed and acceleration were compared between the observed data and the two simulated data sets. The results of the estimation and validation are explained in the next section.

5. Results and discussions

In this section, the ten driving behavior parameters for each vehicle class and each vehicle-following case were estimated separately. Although the parameters for motorcycles were estimated, the discussion mainly focused on the difference in parameters between cars and heavy vehicles.

5.1. CC0

CC0 is the front-to-rear spacing between stationary vehicles. There were only 88 cars, 1 heavy vehicle and 4 motorcycles which either completely stopped or moved at speeds lower than 5.0 ft/s (5.5 km/h). The mean front-to-rear spacing kept by cars behind any lead vehicle was estimated as 13.6 ft (4.0 m). The spacing for heavy vehicles and motorcycles were 15.4 ft (4.7 m) and 12.5 ft (3.8 m), respectively. However, due to a smaller number of heavy vehicles in the observed data, it is difficult to compare the spacing between cars and heavy vehicles.

5.2. CC1

CC1 is the time gap that a following vehicle wants to keep behind the lead vehicle. The differences in the front-to-rear time gaps of cars and heavy vehicles are illustrated in Fig. 6. For each 5-km/h speed interval of the following vehicle speed, the mean gap was computed. The curves on Fig. 6 are local polynomial regression which was fit to the observed data for each vehicle-following case.

For all cases, the gap was generally longer at very low speeds and decreased as the speed of the following vehicle increased. Compared to the CC case, the CH case has shorter gaps at mean speeds lower than 32.5 km/h. This means that car drivers keep shorter gap with the lead heavy vehicle than the lead car at low speeds. This result is different from Aghabayk et al. (2012) which found that car drivers consistently keep longer gap with heavy vehicles at all speeds. We believe this is because the lead car is more likely to change lanes than the lead heavy vehicle at low speeds. As the lead vehicle changes the lane, it generally reduces the speed and consequently the following car is also required to reduce the speed. This driver behavior was actually verified from the data in which 33% of the lead cars changed lanes whereas only 8% of the lead heavy vehicles changed lanes. However, at speeds higher than 32.5 km/h, this trend is opposite where car drivers maintain longer gap with the lead heavy vehicles than the lead car at high speeds. This is because car drivers are more cautious at high speeds and keep longer spacing when they follow heavy vehicles due to their limited visibility. This result is consistent with Aghabayk et al. (2012).

It was also found that heavy vehicle drivers maintain longer gap with cars than car drivers at all speeds. This is different from Aghabayk et al. (2012) who found that heavy vehicle drivers keep shorter gap with cars at speeds lower than 30 km/h

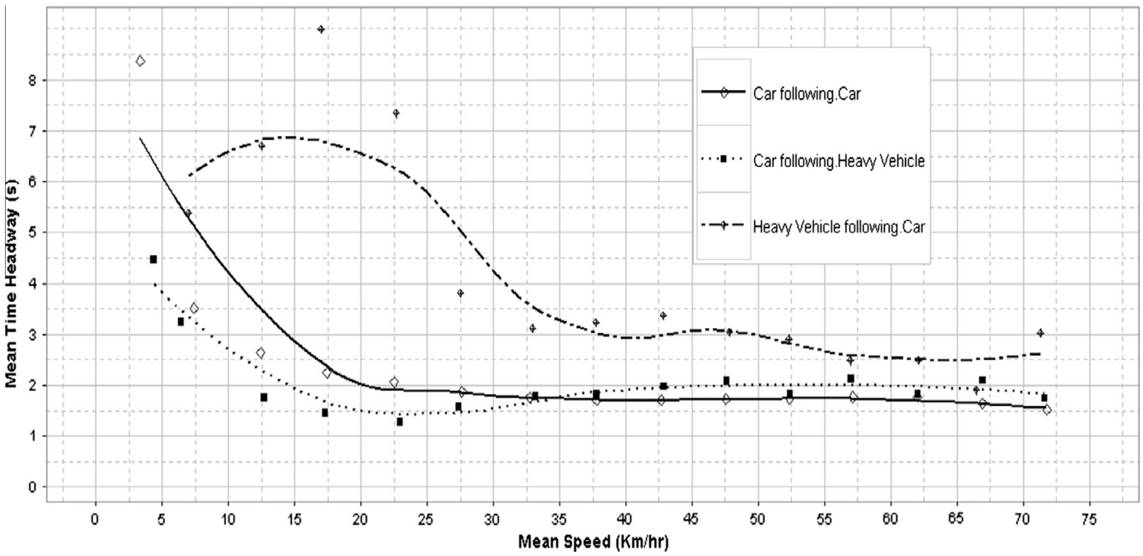

Fig. 6. Comparison of time gaps among different vehicle-following cases.

but longer gap with cars at speeds higher than 30 km/h. However, the reason for this difference is not clear. The weighted means of gaps for different speed intervals were the estimated values of CC1 for each vehicle class. These values were 1.5, 2.7 and 1.2 s for cars, heavy vehicles and motorcycles, respectively.

5.3. CC2

CC2 is the spacing that the following vehicle keeps in addition to the minimum safety distance before it intentionally accelerates. This additional safety distance (X) was estimated based on the spacing between two vehicles during the unconscious following process. Menneni et al. (2009) estimated it as the difference between maximum and minimum spacing on the oscillation loop in the relative speed-spacing plot (i.e., unconscious following process) as shown in Fig. 4. The distribution of X for each vehicle-following case is shown in Fig. 7. The figure suggests that there were large variations in these additional distances for each vehicle-following case. The dashed line shows the mean value.

The mean value of X was higher for the HC case than the CC case. This indicates that the following heavy vehicle maintains longer spacing than the following car when they follow a car. This is because the following heavy vehicle requires longer time to change speeds than the following car. However, the mean value of X was lower for the CH case than the CC case. This is because car drivers are more likely to be conscious when they follow heavy vehicles than cars due to larger size and lower speed of heavy vehicles. This circumstance is not considered as vehicle-following condition defined by the unconscious following process. Due to relatively shorter duration of vehicle-following condition in the CH case, the maximum spacing during the condition is likely to be lower. The mean distances in addition to safety distance for cars, heavy vehicles and motorcycles are 38 ft (11.6 m), 46 ft (14 m) and 30 ft (9.1 m), respectively.

5.4. CC3

CC3 is a measure of number of seconds before reaching the safety distance when a vehicle starts decelerating while perceiving a slower vehicle ahead. It was estimated for each vehicle pair based on the duration of the closing process. It was assumed that the closing process starts when the deceleration is less than or equal to -1 ft/s^2. Fig. 8 shows the distributions of duration of the closing process for each vehicle-following case. Higher mean values of CC3 for the HC case than the CC case suggest that the following heavy vehicle drivers recognize slow-moving lead cars and decelerate sooner than the following car drivers. This is because heavy vehicle drivers' sight distance is longer than car drivers' due to higher position of driver's seat. Similarly, higher mean values of CC3 for the CH case than the CC case indicate that the following car drivers recognize the lead heavy vehicles sooner than the lead cars because of larger size of heavy vehicles than cars.

On average, car drivers start decelerating for about 6 and 4 s before reaching the minimum safety distance behind the lead heavy vehicle and the lead car, respectively (i.e., when the unconscious following process starts). The estimated values of CC3 for cars, heavy vehicles and motorcycles are 4.00, 4.55 and 4.20 s, respectively.

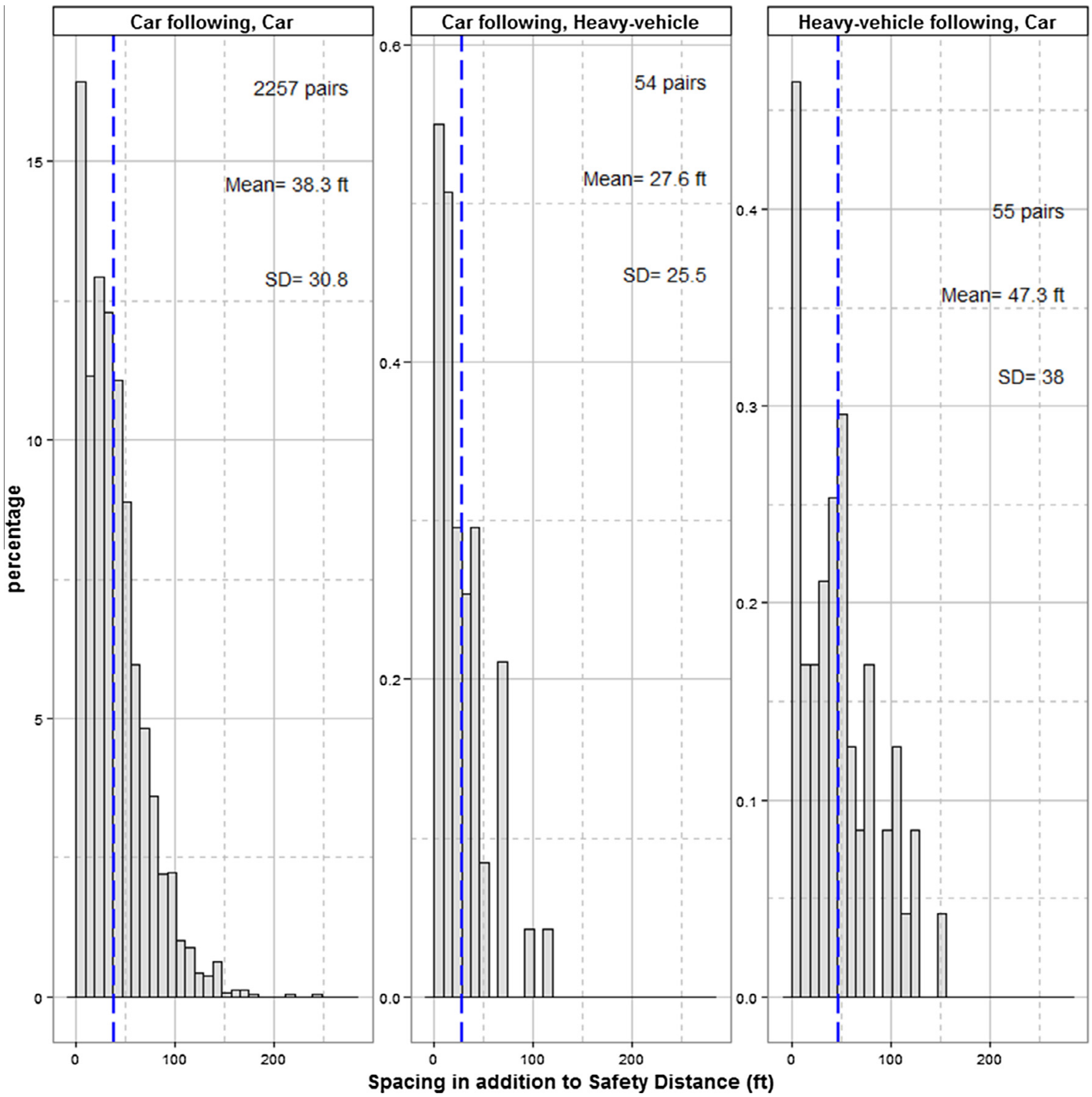

Fig. 7. Comparison of spacing in addition to safety distance among different vehicle-following cases.

5.5. CC4 and CC5

CC4 and CC5 control the variation in relative velocity around zero during the unconscious following process. Because positive relative velocity could not be identified for some vehicle pairs, the absolute value of negative relative velocity was assumed to be values of both CC4 and CC5. Higher mean values of CC4 and CC5 for the HC case than the CC case (Fig. 9) indicate that the following heavy vehicle drivers are less sensitive to accelerations/decelerations of the lead cars compared to the following car drivers. However, car drivers are more sensitive to behavior of the lead heavy vehicle than the lead car. This might be because of larger size of heavy vehicles and the effort to maintain an ideal gap to avoid any emergency braking. The estimated absolute values of relative velocity are 5.4 ft/s (1.65 m/s), 6.8 ft/s (2.07 m/s) and 6.1 ft/s (1.86 m/s) for cars, heavy vehicles and motorcycles, respectively.

5.6. CC7

CC7 is the following vehicle's acceleration during the unconscious following process. It was found that there was not much difference in CC7 among the three vehicle classes. Both car and heavy vehicle drivers apply low acceleration/deceleration during the unconscious following process because they try to maintain the ideal gap at zero relative speed.

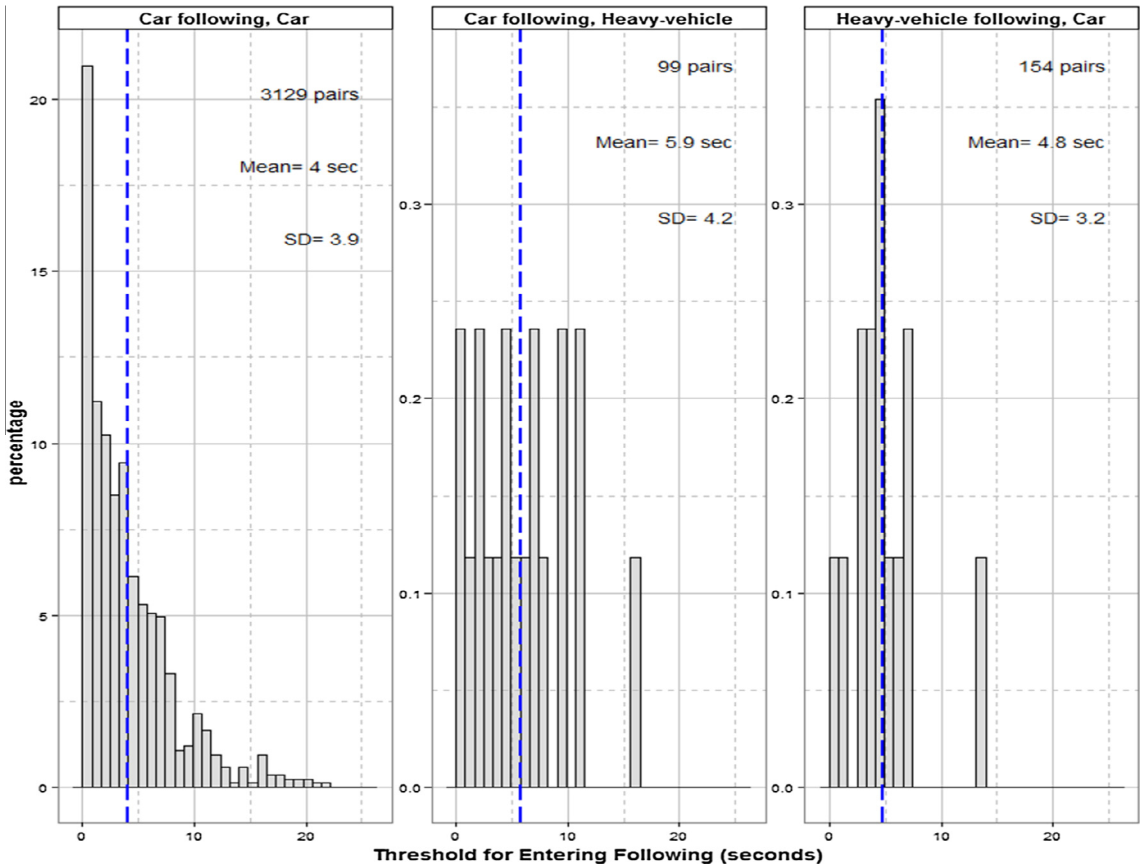

Fig. 8. Comparison of duration of the closing process among different vehicle-following cases.

The suggested values for cars, heavy vehicles and motorcycles are 0.30 ft/s^2 (0.090 m/s^2), 0.32 ft/s^2 (0.097 m/s^2) and 0.28 ft/s^2 (0.085 m/s^2), respectively.

5.7. CC8 and CC9

CC8 is the following vehicle's acceleration rate for slow moving vehicles. It was found from the observed data that the acceleration rates for cars, heavy vehicles and motorcycles were 1.6 ft/s^2 (0.5 m/s^2), 0.9 ft/s^2 (0.3 m/s^2), and 1.2 ft/s^2 (0.4 m/s^2), respectively. Lower acceleration for heavy vehicles than cars and motorcycles is due to their higher weights.

CC9 is the following vehicle's acceleration rate at speed of 80 km/h. It was found that the maximum speeds of cars, heavy vehicles and motorcycles were 94 ft/s (103 km/h), 66 ft/s (73 km/h), and 73 ft/s (80 km/h), respectively. Since the maximum speeds of heavy vehicles and motorcycles were lower than 80 km/hr, acceleration rates at 66 ft/s or above were observed for all vehicle classes. The mean values of cars, heavy vehicles and motorcycles were 1.47 ft/s^2 (0.45 m/s^2), 0.81 ft/s^2 (0.25 m/s^2), and 1.36 ft/s^2 (0.41 m/s^2), respectively. This shows that the acceleration rate of heavy vehicles at high speed was also lower than those observed for cars and motorcycles. It should be noted that VISSIM uses the desired acceleration functions to represent the variation in acceleration with speeds. These functions are defined independently from the parameters CC7, CC8 and CC9.

5.8. Validation of driving behavior parameters

The above estimated parameters were validated by comparing the cumulative distributions of average speed and accelerations between the observed and simulated data for Period 2 (8:05–8:20 am). The parameters were calibrated for Period 2 and the VISSIM simulations were run with the estimated and default parameters. The simulated data with the estimated and default parameters were named 'SIMDATA1' and 'SIMDATA2', respectively.

Fig. 10 illustrates that the variations in average speed and acceleration are closer to the observed data for the simulated data with the estimated parameters (SIMDATA1) than the simulated data with the default parameters (SIMDATA2) for both

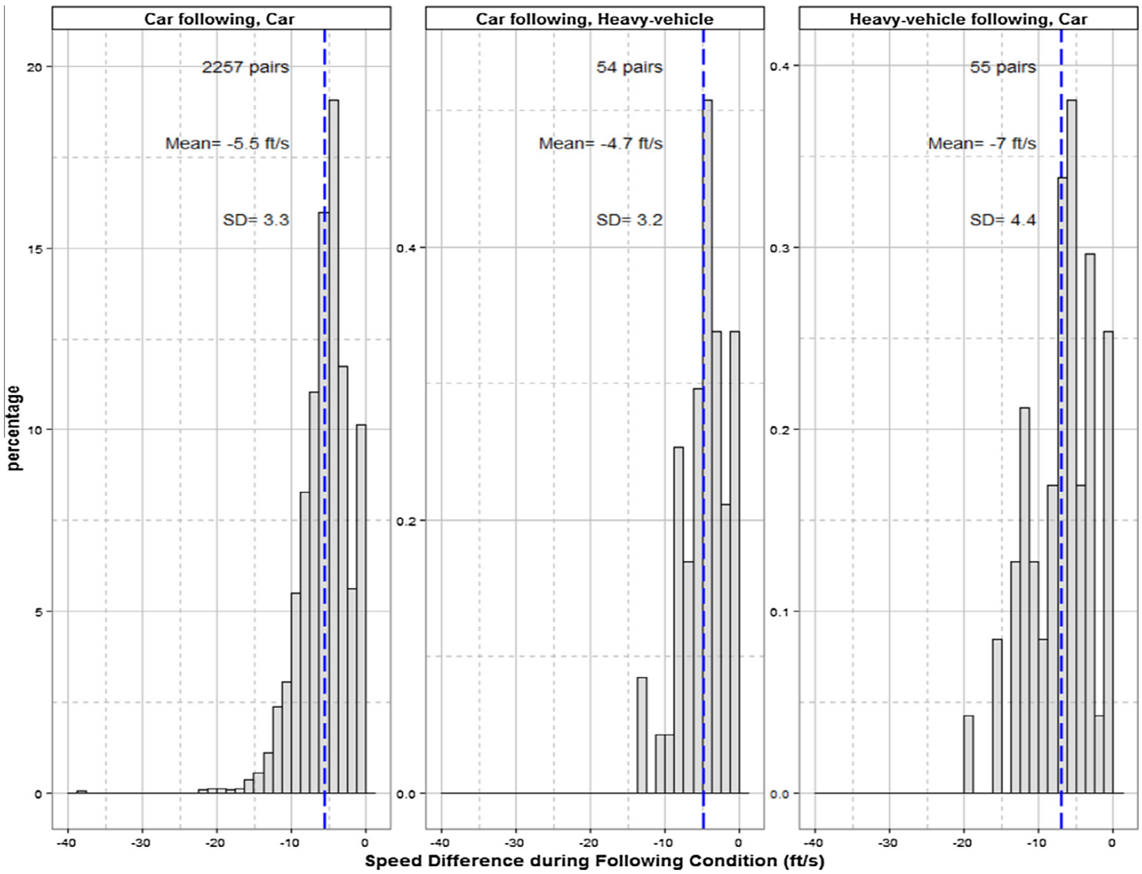

Fig. 9. Comparison of negative maximum relative velocity among different vehicle-following cases.

cars and heavy-vehicles. This indicates that the estimated parameters can better reflect the vehicle interactions for different vehicle types in the observed data than the default parameters.

5.9. Summary

Tables 1 and 2 summarize the driving behavior parameters for each vehicle class and each vehicle-following case, respectively. Table 1 shows that the calibrated parameters were significantly different from the VISSIM default values (except for CC6 which was kept as default). The table also shows that the calibrated parameters were similar for cars and motorcycles. However, the parameters CC0–CC3 and absolute values of CC4 and CC5 were higher for heavy vehicles than cars. This indicates that heavy vehicles tend to maintain longer spacing and time gap, but they are less sensitive to the lead vehicle behavior compared to cars. On the other hand, the parameters CC8 and CC9 were lower for heavy vehicles than cars due to their higher vehicle weight.

Table 2 shows that the parameters for cars were different for different classes of the lead vehicle. CC1 and CC3 were higher but absolute values of CC4 and CC5 were lower for the CH case than the CC case. This indicates that cars tend to maintain longer time gap and more sensitive to the lead vehicle behavior when they follow heavy vehicles.

It is worth to note that these parameters also varied across different vehicle pairs even for the same vehicle class and the same vehicle-following case. Also, different standard deviations of the parameters indicate that the distributions of parameters were also different. In particular, standard deviation of CC1 was substantially lower for heavy vehicles than cars. This is potentially because car driver's driving characteristics are more variable than heavy vehicle driver's and the sample size is much larger for car drivers than heavy vehicle drivers.

Although these calibrated driving behavior parameters are only applicable to the studied highway segment, it is expected that similar differences will be observed at the other locations due to differences in size and vehicle dynamics among different vehicle types.

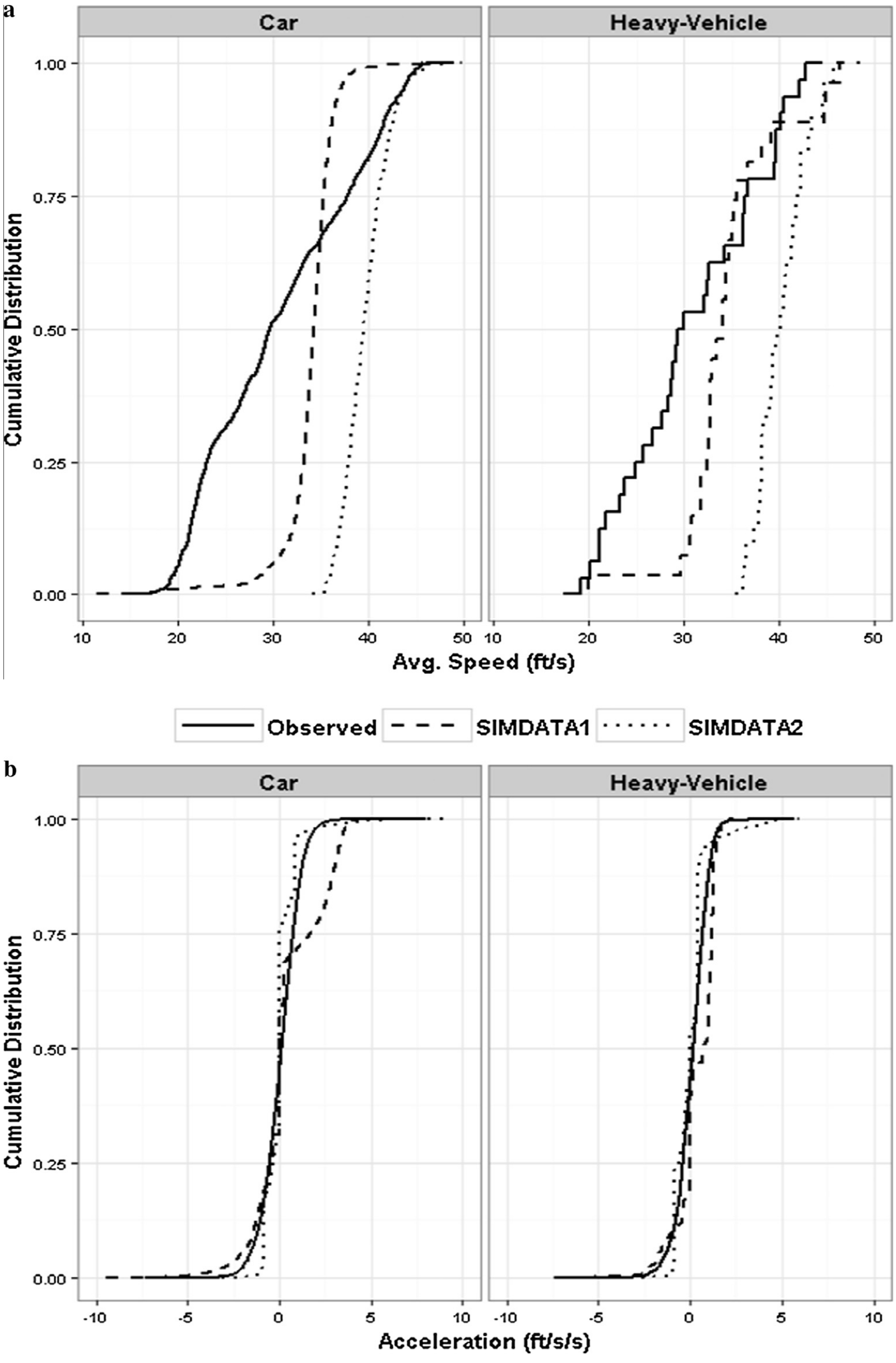

Fig. 10. Comparison of observed and simulated data (a) cumulative distribution of average speed and (b) cumulative distribution of acceleration.

Table 1
Summary of driving behavior parameters for different vehicle classes.

Parameter	Unit	VISSIM default	Car		Heavy vehicle		Motorcycle	
			Mean	SD	Mean	SD	Mean	SD
CC0	ft	4.92	13.6	6.3	15.4	–	12.5	–
CC1	s	0.90	1.5	15.4	2.7	2.6	1.2	0.9
CC2	ft	13.12	38	30.7	46	37.4	30	19.1
CC3	s	−8.00	−4.00	3.9	−4.55	3.3	−4.20	2.9
CC4	m/s	−0.35	−1.65	1.00	−2.07	1.31	−1.86	0.97
CC5	m/s	0.35	1.65	1.00	2.07	1.31	1.86	0.97
CC7	ft/s^2	0.82	0.3	0.6	0.32	0.5	0.28	0.4
CC8	ft/s^2	11.48	1.6	1.0	0.9	0.5	1.2	1.3
CC9	ft/s^2	4.92	1.47	0.8	0.81	0.9	1.36	1.0

Table 2
Summary of driving behavior parameters for different vehicle-following cases.

Parameter	Unit	CC		CH		HC	
		Mean	SD	Mean	SD	Mean	SD
CC0	ft	–	–	–	–	–	–
CC1	s	1.5	15.6	1.7	0.94	2.7	2.7
CC2	ft	38.3	30.8	27.6	25.5	47.3	38
CC3	s	−4	3.9	−6	4.2	−5	3.2
CC4	m/s	−1.68	1.00	−1.43	0.97	−2.13	1.34
CC5	m/s	1.68	1.00	1.43	0.97	2.13	1.34
CC7	ft/s^2	0.31	0.6	0.29	0.7	0.30	0.5
CC8	ft/s^2	1.67	1.0	1.58	1.0	0.91	0.5
CC9	ft/s^2	1.47	0.8	1.14	1.4	0.81	0.9

6. Conclusions and recommendations

This study investigated the differences in vehicle-following behavior among cars, heavy vehicles and motorcycles while accounting for lead vehicle type using vehicle-pair trajectory data on a freeway. The findings suggest that vehicle-following behavior is significantly different among different vehicle classes and different vehicle-following cases.

In comparison with the following cars, the following heavy vehicles kept longer safety distance and longer maximum spacing during following, took more time to decelerate to safety distance, were less sensitive to the lead vehicle behavior, had less variation in following speed, and applied lower acceleration when started from stationary position or while moving at desired speeds. The same trends were observed for heavy vehicles following cars (HC) and cars following heavy vehicles (CH) in comparison with cars following cars (CC). However, the HC case took more time to decelerate to keep safety distance than the CC case but less time than the CH case. These behavioral differences could be attributed to the differences in vehicle size and maximum acceleration/deceleration rates between cars and heavy vehicles. The lead vehicle's size affects the following vehicle's consciousness and its overall sensitivity to the lead vehicle's behavior. Furthermore, there were variations in driving behavior parameters even for the same following vehicle class and the same vehicle-following case. Thus, using mean values of these parameters (similar to the fixed parameters used in the Wiedemann's model) cannot capture these variations.

The estimated parameters for each vehicle class were also validated by comparing the cumulative distributions of average speed and acceleration between the observed and simulated data. The result shows that the estimated parameters generally better reflect the observed acceleration and speed distributions than the default parameters. Thus, the estimated parameters are more reliable and practically useful than the default parameters.

Based on the findings in this study, it is recommended that driving behavior parameters be specified not only for different vehicle classes, but also different vehicle-following cases separately. It is also recommended that the variability of parameters for different vehicle pairs be considered in the form of a distribution of parameters rather than fixed values of parameters. Although this study only focused on the Wiedemann's model, the same concept could be applied to any other type of vehicle-following model.

There are some limitations in this study. Due to a large difference in sample size between cars and heavy vehicles, the mean and standard deviation of the obtained parameters may not be comparable. Also, the analysis was performed for a limited time period when congestion starts to build. The work conducted in this paper forms the basis for future research work. The latter will focus on the investigation of lane-change behavior for different vehicle classes and different vehicle-following cases in a target lane.

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