INCORPORATING RISK TAKING AND DRIVER ERRORS IN CAR-FOLLOWING MODELS

Mohammad Saifuzzaman

BSc (Civil Engineering), MSc (Transport Science)

Submitted in fulfilment of the requirements for the degree of

Doctor of Philosophy (PhD)

School of Civil Engineering and Built Environment

Science and Engineering Faculty

Queensland University of Technology (QUT)

2016

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Keywords

car-following, distraction, driver behaviour, driver error, human factors, mobile phone use while driving, risk compensation, risk taking, driver capability, task demand, task difficulty, TD, TDCF framework, Gipps' model, IDM, TDGipps model, TDIDM, simulation, calibration, validation, road crash, aggressive behavior, non-aggressive behavior, timid behavior, traffic oscillations, traffic hysteresis

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Abstract

Car-following (CF) is one of the two primary driving tasks that drivers routinely perform. CF models describe the decision of the driver to follow the preceding vehicle efficiently and safely. Inappropriate CF behavior can lead to severe consequences including congestion, reduction in roadway capacity, and rear-end collisions. Over the past decades, there has been a considerable development in the modeling of car-following (CF) behavior. Although CF behavior heavily depends on driver characteristics, most of the models seek to understand traffic flow characteristics, ignoring human actions in the driving process. Such ignorance certainly poses serious concerns about the capability of these models to reproduce complex driving situations including traffic crash and near-crash events, and traffic congestions. As an attempt to address this issue, this thesis investigated the effect of distraction (one of the major causes of driver error) on CF behavior and proposed a novel methodology to incorporate risk taking and driver errors in CF modeling.

The impact of distraction on CF behavior was investigated using a carefully designed driving simulator experiment on mobile phone distraction. A repeated measures ANOVA was applied to examine the effect of mobile phone distraction on a range of CF related variables, and a Generalized Estimation Equation (GEE) technique was applied to model drivers' time headways. Overall, drivers were found to select slower driving speeds, larger vehicle spacings, and longer time headways when they were engaged in hands-free or handheld phone conversations, suggesting possible risk compensatory behavior. In addition, phone conversations while driving increased the variability in driving speeds, vehicle spacings, and accelerations, indicating reduced control over driving. Furthermore, driver time headways were modeled using a Generalized Estimation Equation (GEE) method.

Inspired by an established driver behavior theory (Task-Capability Interface model, TCI), a novel Task Difficulty Car-Following (TDCF) framework has been developed to incorporate human factors into CF modeling. The framework contains an innovative task difficulty (TD) formula, which captures the motivation behind driving decisions. A driver's TD level increases when the task demand exceeds their capability (e.g., distracted driving or reduced visibility) and decreases otherwise

(e.g., driving on an empty motorway). Thus TD offers a better explanation of human behavior in complex traffic conditions than the conventional measures, such as speed and headway. The TDCF framework was applied to enhance two conventional CF models: Gipps' model and IDM. The behavioral soundness of the enhanced models was discussed, and their stabilities were analyzed. Both models showed better performance than their predecessors, especially in the presence of human factors.

The proposed TD formula was used to discover the suppressed driver behavior behind the two most puzzling traffic flow phenomena: traffic hysteresis and traffic oscillations. A close connection between the change of drivers' task difficulty and the evolution (such as formation and growth) of stop-and-go traffic oscillations was observed. Different driver behaviors inside an oscillation were identified, and their connection with hysteresis magnitude was established.

Application of the TDCF framework enables the CF models to more realistically reproduce the human factor induced behavior. More importantly, it enables the CF models to simulate crash-prone situations, which would be highly beneficial for investigating traffic safety related issues. In particular, the new model could be used for (but not limited to) investigating traffic crashes and near-crash events, simulating complex driving situations, improving onboard safety devices and achieving a deeper understanding of traffic flow characteristics.

List of Publications

List of publications and submitted manuscripts comprising this Thesis

Saifuzzaman, M., Zheng, Z., Haque, M.M., Washington, S., 2016. Understanding the mechanism of traffic hysteresis and traffic oscillations through the change in task difficulty level. Transportation Research Part B: Methodological. (In review)

Saifuzzaman, M., Zheng, Z., Haque, M.M., Washington, S., 2015b. Revisiting the Task-Capability Interface model for incorporating human factors into Car-following models. Transportation Research Part B: Methodological 82, 1-19.

Saifuzzaman, M., Haque, M.M., Zheng, Z., Washington, S., 2015a. Impact of mobile phone use on car-following behaviour of young drivers. Accident Analysis & Prevention 82, 10-19.

Saifuzzaman, M., Zheng, Z., 2014. Incorporating human-factors in car-following models: A review of recent developments and research needs. Transportation Research Part C: Emerging Technologies 48, 379-403.

Conference presentations and posters related to this Thesis

Saifuzzaman, M., Zheng, Z., Haque, M. M., Washington, S., 2016. Incorporating human factors into Gipps car-following model. Transportation Research Board (TRB) 95th Annual Meeting. (Poster presentation)

Saifuzzaman, M., Haque, M. M., Zheng, Z., Washington, S., 2015. Effect of mobile phone distraction on car-following behaviour. Transportation Research Board (TRB) 94th Annual Meeting. (Poster presentation)

Other publications during this PhD period

Zheng, Z., Lee, B., Saifuzzaman, M., and Sun, J., 2015. Exploring association between perceived importance of travel/traffic information and travel behaviour in natural disasters: a case study of the 2011 Brisbane floods. Transportation Research Part C: Emerging Technologies 51, 243-259.

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a_n	Acceleration applied by driver n (positive or negative)
$\tilde{a}_n$	Desired acceleration of driver n
a_{comf}	The comfortable acceleration/deceleration
$a_{\max}$	Maximum acceleration/deceleration
b_n	Deceleration of driver n
b_{n-1}	Deceleration of driver n-1
$\tilde{b}_n$	Desired deceleration of driver n
$\hat{b}$	An estimate of the deceleration applied by the preceding vehicle
$b_{\max}$	Maximum acceleration
V_n	Speed of subject vehicle
V_n^*	Optimal velocity
$\tilde{V}_n$	Desired speed
ΔV_n	Speed difference between the subject vehicle the preceding vehicle ($V_{n-1} - V_n$)
$V_{\max}$	Maximum velocity
V_{safe}	Safe velocity for a vehicle
V_0, V_1, V_2, C_1, C_2	Constants
x_n, x_{n-1}	Position of vehicle n and n-1 respectively
ΔX_n	Spacing from preceding vehicle, $\Delta X_n = x_{n-1} - x_n$
$\widetilde{\Delta X}_n$	Desired following distance
L_{n-1}	Length of the preceding vehicle
s_{n-1}	The effective length of vehicle n-1 (L_{n-1} + safety gap)
S_{gap}	Safety gap between two vehicle
S_n	Spacing between two vehicles measured from the front edge of the subject vehicle to The rear end of the preceding vehicle, $S_n = \Delta X_n - L_{n-1}$
$\tilde{S}_n$	Desired S_n
W	Width of the preceding vehicle
$S_{\text{jam}}, S_1, \Delta$	Vehicle spacing at standstill situation, Jam spacing
d	Constant which represents minimum spacing

t	Time
τ_n	Reaction time
$\hat{\tau}_n$	Time span for a decision
T_n,T	Time headway, Time shift
$\tilde{T}_n$	Desired time headway
$p_{n,i}$	Probability of being involved in a rear-end collision with the preceding vehicle
$\phi(z)$	A tabulated cumulative distribution function for the standardized Gaussian.
M(.)	Represents a memory function
H(.)	Heaviside function with a value of either 0 or 1
h_n	Headway
h_n^*	Critical headway
$\varepsilon_n^{cf}, \varepsilon_n^{ff}$	Normally distributed error terms for car-following and free-following
$\eta_{ran,0,1}$	Random normal distribution with mean 0 and standard deviation 1
α, β, γ, λ,w	Parameters
k_n	Density of traffic ahead
Φ	Gradient difference in a sag
θ_n	Visual angle subtended by the preceding vehicle
$\tilde{\theta}_n$	Desired visual angle subtended by the preceding vehicle
$d\theta_n/dt$	The rate of change in the visual angle
δ	Risk parameter
φ_n	Reaction time increase (in seconds)
τ_n'	Increased reaction time, $\tau_n' = \tau_n + \varphi_n$

List of Abbreviations

AFVD	Asymmetric Full Velocity Difference model
ATD	Average Task Difficulty
CA	Cellular automata models
CARRS-Q	Centre for Accident Research and Road Safety – Queensland
CBD	Central Business District
CF	Car-Following
DAX	Driving Anger Expression Inventory
DVA	Driving by Visual Angle
FVD	Full Velocity Difference model
GA	Genetic Algorithm
GEE	Generalized Estimation Equation
GHR	Gazis-Herman-Rothery CF models
GLM	Generalized Linear Model(s)
HDM	Human Driver (meta-) Model
IDM	Intelligent Driver Model
IDMM	IDM with memory
OV	Optimal Velocity model
RMSNE	Root Mean Squared Normalized Error
TCI	Task-Capability Interface model
TD	Task Difficulty
TDCF	Task Difficulty Car-Following framework
TTC	Time to Collision
TDIDM	Task Difficulty IDM model
TDGipps	Task Difficulty Gipps’ model

Statement of Original Authorship

The work contained in this thesis has not been previously submitted to meet requirements for an award at this or any other higher education institution. To the best of my knowledge and belief, the thesis contains no material previously published or written by another person except where due reference is made.

QUT Verified Signature

Signature:

Date: 03/10/2016

Acknowledgements

I would like to start the acknowledgement list by expressing my gratitude towards the Almighty, the Lord of everything.

I gratefully acknowledge the financial support provided by QUT over my whole candidature. My deepest gratitude goes to my principal supervisor, Dr. Zuduo Zheng. Being his first PhD student is one of the best things that have happened to me in my life. He really knows how to nurture a young researcher like me. I am impressed by his patience and trust on me, which has given me the confidence to develop new ideas. Dr. Zheng gave me all the possible flexibility, and support that a student may have, which paved a productive and pleasant road for my PhD. He gave me every possible chance to learn, to grow, and to succeed. I am really fortunate to have such an outstanding supervisor and mentor.

My special thanks go to Prof. Simon Washington. He was always optimistic in my research and highly encouraging. He had recommended me to get a faculty 'top-up scholarship' which reduced my stress and helped me to concentrate on my research. Having Prof. Washington in my supervisory team has been a privilege. My gratitude also goes to Dr. Md. Mazharul Haque. This thesis would not have been possible without the high quality data collected by Dr. Haque from a driving simulator experiment. He showed me how to think ahead when processing the data, which saved a lot of my time. His comments and suggestions have improved the quality of this research.

I am thankful to my fellow research mates from transport group for their support in creating a productive research environment. My gratitude also goes to all my friends. I can't imagine my PhD life without their support. Furthermore, I acknowledge the staff members from CEBE School especially Ms. Petula Tam, Ms. Violet Jeavons, and Ms. Julie Williams for their administrative support in managing my travel applications and so on. I also thank Ms Diane Kolomeitz for her proofreading service.

I want to express my appreciations towards Bangladesh University of Technology (BUET) and KTH Royal Institute of Technology for giving me high quality education which gave me a solid background of knowledge for pursuing high quality research.

My wife, Tasmina Akter, has been a constant source of support in this long journey. Her boundless love, sacrifice, and patience helped me to maintain the work-life balance. After a stressful day I regain my energy by playing with my cute little princess Manha Zaman. I feel blessed to have such a lovely family. Finally, words cannot describe my gratitude to my parents. Wherever I go, whatever I do, their unconditional love is with me. Without that, I won’t be who I am.

Last, but by no means the least, I pay my respect to the valiant freedom fighters, 3 million martyrs and 200 thousand women for their sacrifice during the liberation war of Bangladesh—my motherland. Through their supreme sacrifices Bangladesh earned her desired victory.

Chapter 1

Introduction

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1.1. Background

Car-following (CF) is one of the primary driving tasks that drivers routinely perform. It can be defined as 'the decision of the driver to follow the preceding vehicle efficiently and safely' (Saifuzzaman and Zheng, 2014). Inappropriate CF behavior (i.e. maintaining either a very short or very long headway from the preceding vehicle) can lead to severe consequences including congestion, reduction in roadway capacity, and rear-end collisions. Among all crash types, rear-end collisions are the most frequent, accounting for more than 29% of all police-reported crashes in the United States (NHTSA, 2010). A similar figure is also reported for other countries of the world including Australia, Japan and UK (Anderson and Baldock, 2008; Distner, 2009). Erroneous CF behavior mostly occurs from human factors such as intoxication, fatigue, mobile phone use while driving, passenger interactions and negative emotions (Beanland et al., 2013; Gordon et al., 2009).

In traffic flow theory the CF concept was first introduced by Pipes and Reuschel (Pipes, 1953; Reuschel, 1950) to describe the longitudinal interactions of vehicles on the road. As one of the oldest topics in traffic engineering, numerous CF models have been proposed in the literature. The high number of CF models proposed could be motivated by their overall incapability to reproduce both traffic propagation and driver–vehicle interactions without relying on the over-fitting produced by the model parameters (Ciuffo et al., 2012a). Although CF behavior depends heavily on driver characteristics, most of the models seek to understand the traffic flow characteristics while ignoring human actions in the driving process. This effort certainly poses serious concerns about the models' capability to reproduce complex driving situations.

Historically, CF models have attracted considerable attention from both traffic engineers and traffic psychologists, which has led to a parallel development in modeling CF behavior. Traffic engineers seek to understand the characteristics of a traffic stream, while traffic psychologists' motivation lies in describing the human skills, abilities, and errors involved in driving. Engineering CF models that are based on the laws of physics have been criticized for their inability in explaining human driving behaviors during car-following. The limitations first came to debate after the publication of the historical review of car-following models by Brackstone and

McDonald (1999). In a commentary on this review, Hancock (1999) criticized that psychologically plausible characterization of how humans think about and solve the driving problem is not observed in these CF models. As a human, we drive well enough to accomplish the task, without seeking continual improvement in driving skill towards some nominal ‘optimal’ level. So far, very few attempts are found to incorporate human behavior in CF modeling. It is necessary to develop a common understanding of the problem by seamlessly integrating the latest advancements from both sides and by bridging their gap and inconsistency. This thesis attempts to fill this gap by creating a link between these two streams of research.

Prior to stating the research objective, a brief description on risk taking and driver errors is presented below.

1.1.1. Risk taking

Risk taking is a multidisciplinary term and covers a broad continuum of behaviors. In general, risk taking can be defined as a socially unacceptable volitional behavior with a potentially negative outcome, in which precautions are not taken (Turner et al., 2004). Common risk taking behaviors of drivers include speeding, tailgating, and running red/yellow lights (Preusser et al., 1998; Reason et al., 1990; Rhodes et al., 2005; Stephens and Groeger, 2009). Risk taking depends on a driver’s perception of danger: one person’s perception of danger is another person’s perception of caution (Jonah, 1986). For example, a driver may tailgate on an expressway accepting the inherent risk that would be created if the preceding vehicle had to brake suddenly, but is willing to take the risk to avoid having other drivers cutting in front of him/her. Therefore, Shinar (1998) defines two states of aggressive driving behavior: instrumental aggression and hostile aggression. In the first state, the driver intends to move ahead at the cost of infringing on other road users' rights (for example, by weaving and running red lights), to accomplish their goals without the intention of harming others. These drivers are likely to believe that they are capable of navigating risks or do not give sufficient weight to the potential for devastating consequences (Willemsen, 2008). Conversely, in hostile aggression, drivers behave aggressively toward other drivers (for example, by cursing other drivers, obstructing the path of others and weaving). Both states can involve risk taking, but only the latter state incorporates the clear intention to do harm.

Risk taking is reported as one of the primary reasons of traffic accidents and violations (Clarke et al., 2005; Evans and Wasielewski, 1982; King & Parker, 2008; Mann et al., 2007). A recent Australian survey of 3740 drivers aged 18 or over reported the prevalence of aggressive driving, where 50% of the participants were found to be yelling or swearing at another motorist, 38% confessed to giving an obscene gesture and 18% admitted to tailgating (AAMI, 2011). This risk taking behavior imposes an additional safety risk to the car-following behavior. For example, in Queensland, Australia, for the year 2014, about 54.3% fatal crashes were reported to be caused by disobeying road rules and 29.1% fatalities were caused due to speeding (TMR, 2014).

Research has identified several factors that can be responsible for risk taking, including gender, driver age, presence of passengers, congestion and driving anger. The bulk of the evidence indicates that men are more aggressive than women, higher in sensation seeking and higher in committing unsafe driving actions such as speeding and drink driving (Shinar and Compton, 2004; Rhodes and Pivik, 2011). Age also appears to be negatively correlated with risk taking. Relative to older drivers, younger drivers have a lower level of motivation to comply with traffic laws, are over involved in running red lights, underestimate the risks of various violations, and overestimate their driving skill and their ability to recognize hazards (Shinar and Compton, 2004). The presence of passengers, in general, seems to have a calming effect on drivers. For example, driving with family or with older passengers was associated with lower speeds than driving alone (Baxter et al. 1990; Shiner, 2001). However, young male passengers can have a ‘speeding-up’ effect on young male drivers (Baxter et al. 1990). Congestion related delays may create frustration in a driver’s mind, especially when drivers are under time pressure as is often the case during rush hours. Congestion increases the likelihood of increasing risk taking behavior by ordinary traffic violations such as running red lights and speeding (Lajunen et al., 1999; Shinar, 1998). The congestion effect on risk taking behavior is greatest during rush hours when the value of time is highest, and least in the weekend period when the value of time is lowest (Shinar and Compton, 2004).

A number of studies show a high correlation between driving anger and risk taking (Abdu et al., 2012; Dahlen et al., 2004; Matthews, 2002; Nesbit et al. 2007). Deffenbacher et al. (2002) identified four ways people express their anger while driving: verbal aggressive expression, physical aggressive expression, use of the vehicle to express anger and adaptive/constructive expression. In general, being high on the personal characteristic of becoming angry behind the wheel predisposes a person to more frequent and intense anger and more frequent aggressive and risky behavior on the road. For example, in a driving simulator experiment, Deffenbacher et al. (2003) observed that high anger drivers showed more risk taking behavior (speeding and erratic driving) and experienced approximately twice the crash rate than low anger drivers. The experimental finding was further supported by the participants' travel diary data, where it was found that the high anger drivers committed 2-4 times more aggressive acts than low anger drivers. These findings do not imply that risk taking behavior is always mediated by angry feelings, only that they are highly correlated. However, high anger drivers appear to have a tendency to engage in more risky behavior, even when they are not angry (Deffenbacher et al., 2003).

In this thesis, Driving Anger Expression Inventory (DAX; Deffenbacher et al. 2002) is used to identify aggressive and non-aggressive driver groups. The detail about the CF behavior of these two driver groups can be found in Chapter 5 Section 5.2.

<u>Driver behavior theories to explain risk taking</u>

Perhaps the most discussed theory to explain risk taking behavior is the "risk homeostasis theory (RHT)" proposed by Wilde (1976, 1982, 2001). RHT states:

"At any moment of time the instantaneously experienced level of risk is compared with the level of risk the individual wishes to take, and decisions to alter ongoing behavior will be made whenever these two levels are discrepant."

If the experienced risk exceeds the target level, then adjustments are made to decrease that, for example by reducing driving speed. The opposite is observed when perceived risk is less than the target level. According to Wilde, it might be possible manipulate the drivers towards safe driving by lowering their target risk, providing incentives for cautious driving and penalties for risky behavior. While RHT theory has merit in its attempt to explain risk taking behavior and accident causation, it faced considerable criticism both from a theoretical and an empirical perspective (e.g. Slovic and Fischoff, 1982). Researchers have shown that drivers do not adapt their behavior to the extent that RHT predicts (Sumala, 1985; (Evans et al., 1982; O'Neill et al., 1985; Fuller, 2008).

The role of risk perception has been rejected in the zero-risk theory, originally presented by Näätänen and Summala (1976) and elaborated by Summala (1988), arguing that experience makes the driving a habitual and automatized activity in which drivers are not able to take into account the minor changes in traffic environment (especially small stochastic risks). Ongoing risk assessments and risk experience play no role in this model. Driver behavior is determined by the maintenance of safety margins which is learned through experience and becomes automatized.

Reconciliation between these opposing viewpoints is proposed in the task–capability interface (TCI) model and associated hypothesis of task difficulty homeostasis (Fuller, 2000, 2005). The task difficulty homeostasis theory suggests that in normal driving conditions, drivers operate with zero risks, but in complex and more demanding situations drivers may unknowingly perceive some risk and adopt a safer speed to avoid uncertain penalty of a collision. In this model, the perceived difficulty of a driving task arises out of the interaction between driving task demand and driver capability. The task difficulty homeostasis theory proposes that drivers usually opt for speed, which keeps them within a band of acceptable difficulty, thus avoiding any risk of collision. Drivers in this condition have the equivalent of Summala's zero risk status. However, in complex situations (for example, in adverse weather, or in the event of sudden braking of the preceding vehicle) the task difficulty may rise unexpectedly. Under these situations, drivers perceive the risk that an event might occur which is beyond their capability and might lead to a collision. Drivers in this condition would be in a state more equivalent to Wilde's target risk.

In this thesis, the TCI model is adopted to characterize both normal and risk-taking behavior. More discussion on this model is provided in Chapter 4.

1.1.2. Driver errors

Human drivers are prone to making driving errors, which are responsible for crashes in most cases. Research has shown that driver error contributes up to 75% of all roadway crashes (Stanton and Salmon, 2009). In another study, Klauer et al. (2006) found that nearly 80% of crashes and 65% of near-crashes included inattention as a contributing cause. A recent study has attributed driver error as the critical reason (last failure in the causal chain of events leading up to the crash) in about 94% of the analyzed crashes (NHTSA, 2015).

'Human error' is a broad term that has been used rather loosely to encompass almost all the unsafe acts that lead to crashes. Reason (1990) classifies unsafe acts into two distinct classes of behavior: errors and violations. An 'error' can be defined as the failure of planned actions to achieve the desired outcome, whereas a 'violation' is the deliberate infringement of some regulated or socially accepted code of behavior (Parker et al., 1995). A violation can be committed for a variety of reasons and can be distinguished through the issue of intentionality. Parker et al. (1995) found that the tendency to commit driving violations is a positive predictor of crash involvement, whereas no link between error-proneness and crash involvement was found. Stanton and Salmon (2009) further categorize driver errors into five groups: action errors, cognitive and decision-making errors, observation errors, information retrieval errors, and violations. CF can be affected by any of these errors.

A driver's competence of driving a vehicle is determined by many factors, e.g., driver's basic physiological characteristics, education, training, and experience, which together define a driver's optimal capability. However, what a driver actually delivers (also referred to as driving performance) often falls short of the optimal capability because of various factors that can impair driving performance, including (but not limited to) distraction, fatigue, drowsiness, and alcohol and drug use. These factors are collectively named as human factors (Fuller, 2002). Although human factors are mostly responsible for driver errors in car-following, they are generally ignored in CF models. Such ignorance overestimates driver capability and leads to most CF models' inability in realistically explaining human driving behaviors.

In this thesis, two specific human factor parameters are included in the proposed modifications of CF models to capture the effect of human factors. Furthermore, a specific example is presented to demonstrate how an accident can happen from erroneous CF behavior. More details can be found in Chapter 4.

1.2. Research objectives

This research focuses on a challenging task in the field of traffic flow modeling: understanding and modeling human behavior in car-following in both normal and demanding situations. The title of this thesis reflects its primary objective, which is to incorporate risk taking and driver errors in car-following models. Specific objectives of this thesis are as follows:

(i) To understand the need to integrate human factors in CF modeling.

(ii) To identify the impact of distraction on car-following behavior.

(iii) To develop a novel methodology to incorporate human factors into conventional car-following models.

(iv) To understand the mechanism of the two most puzzling traffic flow phenomena: traffic oscillations[1] and traffic hysteresis[2], from a behavioral perspective using the proposed method.

1.3. Research contributions

The main contributions of this study are as follows:

[1] Traffic oscillations refer to the stop-and-go driving conditions in congested traffic that cause drivers to exhibit oscillatory trajectories with regular deceleration/acceleration cycles (Zheng et al., 2011).

[2] Traffic hysteresis is a phenomenon characterized by that the acceleration and deceleration flow have different speed-density (and flow-density) curves. It was found that the relationship exhibited obvious loops. Generally, traffic hysteresis is characterized with retardation in speed recovery (Zhang, 1999).

(i) It performs a comprehensive literature review on the state-of-art on CF modeling focusing on the need to integrate human factors into CF models.

(ii) It unveils the impact of mobile phone distraction on CF behavior. The CF variables that are affected from distraction are systematically identified. A statistical model of a driver's time headway selection is developed considering the level of distraction, driver demographic and CF variables.

(iii) It develops a Task Difficulty Car Following (TDCF) framework to incorporate human factors into conventional car-following models. Two popular CF models have been upgraded under the proposed TDCF framework. The new models are checked for stability and are properly calibrated and validated with collected data. The new models are found to outperform their predecessors in both normal and distracted car-following.

(iv) It shows how the CF behaviors of aggressive and non-aggressive drivers differ in both normal and distracted conditions.

(v) It explains the mechanism of traffic hysteresis and the origin and propagation of traffic oscillation using drivers' task difficulty profile. A new categorization of traffic hysteresis is proposed, based on driver characteristics to get a detailed understanding of different driver behaviors within an oscillation.

Overall, the thesis can help researchers and traffic operators to understand complex traffic problems caused by human errors, for example, road crashes and traffic jams.

1.4. Thesis outline

This thesis comprises six chapters. This chapter describes the background of this research, establishes the research objectives to be achieved and describes the contributions of this research. The next four chapters of the thesis address the four specific objectives mentioned in Section 1.2 respectively. A brief detail about these chapters and their linkage to the research objectives is presented in the following paragraphs. A flow chart is presented in Figure 1.1 to highlight the flow of the contents of this thesis.

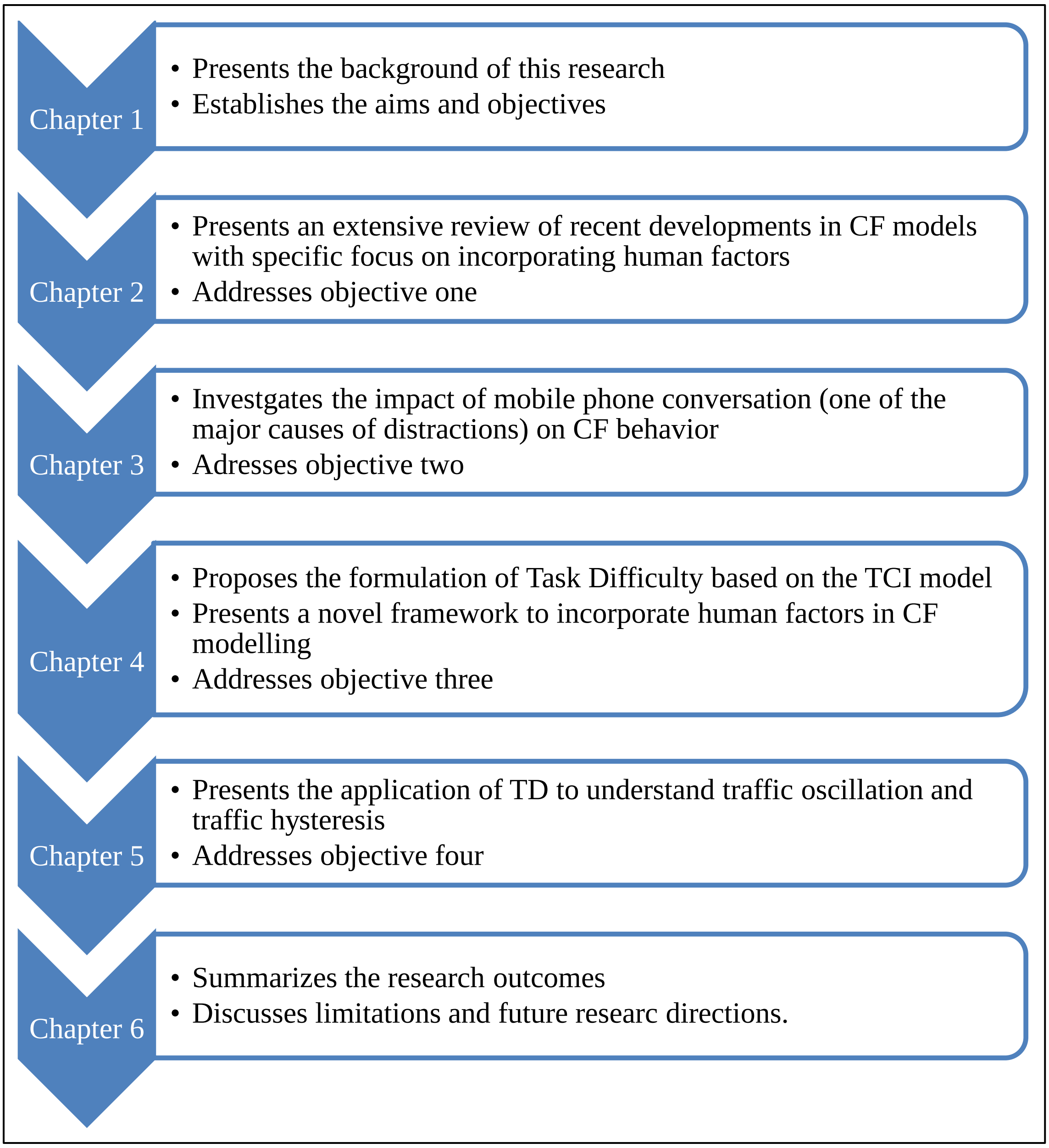

Figure 1.1 Thesis outline

Chapter 2: *Incorporating human factors in car-following models: A review of recent developments and research needs.*

This chapter emphasizes the necessity to consider human factors in CF modeling for a more realistic representation of CF behavior in complex driving situations (for example, in traffic breakdowns, crash-prone situations, and adverse weather conditions) to improve traffic operations and to better understand traffic problems caused by human errors, for example, road crashes and traffic jams. While there are some excellent reviews of CF models available in the literature, none of these specifically focuses on the human factors in these models. To address this gap an extensive review of the available literature is performed with a specific focus on the latest advances in car-following models from both the engineering and human behavior points of view. In so doing, it analyses the benefits and limitations of various models and highlights future research needs in the area.

Chapter 3: *Impact of mobile phone use on car-following behavior for young drivers.*

This chapter investigates the impact of mobile phone conversations on car-following behavior. It addresses the second objective of this thesis, which is to identify the impact of distraction on CF behavior. In particular, the distraction caused by the concurrent use of a mobile phone and operating a motor vehicle is considered. The CARRS-Q Advanced Driving Simulator was used to test a group of young Australian drivers aged 18 to 26 years on a car-following task in three randomized phone conditions: baseline (no phone conversation), hands-free and handheld. CF variables that are significantly affected by the distraction are identified through statistical techniques. Findings from this study are considered in developing a framework to incorporate human factors in CF models, as discussed in the next chapter.

Chapter 4: *Revisiting the Task-Capability Interface model for incorporating human factors into Car-following models.*

This chapter addresses the third objective of this thesis. A new formulation of task difficulty (TD) is proposed based on the famous well-known Task Capability Interface (TCI) model, which explains the motivations behind driver's decision making through the interaction between driving task demand and driver capability. Two human factor parameters are introduced into the TD formulation to capture a driver's risk perception and reaction time in different driving circumstances. A Task Difficulty Car Following (TDCF) framework is developed to incorporate TD into conventional CF models. Proper application of the TDCF framework should improve the performance of CF models as it enables them to better represent human CF behavior. The soundness of the TDCF framework is tested on two popular CF models: Gipps' model and IDM. Both the enhanced models showed better performance than their predecessors, especially in the presence of distraction.

Chapter 5: *Understanding the mechanism of traffic hysteresis and traffic oscillations through the change in task difficulty level.*

This chapter addresses the last objective, which is the application of the proposed TD formula to understand the mechanism of traffic hysteresis and traffic oscillations. The change in driver's task difficulty level is closely observed to find its relation with traffic hysteresis and the formation and propagation of traffic oscillation. Driver behaviors inside an oscillation are categorized based on the task difficulty profile. The categorization provides a detailed understanding about the existence of different CF behaviors inside the oscillatory region and their relations with hysteresis and oscillation properties.

Chapter 6: *Conclusion and recommendations*

This chapter highlights the key findings of the study and discusses some possible applications of the research findings. It also explains limitations of this study and future research needs.

References

AAMI (2011). Crash Index: October 2011. Retrieved at: http://www.aami.com.au/sites/default/files/fm/news/AAMI%20Crash%20Index%202011%20FINAL.pdf

Abdu, R., Shinar, D., Meiran, N., 2012. Situational (state) anger and driving. Transportation research part F: Traffic psychology and behaviour 15 (5), 575-580.

Anderson, R., Baldock, M., 2008. Vehicle improvements to reduce the number and severity of rear end crashes. Centre for Automotive Safety Research. The university of Adelaide, Australia.

Baxter, J. S., Manstead, A. S., Stradling, S. G., Campbell, K. A., Reason, J. T., Parker, D., 1990. Social facilitation and driver behaviour. British Journal of Psychology 81 (3), 351-360.

Beanland, V., Fitzharris, M., Young, K.L., Lenné, M.G., 2013. Driver inattention and driver distraction in serious casualty crashes: Data from the Australian National Crash In-depth Study. Accident Analysis & Prevention 54, 99-107.

Brackstone, M., McDonald, M., 1999. Car-following: a historical review. Transportation Research Part F: Traffic Psychology and Behaviour 2, 181-196.

Ciuffo, B., Punzo, V., Montanino, M., 2012. The calibration of traffic simulation models. Report on the assessment of different goodness of fit measures and optimization algorithms. MULTITUDE Project–COST Action TU0903. JRC Scientific Report.

Clarke, D.D., Ward, P., Truman, W., 2005. Voluntary risk taking and skill deficits in young driver accidents in the UK. Accident Analysis & Prevention 37, 523-529.

Dahlen, E. R., Martin, R. C., Ragan, K., Kuhlman, M. M., 2004. Boredom proneness in anger and aggression: Effects of impulsiveness and sensation seeking. Personality and Individual Differences 37, 1615–1627.

Deffenbacher, J. L., Lynch, R. S., Oetting, E. R., Swaim, R. C., 2002. The Driving Anger Expression Inventory: a measure of how people express their anger on the road. Behaviour research and therapy 40 (6), 717-737.

Deffenbacher, J. L., Deffenbacher, D. M., Lynch, R. S., ichards, T. L., 2003. Anger, aggression, and risky behavior: a comparison of high and low anger drivers. Behaviour research and therapy 41 (6), 701-718.

Distner, M., Bengtsson, M., Broberg, T., Jakobsson, L., 2009. City safety—a system addressing rear-end collisions at low speeds. In: Proceedings of the 21st International Technical Conference on the Enhanced Safety of Vehicles. Sweden.

Evans, L., Wasielewski, P., 1982. Do accident-involved drivers exhibit riskier everyday driving behavior? Accident Analysis & Prevention 14, 57-64.

Evansm, L., Wasielewski, P., Von Buseck, C.R., 1982. Compulsory seat belt usage and driver risk-taking behavior. Human Factors: The Journal of the Human Factors and Ergonomics Society 24, 41-48.

Fuller, R., 2002. Psychology and the highway engineer, in: Fuller, R., Sanots, J.A. (Eds.), Human factors for highway engineers. Elsevier Science Ltd., Oxford, UK, pp. 1-10.

Fuller, R., 2005. Towards a general theory of driver behaviour. Accident Analysis & Prevention 37, 461-472.

Fuller, R., McHugh, C., Pender, S., 2008. Task difficulty and risk in the determination of driver behaviour. Revue Européenne de Psychologie Appliquée/European Review of Applied Psychology 58, 13-21.

Hancock, P., 1999. Is car following the real question–are equations the answer? Transportation research part F: traffic psychology and behaviour 2, 197-199.

Jonah, B.A., 1986. Accident risk and risk-taking behaviour among young drivers. Accident Analysis & Prevention 18, 255-271.

King, Y., Parker, D., 2008. Driving violations, aggression and perceived consensus. Revue Européenne de Psychologie Appliquée/European Review of Applied Psychology 58(1), 43-49.

Klauer, S.G., Dingus, T.A., Neale, V.L., Sudweeks, J.D., Ramsey, D.J., 2006. The Impact of Driver Inattention on Near-Crash/Crash Risk: An Analysis Using the 100-Car Naturalistic Driving Study Data, Report No. DOT HS 810 594, National Highway Traffi c Safety Administration, Washington, D.C.

Lajunen, T., Parker, D., Summala, H., 1999. Does traffic congestion increase driver aggression?. Transportation research part F: traffic psychology and behaviour 2 (4), 225-236.

Mann, R. E., Zhao, J., Stoduto, G., Adlaf, E. M., Smart, R. G., Donovan, J. E. (2007). Road rage and collision involvement. American Journal of Health Behavior, 31 (4), 384-391.

Matthews, G., 2002. Towards a transactional ergonomics for driver stress and fatigue. Theoretical Issues in Ergonomic Science 3(2), 195–211.

Nesbit, S. M., Conger, J. C., Conger, A. J., 2007. A quantitative review of the relationship between anger and aggressive driving. Aggression and Violent Behavior 12 (2), 156-176.

NHTSA, 2010. Development of a simulation model to assess effectiveness and safety benefits of enhanced rear brake light countermeasures. Traffic Safety Facts. Paper No. DOT HS 811331. National Highway Traffic Safety Administration, Washington, DC.

NHTSA, 2015. Critical Reasons for Crashes Investigated in the National Motor Vehicle Crash Causation Survey. Traffic Safety Facts. Paper No. DOT HS 812115. National Highway Traffic Safety Administration, Washington, DC.

Näätänen, R., Summala, H., 1976. Road-user behaviour and traffic accidents. Publication of: North-Holland Publishing Company.

O'Neill, B., Lund, A.K., Zador, P., Ashton, S., 1985. Mandatory belt use and driver risk taking: an empirical evaluation of the risk-compensation hypothesis. Human behavior and traffic safety. Springer, pp. 93-118.

Parker, D., Reason, J. T., Manstead, A. S. R., Stradling, S. G., 1995. Driving errors, driving violations and accident involvement. Ergonomics 38 (5), 1036-1048.

Pipes, L.A., 1953. An operational analysis of traffic dynamics. Journal of applied physics 24, 274-281.

Preusser, D.F., Ferguson, S.A., Williams, A.F., 1998. The effect of teenage passengers on the fatal crash risk of teenage drivers. Accident Analysis & Prevention 30 (2), 217–222.

Reason, J., Manstead, A., Stradling, S., Baxter, J., Campbell, K., 1990. Errors and violations on the roads: a real distinction? Ergonomics 33, 1315–1332.

Reuschel, A., 1950. Fahrzeugbewegungen in der Kolonne. Oesterreichisches Ingenieur-Archiv 4, 193-215.

Rhodes, N., Pivik, K., 2011. Age and gender differences in risky driving: The roles of positive affect and risk perception. Accident Analysis & Prevention 43 (3), 923-931.

Shinar, D., 1998. Aggressive driving: The contribution of the drivers and the situation. Transportation Research Part F: Traffic Psychology and Behaviour 1,137–159.

Shinar, D., 2001. Driving speed relative to the speed limit and relative to the perception of safe, enjoyable, and economical speed. In: Proceedings of the Conference on Traffic Safety on Three Continents. Russia, pp. 19-21.

Shinar, D., Compton, R., 2004. Aggressive driving: An observational study of driver, vehicle, and situational variables. Accident Analysis and Prevention 36, 429–437.

Summala, H., 1988. Risk control is not risk adjustment: the zero risk theory of driver behaviour and its implications. Ergonomics 31, 491–506.

Stanton, N. A., Salmon, P. M., 2009. Human error taxonomies applied to driving: A generic driver error taxonomy and its implications for intelligent transport systems. Safety Science 47 (2), 227-237.

TMR, 2014. 2014 Summary Road Crash Report: Queensland Road Fatalities.Department of Transport and Main Roads, Queensland, Australia.

Turner, C., McClure, R., Pirozzo, S., 2004. Injury and risk-taking behavior—a systematic review. Accident Analysis & Prevention 36 (1), 93-101.

Saifuzzaman, M., Zheng, Z., 2014. Incorporating human-factors in car-following models: A review of recent developments and research needs. Transportation Research Part C: Emerging Technologies 48, 379-403.

Shinar, D., 1998. Aggressive driving: The contribution of the drivers and the situation. Transportation Research Part F: Traffic Psychology and Behaviour 1,137–159.

Slovic, P., Fischhoff, B., 1982. Targeting risks. Risk Analysis 2, 227-234.

Stephens, A.N., Groeger, J. A., 2009. Situational specificity of trait influences on drivers' evaluations and driving behavior. Transportation Research Part F: Traffic Psychology and Behaviour 12 (1), 29–39.

Summala, H., 1985. Modeling driver behavior: A pessimistic prediction. Springer.

Wilde, G.J., 1982. The theory of risk homeostasis: implications for safety and health. Risk analysis 2, 209-225.

Willemsen, J., Dula, C. S., Declercq, F., Verhaeghe, P., 2008. The Dula Dangerous Driving Index: An investigation of reliability and validity across cultures. Accident Analysis & Prevention 40 (2), 798-806.

Zhang, H.M., 1999. A mathematical theory of traffic hysteresis. Transportation Research Part B: Methodological 33, 1-23.

Zheng, Z., Ahn, S., Chen, D., Laval, J., 2011. Freeway traffic oscillations: Microscopic analysis of formations and propagations using Wavelet Transform. Transportation Research Part B: Methodological 45, 1378-1388.

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Chapter 2

Incorporating human-factors in car-following models: A review of recent developments and research needs

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Incorporating human-factors in car-following models: A review of recent developments and research needs

Mohammad Saifuzzaman[1], Zuduo Zheng[1]

[1] School of Civil Engineering & Built Environment, Science and Engineering Faculty, Queensland University of Technology (QUT), Brisbane, Australia

Publication status: This article is published in *Transportation Research Part C: Emerging Technologies.* Volume: 48, pages: 379-403, published: November, 2014. doi:10.1016/j.trc.2014.09.008

Journal quality: The journal in which this paper appears is a peer-reviewed publication with an international readership. The journal's Impact Factor is 2.818, and ranks Q1, 9/69 (Transportation) according to the SCImago Journal Rank.

Foreword: This chapter (article) provides a comprehensive review of the state-of-the art in car-following (CF) models. It also identifies the research need on the human-factors oriented developments in CF models which is the first objective of this thesis, stated in Section 1.2 of chapter 1.

Statement of contribution of co-authors for thesis by published paper

Publication title: Incorporating human-factors in car-following models: A review of recent developments and research needs

The authors listed below have certified that:

- They meet the criteria for authorship in that they have participated in the conception, execution, or interpretation, of at least that part of the publication in their field of expertise;
- They take public responsibility for their part of the publication, except for the responsible author who accepts overall responsibility for the publication;
- There are no other authors of the publication according to these criteria;
- Potential conflicts of interest have been disclosed to (a) granting bodies, (b) the editor or publisher of journals or other publications, and (c) the head of the responsible academic unit, and
- They agree to the use of the publication in the student's thesis and its publication on the Australasian Digital Thesis database consistent with any limitations set by publisher requirements.

Each author's contributions are listed below:

Contributor	*Statement of contribution*
Mohammad Saifuzzaman Signature: Saifuzzaman Date: 15/06/2016	Read all the papers for critical review and wrote the manuscript. The candidate was also responsible for any revisions made at the suggestions of journal reviewers
Zuduo Zheng	Supervised the research, reviewed the manuscript and played the role of the corresponding author.

Principal Supervisor Confirmation:

I have sighted email or other correspondence from all co-authors confirming their certifying authorship.

Dr. Zuduo Zheng		15/06/2016
(Name)	(Signature)	(Date)

Incorporating human-factors in car-following models: A review of recent developments and research needs

Mohammad Saifuzzaman, Zuduo Zheng

Abstract

Over the past decades there has been a considerable development in the modeling of car-following (CF) behavior as a result of research undertaken by both traffic engineers and traffic psychologists. While traffic engineers seek to understand the behavior of a traffic stream, traffic psychologists seek to describe the human abilities and errors involved in the driving process. This paper provides a comprehensive review of these two research streams.

It is necessary to consider human-factors in CF modeling for a more realistic representation of CF behavior in complex driving situations (for example, in traffic breakdowns, crash-prone situations, and adverse weather conditions) to improve traffic safety and to better understand widely-reported puzzling traffic flow phenomena, such as capacity drop, stop-and-go oscillations, and traffic hysteresis. While there are some excellent reviews of CF models available in the literature, none of these specifically focuses on the human factors in these models.

This paper addresses this gap by reviewing the available literature with a specific focus on the latest advances in car-following models from both the engineering and human behavior points of view. In so doing, it analyzes the benefits and limitations of various models and highlights future research needs in the area.

2.1. Introduction

Car-following (CF) rules describe longitudinal interactions of vehicles on the road. The CF concept was first introduced by Pipes and Reuschel (Pipes, 1953; Reuschel, 1950). It can be defined as 'the decision of the driver to follow the preceding vehicle efficiently and safely'. Over the past decades, traffic engineers and traffic psychologists have contributed to the development of CF behavior modeling. Traffic engineers seek to understand characteristics of a traffic stream and apply Newtonian laws of motion to approximate CF behaviors in what this paper refers to (for the convenience of discussion) as 'Engineering CF models'. Traffic psychologists, on the other hand, are motivated to describe the human abilities and errors involved in CF, and their impact on traffic safety. Another mainstream driver behavior – lane-changing maneuvers – is reviewed in Zheng (2014) and is beyond the scope of this paper.

A large number of Engineering CF models have been developed in an attempt to describe CF behavior under a wide range of traffic conditions, ranging from free-flow to extreme situations. Some of these models have been used in commercial packages of microscopic traffic simulations (Barceló, 2010), and to guide the design of advanced vehicle control and safety systems (Yang and Peng, 2010). However, the limitations of Engineering CF models were the subject of spirited debate after the publication of Brackstone and McDonald's (1999) historical review of car-following models. In a commentary of this review, Hancock (1999) criticized the fact that the psychologically plausible characterization of how humans think about, and solve, the driving problem is not observed in these CF models.

Each driver is different so as their driving styles and risk-taking capabilities. Age and gender, for example, play an important role in the perception of risky driving situations. In addition, particular driving needs can influence aggressive driving, which is a potential source of driving error. While research shows that driver error contributes to up to 75% of all roadway crashes (Stanton and Salmon, 2009), few CF models can capture driver behavior in various driving conditions, especially in crash-prone conditions, such as traffic breakdowns, the undertaking of risk-taking behaviors, distraction, and adverse weather conditions.

To address this serious issue, a richer representation of the cognitive processes engaged during CF is required to describe driver responses, and the consequences of these responses, in adverse driving conditions. Moreover, CF models with the capability of mimicking a driver's mistakes and, consequently, with the ability to generate crash or near-crash scenarios can be important tools for evaluating safety-related technologies and policies. Unfortunately, most Engineering CF models do not include such scenarios.

Given the importance of the human factor in the driving process, it is necessary to integrate the latest CF modeling advances from both engineering and psychological perspectives, and to bridge any gaps or inconsistences in these perspectives. Such a union will be of great value in transportation research, especially in micro-simulation models for better prediction of driving behavior. This paper explores the existing CF models and their advances in describing human driving behavior.

Although some excellent reviews of CF models are available (Brackstone and McDonald, 1999; Hamdar, 2012; Olstam and Tapani, 2004; Panwai and Dia, 2005; Toledo, 2007), all have their limitations. For example, Brackstone and McDonald (1999) review CF models developed before 1999. Since then, however, there have been notable advancements in CF modeling. Furthermore, the Brackstone and McDonald review (1999) ignores cellular automation (CA)-based CF models, and their review is limited to Engineering CF models only. Similar conclusions can be drawn from the reviews by Olstam and Tapani (2004), Panwai and Dia (2005), and Toledo (2007). (Note, however, that Toledo (2007) does include CA-based CF models). In contrast, few efforts are observed on identifying human factors responsible for car-following with two exceptions. Hamdar (2012) summarized a list of human factors and situational environmental factors which may affect CF behavior. In a recent review, Treiber and Kesting (2013) described seven human factors (finite reaction time, estimation error, imperfect driving, spatial and temporal anticipation, context sensitivity and perceptual threshold) which could affect CF behavior, and applied them to a CF model using some hypothetical cases.

This paper provides a comprehensive review of the important recent developments in CF modeling from both engineering and human behavior perspectives. In particular, the paper focuses on notable efforts to integrate human behaviors into the traditional CF models, and on the future research that is needed to build on these efforts. For the sake of clarity and focus, the paper concentrates on representative CF models in the literature, rather than attempting to exhaustively cover all existing models.

To this end, the paper is organized as follows: Section 2 reviews notable traditional CF models and their extensions; Section 3 presents Engineering CF models that attempt to incorporate one or more human factors; and Section 4 discusses the major issues arising from these previous modeling attempts, determines what future research is needed in the area, and summarizes the conclusions arising from the review.

2.2. Car-following models: the engineering perspective

Numerous mathematical models have been developed to describe CF behavior under a wide range of conditions. In general, these models are based on the stimulus-response framework that was first developed at the General Motors research laboratories (Chandler et al., 1958; Gazis et al., 1961). The framework assumes that each driver responds to a given stimulus according to the following relationship:

$$response = sensitivity \times stimulus$$

Over the years, various researchers have used different factors as the stimuli to explain the response (acceleration) of the subject vehicle. While varying notations are used in the literature, for the sake of consistency and clarity, the same notations are used throughout this paper (These are listed in Appendix).

2.2.1. GHR model and its extensions

Gazis-Herman-Rothery (GHR) CF models is probably the most studied models in the area of CF modeling. The first version is the linear CF model developed by Chandler et al. (1958) and Herman et al. (1959), as shown in Equation (2.1)

$$a_n(t) = \lambda . \Delta V_n(t - \tau_n) \tag{2.1}$$

where $a_n(t)$ is the acceleration of the subject vehicle *n* at time *t*, $\Delta V_n(t-\tau_n)$ is the speed difference between the subject vehicle and the preceding vehicle at time $(t-\tau_n)$, τ_n denotes the reaction time, and λ is a sensitivity parameter. The sensitivity parameter λ can have several functional forms

(a)	$\lambda = C,$	a constant
(b)	$\lambda = \begin{cases} C_1, & \Delta X_n \le \Delta X_{critical} \\ C_2, & \Delta X_n > \Delta X_{critical} \end{cases}$	a step function
(c)	$\lambda = C/\Delta X_n\ ,$	reciprocal spacing
(d)	$\lambda = C \cdot V_n/\Delta X_n,$	used in Edie's model (Edie, 1961)
(e)	$\lambda = C/\Delta X_n^2\ ,$	yields Greenshield's (Greenshields et al., 1935) macroscopic flow-density relationship

where, ΔX_n is the spacing from the preceding vehicle, $\Delta X_{critical}$ is a threshold specified by the modeler, V_n is the speed of the subject vehicle, and C, C_1, C_2 are constant. Gazis et al. (1961) combine the last three (c, d, e) functional forms of λ in a general expression of sensitivity, and propose a non-linear CF model, as defined in Equation (2.2)

$$a_n(t) = \alpha V_n(t)^{\beta} \frac{\Delta V_n(t-\tau_n)}{\Delta X_n(t-\tau_n)^{\gamma}} \tag{2.2}$$

where α, β, γ are parameters.

GHR models have been extensively studied (For a detailed review, see Brackstone and McDonald, 1999). The main advantage of GHR model is its simplicity. However, it was built upon several strong assumptions, and this leads to the serious limitations as being frequently reported by researchers (Siuhi and Kaseko, 2010). For example, identical reaction time for all drivers does not capture inter-driver heterogeneity; the human ability to perceive small changes in driving conditions, such as spacing and relative velocity, is overestimated; and single value estimation for each of the model parameters does not consider behavioral differences in different circumstances (such as acceleration or deceleration). In an attempt to overcome these limitations, several enhanced versions of the GHR model have been developed, as elaborated below.

Memory functions: Assuming that a driver reacts to the relative speed of the preceding vehicle over a period of time, rather than in an instant, Lee (1966) introduces a memory function into the linear GHR model to store the information of relative speed during CF, as shown in Equation (2.3)

$$a_n(t) = \int_0^t M(t-s)\Delta V_n(s)ds \tag{2.3}$$

where M represents a memory function; that is, the way a driver acts on information that has been collected over the driving period. This function is similar to a weighting function. Lee (1966) proposes several forms of the memory function, and analyzes the stability of the resulting response to periodic changes in the preceding vehicle's speed. Although the model removes unrealistic peaks in acceleration profile, the implementation of the model in traffic simulation is considerably more complex due to the need of maintaining an array of past conditions for each vehicle.

Acceleration and deceleration asymmetry: Herman and Rothery (1965) were the first to hypothesize that most passenger cars have a greater deceleration than acceleration capacity. This was later confirmed by Subramanian (1996) and Siuhi and Kaseko (2010). In congested traffic, drivers are more sensitive to deceleration than to acceleration. Ahmed (1999) extends the GHR model to accommodate this acceleration/deceleration asymmetry. In this model, driver heterogeneity in terms of reaction time is also considered. In addition, two states of driving – free flow and CF – are modeled separately within the model. The state of driver behavior (that is, free-flow or car-following) is determined by comparing the headway (h_n) to a critical value (h_n^*) which is distributed among the drivers. If $h_n(t-\tau_n) \leq h_n^*$ then the vehicle is in the CF state; otherwise, it is in the free-flow state. The model is shown in Equation (2.4)

$$\begin{aligned} a_n^{cf,g}(t) = \alpha^g \frac{V_n(t-\varphi\tau_n)^{\beta^g}}{\Delta X_n(t-\varphi\tau_n)^{\gamma^g}} k_n(t-\varphi\tau_n)^{\delta^g} \Delta V_n(t-\varphi\tau_n)^{\rho^g} \\ + \varepsilon_n^{cf,g}(t) \end{aligned} \tag{2.4}$$

$$a_n^{ff,g}(t) = \lambda^{ff}\left[\tilde{V}_n(t-\tau_n) - V_n(t-\tau_n) + \varepsilon_n^{ff}(t)\right]$$

where *cf* and *ff* refer to CF and free-flow states respectively; g ϵ [acceleration, deceleration]; $k_n(t - \varphi\tau_n)$ is the traffic density ahead of the subject vehicle within its view (a visibility distance of 100m was used) at time $(t - \varphi\tau_n)$; $\varphi \in [0,1]$ is a sensitivity lag parameter; λ is the constant sensitivity; $\tilde{V}_n$ is the desired speed; and ε_n^{cf} and ε_n^{ff} are normally distributed error terms for CF and free-following states, respectively.

Koutsopoulos and Farah (2012) discovered some ambiguity in the previous assumption of the GHR model, where it is assumed that drivers accelerate when the speed difference relative to the preceding vehicle is positive, and decelerate when the speed difference is negative. In fact, after analyzing two existing traffic flow databases (Next Generation Simulation (Alexiadis et al., 2004), and Federal Highway Administration (FHWA, 1985)) they found that, in many cases, the opposite is true. Hence, they relax the assumption and extend the GHR model to consider three states of driving: accelerating, doing nothing, and decelerating.

Multiple-vehicle interaction: The models discussed above are based on the assumption that each driver reacts in some specific manner to some stimuli from the preceding vehicle. In the real world, however, drivers most likely adjust their behaviors according to their observations of more than one vehicle ahead. Multi-vehicle interaction was first introduced by Herman and Rothery (1965) and Bexelius (1968). Assuming that drivers follow more than one preceding vehicle, they extend the linear GHR model with added sensitivity terms for up to *m* vehicles ahead. The mathematical form of the model is presented in Equation (2.5)

$$a_n(t) = \sum_{i=1}^{m} \alpha_i \Delta V_{n,n-1}(t - \tau_n) \tag{2.5}$$

where $\Delta V_{n,n-1}(t - \tau_n)$ is the relative speed with respect to the nearest i^{th} leader at time $(t - \tau_n)$, and α_i is a parameter. Although the notion behind the model is a realistic one, this research direction received little attention in the literature until recently, when multi-vehicle interaction has re-gained some attention (Hoogendoorn and Ossen, 2005; Lenz et al., 1999; Peng and Sun, 2010; Treiber et al., 2006). (This is discussed later in this paper.)

Fuzzy-logic: Fuzzy-logic is applied to enhance the GHR model because its use is often reported to enable a better mimicking of the cognitive and perceptional uncertainties that drivers frequently encounter in real-world CF processes (Brackstone et al., 1998). Aforementioned models assume that the drivers know their exact speed, their distance from other vehicles, and other situational factors. Clearly, this assumption is an unrealistic one. Fuzzy-logic-based models, on the other hand, acknowledge the imperfection of a driver's capability by dividing their perception into a number of overlapping fuzzy sets using predefined fuzzy-logics. For example, time headway of less than 0.5s is defined as *too close*. This definition can then be used in logical rules such as, *if too close, then use emergency deceleration*. Kikuchi and Chakroborty (1992) were the first to use this type of model to 'fuzzify' the traditional GHR model. More work with the fuzzy-logic-based model is reported in Wu et al. (2000). However, among many other issues, defining fuzzy sets and their associated membership functions is challenging (Ross, 2010), and makes the calibration and validation of fuzzy-logic-based CF models extremely difficult.

2.2.2. Desired measures models

Helly's model: According to the aforementioned CF models (Chandler et al., 1958; Gazis et al., 1961), for two vehicles that are travelling at the same speed, any value of spacing between them is acceptable. To address this shortcoming, Helly (1959) introduces a new assumption that each driver has a desired following distance, and the driver seeks to minimize both the speed difference and the difference between the actual space headway and the desired headway. The functional form of Helly's model is expressed in Equation (2.6)

$$\begin{gathered} a_n(t) = \alpha_1 \Delta V_n(t-\tau_n) + \alpha_2\left[\Delta X_n(t-\tau_n) - \widetilde{\Delta X}_n(t)\right], \\ \widetilde{\Delta X}_n(t) = \beta_1 + \beta_2 V_n(t-\tau_n) + \beta_3 a_n(t-\tau_n). \end{gathered} \tag{2.6}$$

where $\alpha_1, \alpha_1, \beta_1, \beta_2, \beta_3$ are parameters; $\widetilde{\Delta X}_n$ is the driver's desired following distance, which is assumed to be dependent on their speed and acceleration. However, Helly (1959) and other researchers (Koshi et al., 1992; Van Winsum, 1999; Xing, 1995) show that the desired following distance can be reasonably determined by using the speed of the subject vehicle alone (that is, $\beta_3 = 0$).

A non-linear extension of Helly's model in combination with the GHR model is proposed by Koshi et al. (1992) and, later, by Xing (1995). The general form of their model is presented in Equation (2.7)

$$a_n(t) = \alpha_1 \frac{\Delta V_n(t-\tau_1)}{\Delta X_n(t-\tau_1)^l} + \alpha_2 \frac{\left[\Delta X_n(t-\tau_2) - \widetilde{\Delta X}_n(t)\right]}{\Delta X_n(t-\tau_2)^m} - \gamma \sin\varphi + \lambda[\tilde{V}_n - V_n(t-\tau_3)] \tag{2.7}$$

where τ_1, τ_2, τ_3 are time lags, φ is the gradient difference in a sag, $\widetilde{\Delta X}_n$ is the desired following distance as a function of the vehicle speed, $\tilde{V}_n$ is desired speed, and $\alpha_1, \alpha_2, \gamma, \lambda, l, m$ are parameters. The first term of the model represents the standard driving situation, the second term describes acceleration from a standing queue, the third term controls the effect of gradient, and the fourth term represents acceleration in free-flow conditions. Note that, while the physical condition of the road in terms of gradient is considered in this model, horizontal curvature effect is neglected.

Intelligent driver model (IDM): One of the most popular models using desired measures is the intelligent driver model (IDM) proposed by Treiber et al. (2000). This model considers both the desired speed and the desired space headway, as defined in Equation (2.8)

$$a_n(t) = a_{\max}^{(n)} \left[1 - \left(\frac{V_n(t)}{\tilde{V}_n(t)}\right)^{\beta} - \left(\frac{\tilde{S}_n(t)}{S_n(t)}\right)^2\right] \tag{2.8}$$

where $a_{\max}^{(n)}$ is the maximum acceleration/deceleration of the subject vehicle n, $\tilde{V}_n$ is the desired speed, S_n is spacing between two vehicles measured from the front edge of the subject vehicle to the rear end of the preceding vehicle ($S_n = \Delta X_n - L_n$; where L_n is vehicle length), $\tilde{S}_n$ is the desired spacing, and β is a parameter. When preceding vehicle is far away, the third term in this equation becomes negligible small and the model performs as a free flow model where the desired speed of the driver governs the acceleration. Use of one equation ensures a smooth transition between free-flow and car-following situations. The desired space headway (or following distance) in IDM is dependent on several factors: speed, speed difference (ΔV_n), the maximum acceleration ($a_{\max}^{(n)}$), a comfortable deceleration ($a_{comf}^{(n)}$), the minimum spacing at the standstill situation ($S_{\text{jam}}^{(n)}, S_1^{(n)}$), and the desired time headway ($\tilde{T}_n$). Mathematically, the desired following distance can be calculated using Equation (2.9):

$$\tilde{S}_n(t) = S_{\text{jam}}^{(n)} + S_1^{(n)}\sqrt{\frac{V_n(t)}{\tilde{V}_n(t)}} + V_n(t)\,\tilde{T}_n(t) - \frac{V_n(t)\,\Delta V_n(t)}{2\sqrt{a_{\max}^{(n)} a_{comf}^{(n)}}} \tag{2.9}$$

The introduction of both a maximum acceleration and a comfortable deceleration rate prevents the model from producing unrealistically high accelerations/decelerations. This feature is absent in most of the earlier models. In calibrating this model, identical vehicles with the same acceleration and deceleration capability were used (a maximum value of 0.73m/s^2 was used). Reaction time is ignored in this model.

Later, Treiber and Helbing (2003) extended IDM to capture driver's adaptation effect to the surrounding environment using a memory function. Their model is called IDMM; that is, IDM with memory. The extension is based on the observation that, after being in congested traffic for some time, most drivers adapt their driving style; for example, by increasing their preferred time gap. Treiber and Helbing (2003) assume that the subjective level of service (λ_n) influences the desired time gap decision. Hence, the desired time gap $\tilde{T}_n(t)$ in Equation (2.9) is replaced by $T_n(\lambda)$. This is shown in Equation (2.10)

$$T_n(\lambda) = \tilde{T}_n[\beta_{\mathrm{T}} + \lambda_n(1-\beta_{\mathrm{T}})];\ \beta_{\mathrm{T}} = T_{\text{jam}}/\tilde{T}_n \tag{2.10}$$

where, β_{T} is an adaptation factor. For each driver, the subjective level of service (λ_n) is given by the exponential moving average of the instantaneous level of service experienced within the adaptation time (typically 600 sec).

The main difficulty of models with desired measures (for example, desired spacing, desired time headway, desired speed) is that most of the parameters are unobservable in nature, and this makes their estimation more challenging. Therefore, many of the models described in this sub-section were not empirically estimated using real traffic data.

2.2.3. Safety distance or collision avoidance models

Safety distance models differ from GHR models by hypothesizing that the driver reacts to spacing relative to the preceding vehicle, rather than to the relative speed. This idea was first proposed by Kometani and Sasaki (1959). In their model, the subject vehicle seeks to keep the minimum safety distance from the preceding vehicle, as shown in Equation (2.11)(2.11)

$$\Delta X_n(t-\tau_n) = \alpha V_{n-1}^2(t-\tau_n) + \beta V_n^2(t) + \gamma V_n(t) + d \tag{2.11}$$

where, V_n and $V_{n-1}$are the speeds of the subject vehicle and the preceding vehicle, respectively; α, β, γ are parameters; and d is a constant which represents the minimum spacing and prevents the model from collisions. Later, Newell (1961) proposed a non-linear version of this model, which assumes that the speed of the subject vehicle is a non-linear function of the spacing to the preceding vehicles, as shown in Equation (2.12)

$$V_n(t) = V_{\max}[1 - \exp(-\lambda(\Delta X_n(t-\tau_n) + d)/V_{\max})] \tag{2.12}$$

where V_{max} and d are the maximum speed and the minimum space headway, respectively; λ is a parameter. Newell assumes different functional forms for acceleration and deceleration decisions. This model is directly dependent on density (spacing between vehicles), and this dependence might result in unrealistic accelerations or decelerations. To address this issue, Bando et al. (1995) modified Newell's model by controlling the change in speed. (This is discussed in Section 2.4 below.)

The most popular safety distance model was developed by Gipps (1981). The model assumes that the speed is selected by the driver in a way to ensure that the vehicle can be safely stopped in case the preceding vehicle should suddenly brake. Gipps' model includes two modes of driving: free-flow and CF. The driver chooses the smaller one from the speeds obtained from the free-flow and CF modes, as shown in Equation (2.13)

$$V_n(t+\tau_n) = \min\left\{\begin{array}{c} V_n(t) + 2.5\tilde{a}_n\tau_n\left(1 - V_n(t)/\tilde{V}_n\right)\left(0.025 + V_n(t)/\tilde{V}_n\right)^{1/2} \\ \tilde{b}_n\tau_n + \sqrt{\tilde{b}_n^2\,\tau_n^2 - \tilde{b}_n\left[2(\Delta X_n(t) - s_{n-1}) - V_n(t)\tau_n - \dfrac{V_{n-1}(t)^2}{\hat{b}}\right]} \end{array}\right. \qquad (2.13)$$

where $\tilde{a}_n$is the desired acceleration, $\tilde{b}_n$ is the desired deceleration, s_{n-1} is the effective length of vehicle *n*-1 (length of the vehicle plus a safety distance into which the following vehicle is not willing to intrude even when at rest), $\hat{b}_n$is an estimate of the deceleration applied by the preceding vehicle (b_{n-1}), and $\tilde{V}_n$ is the desired speed of vehicle *n*. A constant reaction time τ_n is used for all vehicles. A smooth transition between free-flow and CF modes occurs most of the time, except when the leading vehicle brakes harder than anticipated (i.e. $b_{n-1} > \hat{b}_n$), when the preceding vehicle moves to an adjacent lane, or when a new vehicle moves in front of the subject vehicle from an adjacent lane. Besides its Newtonian equations of motion, Gipps' model offers some behavioral parameters, for example, the desired acceleration, desired deceleration and desired speed, reaction time, and estimation of the preceding vehicle's deceleration. It has been used in many simulation models, including AIMSUN (Barceló and Casas, 2005).

2.2.4. Optimal velocity model

The optimal velocity (OV) model, introduced by Bando et al. (1995) has received considerable attention in the CF literature. OV model assumes that each vehicle has an optimal (safe) velocity, which depends on the distance from the preceding vehicle, and that the acceleration of the n^{th} vehicle can be determined according to the difference between the actual velocity V_n, and the optimal velocity V_n^*. Mathematically, the model can be defined as in Equation (2.14)

$$a_n(t) = \alpha\left[V_n^*\left(\Delta X_n(t)\right) - V_n(t)\right] \qquad (2.14)$$

where α is the constant sensitivity coefficient, and V_n^* is the optimal velocity and depends on the headway ΔX_n to the preceding vehicle, and can be defined as

$$V_n^*\big(\Delta X_n(t)\big) = V_0\left[\tanh\left(\frac{\Delta X_n(t) - L_{n-1}}{b} - C_1\right) + C_2\right]$$

where L_{n-1} is the length of the preceding vehicle (typically 5m), and b is the length scale while V_0, C_1 and C_2 are constant. Helbing and Tilch (1998) calibrated the OV model using the following optimal velocity function:

$$V_n^*\big(\Delta X_n(t)\big) = V_1 + V_2\tanh[C_1(\Delta X_n(t) - L_{n-1}) - C_2]$$

where V_1, V_2, C_1, C_2 are parameters, and their estimated optimal values are: V_1=6.75 m/s, V_2=7.91 m/s, C_1=0.13m^{-1}, C_2=1.57. Driver reaction time is not considered in the OV model described above, which has been updated in the later version (Bando et al., 1998), as shown in Equation (2.15):

$$a_n(t) = \alpha\big[V_n^*\big(\Delta X_n(t-\tau_n)\big) - V_n(t-\tau_n)\big] \tag{2.15}$$

Although OV model was created to address the issue of the unrealistically high acceleration and deceleration observed in Newell's (1961) model, comparison with the field data shows that it still produces unrealistic accelerations and decelerations. The reason is that the optimal velocity is dependent on the following distance; hence, the density is still affecting the model. To handle unrealistic decelerations, Helbing and Tilch (1998) added velocity difference to the OV model; this comes into play when the velocity of the preceding vehicle is lower than that of the subject vehicle. They called the model the 'Generalized Force' (GF) Model, as presented in Equation (2.16)

$$a_n(t) = \alpha\big[V_n^*\big(\Delta X_n(t)\big) - V_n(t)\big] + \lambda\big(\Delta V_n(t)\big) \cdot H\big(-\Delta V_n(t)\big) \tag{2.16}$$

where H is a Heaviside function, whose value is 1 when the velocity of the preceding vehicle is lower than that of the subject vehicle, and 0 otherwise; and λ is the sensitivity constant. As both the acceleration and deceleration rate could be unreasonably high, Jiang et al. (2001) extended the GF model to consider both negative and positive velocity differences (that is, to explicitly consider velocity difference), and named it the 'Full Velocity Difference' (FVD) Model, as shown in Equation (2.17):

$$a_n(t) = \alpha\left[V_n^*\left(\Delta X_n(t)\right) - V_n(t)\right] + \lambda\left(\Delta V_n(t)\right) \tag{2.17}$$

Jiang et al. (2001) use the same OV function as is used in Helbing and Tilch (1998). However, the FVD model is indifferent to acceleration and deceleration behavior, which could be problematic. Previous research shows that drivers behave differently during acceleration and deceleration (as discussed in Section 2.1). Having a single parameter for both acceleration and deceleration might lead to an unrealistic situation where the subject vehicle brakes insufficiently, even if the distance to the preceding vehicle is extremely short. Thus, Gong et al. (2008) propose an asymmetric full velocity difference (AFVD) model by enabling different responses in acceleration and deceleration, as shown in Equation (2.18)

$$\begin{aligned} a_n(t) = \alpha\left[V_n^*\left(\Delta X_n(t)\right) - V_n(t)\right] + \lambda_1\left(\Delta V_n(t)\right) \\ \cdot H\left(-\Delta V_n(t)\right) + \lambda_2\left(\Delta V_n(t)\right) \cdot H\left(\Delta V_n(t)\right) \end{aligned} \tag{2.18}$$

where λ_1, λ_2 are sensitivity coefficients used for deceleration and acceleration respectively. Compared with the FVD model, the AFVD model takes longer time to become stable.

Davis (2003) simulated the OV model (Bando et al., 1998) using different reaction times. For a small reaction time 0.1s, flow was stable for a platoon of 100 vehicles. However, if the reaction time increased to 0.3s, only the first 14 vehicles avoided collision and the situation became worse for longer driver reaction times. This indicates that the OV model is unrealistically sensitive to delay time. To overcome this problem, the OV function for time-varying situations is modified by assuming that drivers can change the relative velocity as well as headway, as shown in Equation (2.19):

$$a_n(t) = \alpha\left[V_n^*\left(\Delta X_n(t-\tau_n) + \tau_n \Delta V_n(t-\tau_n)\right) - V_n(t)\right] \tag{2.19}$$

For small reaction times, this model closely represents the original OV model. For long reaction times ($\tau_n \leq 1$s), the model performs well without any collisions for a platoon of 100 vehicles. The model calculates the relative distance and the relative velocity at time $(t-\tau_n)$, and calculates speed of the subject vehicle at time *t*, which is odd and needs a behavioral justification.

Lenz et al. (1999) extended the OV model by considering multi-vehicle interactions, as defined in Equation (2.20)

$$a_n(t) = \sum_{i=1}^{m} \alpha_i \left[V_n^* \left(\frac{\Delta X_{n,n-i}(t)}{i} \right) - V_n(t) \right] \tag{2.20}$$

where $\Delta X_{n,n-i}(t)$ is the spacing with respect to the nearest i^{th} leader at time *t*. For m=1, the above equation collapses to the original OV model. The same optimal velocity function for V_n^* is used as in the OV model. Compared with the original OV model, consideration of multi-vehicle interactions increases the extended model's stability.

Peng and Sun (2010) propose a similar extension for the FVD model. Neither Lenz et al. (1999) nor Peng and Sun (2010) consider driver reaction time. These two models were calibrated using numerical simulations; however, they have not yet been tested with real data.

2.2.5. Newell's simplified CF model and its extensions

Newell (2002) developed a parsimonious CF model following a very simple CF rule: the time-space trajectory of a vehicle in congested traffic on a homogenous highway is identical to the preceding vehicle's trajectory except for space and time shifts, as defined in Equation (2.21)

$$x_n(t+T) = \min \begin{cases} x_n(t) + uT & [\text{free} - \text{flow}] \\ x_{n-1}(t) - \Delta & [\text{congestion}] \end{cases} \tag{2.21}$$

where $T = 1/(wk)$ is the wave trip time (or time shift) between two consecutive trajectories having *w* and *k* as the absolute values of wave speed and jam density respectively, $\Delta = 1/k$ is jam spacing (or space shift), and $x_n(t+T)$ represents the longitudinal position of vehicle *n* at time $(t+T)$. Newell conjectures that the gap between two trajectories at time *t* depends on speed, and remains nearly constant if the highway is homogeneous. Newell further proposes that (T, Δ) vary as if they were sampled independently from some joint probability distribution.

Besides its parsimoniousness (i.e., only two parameters T and δ are required), Newell's model has direct linkage to the macroscopic LWR theory (Lighthill and Whitham, 1955; Richards, 1956). Therefore, Newell's model is often adopted as the base theory in studying complex issues (Zheng et al., 2011a; Zheng et al., 2011b; Chen et al., 2012; Chen et al., 2012; Chen et al., 2014). For example, Zheng et al., (2013) use Newell's CF model to quantitatively measure the impact of lane-changing maneuvers on the immediately following vehicle.

Newell's CF model has also been extended to capture traffic oscillations. Oscillatory behaviors are generally caused by instabilities of the models. For example, in the stimulus-response- type models, instability arises when a following vehicle becomes highly sensitive to the preceding vehicle's stimulus (Herman et al., 1959). Newell's CF theory cannot be directly used for predicting characteristics of traffic oscillations because disturbances do not change in magnitude in this model due to the fact that a follower's trajectory is essentially replicated from the leader's by shifting in time and space. Thus, Laval and Leclercq (2010) relax the assumption of constant time shift (*T*) and make it time-dependent. By doing so, an oscillation can be interpreted as a deviation of *T* from the equilibrium *T*. They assume that, in congestion, deceleration waves can trigger some drivers (who are initially in equilibrium) to switch to "timid" or "aggressive" non-equilibrium modes. In their model, the trajectory of vehicle *n* is described as in Equation (2.22)

$$x_n(t) = \min\begin{cases} x_n(t-T) + \min\{uT, \tilde{x}_n(t)\} & [\text{free} - \text{flow}] \\ x_{n-1}(t-\eta_n(t)T) - \eta_n(t)\Delta & [\text{congestion}] \end{cases} \tag{2.22}$$

where $\tilde{x}_n$ is the desired distance travelled by vehicle *n* during T, and $\eta_n(t)$ is a dimensionless variable introduced to capture deviations from Newell's model.

Chen et al. (2012) extended Laval and Leclercq's model, and developed a behavioral CF model based on empirical observations. They report that the model is capable of reproducing the spontaneous formation and ensuing propagation of stop-and-go waves in congested traffic.

2.2.6. Cellular Automata (CA) models

Cellular automata (CA) were historically proposed in the 1940s (Neumann, 1948) and popularized in the 1980s (Wolfram, 1983) to accurately reproduce macroscopic behavior of a complex system using minimal microscopic descriptions. A typical CA model constitutes four key components: the physical environment, the cells' states, the cells' neighborhoods, and local transition rules. The physical environment in which CA is applied for modeling traffic flow is obviously the road segment of interest, which consists of a one-dimensional lattice for a single-lane road. The lattice and the time are discretized into equal-length cells, typically equal to the vehicle length and the driver's average reaction time, respectively. The corresponding speed increment is computed as $\Delta x/\Delta t$. The state of each cell can be 0 (empty) or 1 (occupied), with two implicit assumptions: i) typically each cell is exactly occupied by one vehicle; and ii) drivers cannot react to any events between consecutive time steps (Zheng, 2014).

Nagel and Schreckenberg (1992) made the first notable contribution to the development of a CF model using cellular automata. They introduced a stochastic discrete CA model for freeway traffic. The road is discretized into cells of fixed width (7.5 meters in Nagel and Schreckenberg (1992)). At each time step, the model updates four consecutive steps, which are performed in parallel for all vehicles:

a. Acceleration: If the velocity V of a vehicle is lower than V_{max}, and if the distance to the next car is larger than V+1, the speed is increased by one [$V \rightarrow V$+1].
b. Deceleration: If a vehicle at cell i finds the next vehicle at cell i+j (with j≤V), it reduces its speed to j-1 [V→j-1].
c. Randomization: With probability p, the non-zero velocity of each vehicle is decreased by one [V→V-1].
d. Car motion: Each vehicle is advanced by V cells.

Although the discreteness of the model does not correspond directly to any property of real traffic, this simple model shows nontrivial and realistic behavior of traffic flow.

Krauss et al. (1996) argue that the discrete nature of the Nagel-Schreckenberg model hides many of its interesting features (for example, vehicle spacing cannot be less than the width of one cell, difficult to calibrate with real data etc.). Thus, they present a continuous version of the Nagel-Schreckenberg model, as shown in Equation (2.23).

$$\begin{aligned} \tilde{V}_n(t+1) &= \min\left[V_n(t) + a_{\max}, V_{\max}, S_{gap}(t)\right] \\ V_n(t+1) &= \max\left[0, \left(\tilde{V}_n(t+1) - b_{\max}, \eta_{ran,0,1}\right)\right] \\ x_n(t+1) &= x_n(t) + V_n(t+1) \end{aligned} \tag{2.23}$$

where $\tilde{V}_n$ is the desired speed, $a_{\max}$ is the maximum acceleration, $b_{\max}$ is the maximum deceleration, S_{gap} is the free space to the vehicle ahead, and $\eta_{ran,0,1}$ is a random number in the interval (0,1). Some randomness due to deceleration noise is considered when calculating the speed of the vehicle in each time step.

Krauss et al.'s (1996) continuous version of the Nagel-Schreckenberg model generates similar dynamics to those in the Nagel-Schreckenberg model except at high densities. Furthermore, unrealistic deceleration is observed because the safe velocity is calculated using the gap between two consecutive vehicles. To overcome this problem, Krauss and Wagner (1997) developed a model (known as S-K model), as shown in Equation (2.24)

$$\begin{aligned} V_n^*(t+1) &= \min\left[V_n(t) + a_{\max}, V_{\max}, V_{safe}\right] \\ V_0(t+1) &= V_n^*(t+1) \\ &\qquad - \epsilon\left(V_n^*(t+1) - (V_n(t) - b_{\max})\right) \\ V(t+1) &= V_{ran,V_0,V_n^*} \\ x_n(t+1) &= x_n(t) + V_n(t+1) \end{aligned} \tag{2.24}$$

where V_n^* is the optimal velocity, V_{ran,V_0,V_n^*} is a random term between the optimal velocity and the deviation from the optimal velocity V_0, ε is the parameter determining the deviation from the optimal velocity, V_{safe} is a safe velocity below which no crashes are generated. The main difference between the Nagel-

Schreckenberg model and the S-K model is that the S-K model calculates V_{safe} based on maximum allowable deceleration (as adopted from Gipps' model). It is reported that the S-K model outputs more realistic traffic characteristics at the macroscopic level. (For a detailed review of other CA-based CF models, see Maerivoet and De Moor, 2005.)

2.3. Car-following models: The Human perspective

The aforementioned Engineering CF models mostly focus on a driver's physical signals, rather than on their psychological reactions. Boer (1999) criticizes the inability of these models to explain human driving behaviors during CF. This is because they assume that: (i) drivers aim for optimal performance; (ii) driving is equivalent to the continuous application of a single control law; (iii) drivers use inputs that they may not be able to perceive, but are somehow able to compute; and that (iv) everything that cannot be explained by the model is noise, and can be attributed to perceptual and control limitations.

Most of the Engineering CF models provide no psychologically plausible characterization of how humans think about, and address, the driving problem. In normal and often complex driving situations, humans adopt strategies that are adequate rather than optimal because of their incomplete knowledge or insufficient time to evaluate all possible alternatives. If the current driving situation is acceptable, there is no reason to look for, and evaluate, alternatives; for example, if the speed is acceptable, there is no need to accelerate or waste resources to look for opportunities to overtake. This phenomenon contradicts traditional CF models where optimality requires that drivers expend all resources on trying to improve performance (Boer, 1999; Hancock, 1999). These criticisms of Engineering CF models are supported by the findings detailed below.

First, the surrounding environment plays an important role in close-following situations (such as urban areas and traffic congestion). In these situations, it is unlikely that drivers drive with the worst-case safety assumptions in mind. For example, despite the suggested minimum headway of 2 sec, 95.8% of drivers follow a headway less than 2 sec, and 47.9% have headways even less than 1 sec on the M27 motorway in UK (Brackstone et al., 2002). Similar situations have been observed on German freeways, where prevalent headways are 0.9 ~ 1 sec; in some instances, headways are found to be as low as 0.3 sec (Treiber et al., 2006). Research suggests that the surrounding environment (i.e. considering next-nearest neighboring vehicles, visual distractions, etc.) can have a significant influence on driver's confidence and driving behavior (Muhrer and Vollrath, 2011; Treiber et al., 2006). Therefore, the surrounding environment should be considered in CF models.

Second, each driver and driving style is different. Age and gender, for example, affect a driver in his/her perception of risky driving situations. A survey of drivers from Alabama, US, for example, shows that male teenagers engage more frequently in risky driving situations (e.g. close following, driving faster than the speed limit, etc.) than female adult drivers (Rhodes and Pivik, 2011). Ossen and Hoogendoorn (2011) found that considerable differences exist between the car-following behaviors of passenger car drivers. They observed clear differences in desired spacing and desired time headways among the drivers. Driver heterogeneity is also observed among car drivers and truck drivers where the latter group in general appears to drive with a more constant speed. Use of intelligent transportation systems and cooperative systems also influences driving styles (Farah et al., 2012).

Meanwhile, driving needs may also influence driving styles. Boer and Hoedemaeker (1998) categorize driving needs into 'motivational' and 'constraining' situations. Motivational driving involves situations such as the need to get somewhere fast or the enjoyment of high speed or pleasure (e.g., favoring certain routes, enjoying the surroundings), whereas constraining situations can be related to safety, workload, economic cost, social compliance and the need for comfort (in terms of acceleration and jerk).

Finally, a list of human factors based on the literature (e.g., Hamdar, 2012; Treiber and Kesting, 2013) is presented here:

a. Socio-economic characteristics (e.g., age, gender, income, education, family structure)
b. Reaction time
c. Estimation errors: Spacing and speeds can only be estimated with limited accuracy

d. Perception threshold: Human cannot perceive small changes in stimuli
e. Temporal anticipation: Drivers can predict traffic situation for the next few seconds
f. Spatial anticipation: Drivers consider the immediate preceding and further vehicles ahead
g. Context sensitivity: Traffic situation may affect driving style
h. Imperfect driving: For the same condition drivers may behave differently in different times
i. Aggressiveness or risk-taking propensity
j. Driving skills
k. Driving needs
l. Distraction
m. Desired speed
n. Desired spacing
o. Desired time headway

This section reviews the notable developments in attempts to incorporate these various human factors into the Engineering CF models.

2.3.1. Use of perceptual thresholds

Engineering CF models unrealistically assume that drivers can perceive and react even to small changes in the driving environment (for example, to slight change in speed difference or spacing). To overcome this problem, Wiedemann (1974) introduces the term ‘perceptual threshold’ to define the minimum value of the stimulus a driver can perceive and will react to. The models based on perceptual threshold are also known as ‘psycho-physical’ models. The threshold is expressed as a function of speed difference and spacing between the preceding and subject vehicles, and is different for acceleration and deceleration decisions. It increases driver alertness when spacing is small, and provides more freedom when it is large. An example of the distribution of the thresholds is shown in Figure 2.1. The thresholds are defined as:

AX The desired spacing between the front sides of two successive vehicles in a standing queue

BX The desired minimum following distance, which is a function of AX, the safety distance, and speed

SDV The action point where a driver consciously observes that he/she is approaching a slower leading vehicle; SDV increases with increasing speed difference

CLDV Closing delta velocity (CLDV) is an additional threshold that accounts for additional deceleration by the application of brakes

OPDV The action point where a driver notices that he/she is slower than the leading vehicle and starts to accelerate again

SDX A perception threshold to model the maximum following distance, which is approximately 1.5–2.5 times BX

The dark line in Figure 2.1 shows the decision path of an approaching vehicle. A vehicle travelling faster than the leader will get close to it until the deceleration perceptual threshold (SDV) is crossed (at Point A). The driver will then decelerate to match the leader's speed. However, as a human being, the driver is unable to accurately replicate the leader's speed, and spacing will increase until the acceleration perceptual threshold (OPDV) is reached (at Point B). The driver will again accelerate to match the leader's speed and the process continues, as shown in the unconscious reaction zone.

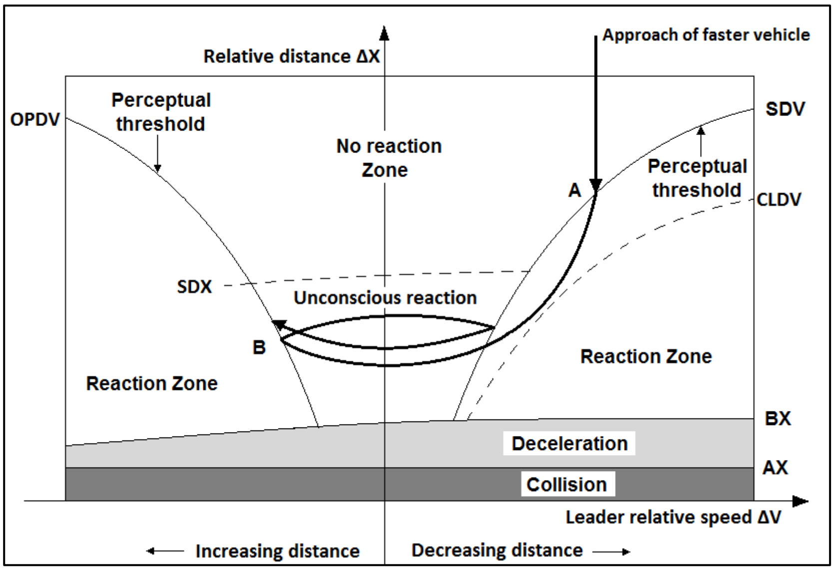

Figure 2.1 Wiedemann's CF model

(Source: Wiedemann, 1974)

A modified version of the original Wiedemann model has been used in the commercial microsimulation software VISSIM (Fellendorf and Vortisch, 2010). Several calibration attempts for VISSIM model exist in the literature. For example, Park and Qi (2006) used Genetic Algorithm (Goldberg, 1989) to estimate model parameters; Gomes et al. (2004) manually calibrated four driver behavior parameters (among ten) while kept the others as default; Ištoka Otković et al. (2013) used neural network approach to calibrate the model parameters; and Lownes and Machemehl (2006) conducted sensitivity analysis of the simulation capacity output under various driver behavior parameters.

In a similar CF model by Fritzsche (1994), the CF plane is divided into five regions, as shown in Figure 2.2. For clarity, the figure is drawn for a CF case with two vehicles where the preceding vehicle is travelling at 20 m/s.

PTN Perception Threshold Negative is the negative relative speed, i.e. $\mathrm{V_n} > \mathrm{V_{n-1}}$.

PTP Perception Threshold Positive is the positive relative speed, i.e. $\mathrm{V_n} < \mathrm{V_{n-1}}$.

AD Desired distance threshold represents a comfortable driving distance: $\mathrm{AD} = \mathrm{A_0} + \widetilde{\mathrm{T}}.\mathrm{V_n}$, where A0 is the standstill distance from the leader and $\widetilde{\mathrm{T}}$ is the desired time headway.

AR Risky distance threshold is defined for conditions when spacing is too small for comfortable driving: $\mathrm{AR} = \mathrm{A_0} + \mathrm{T_f}.\mathrm{V_{n-1}}$, where Tf is a fixed time headway with a magnitude of 0.5s.

AS Safety distance threshold represents situations when the follower realizes that he/she decelerates too much and reaches a safety distance with a positive speed difference. The follower then accelerates to match the leader's speed: $\mathrm{AS} = \mathrm{A_0} + \mathrm{T_s}.\mathrm{V_n}$, where $\mathrm{T_s}$ is the safe time headway, and is considered as 1s. The model requires that $\widetilde{\mathrm{T}} > \mathrm{T_s} > \mathrm{T_f}$.

AB Breaking distance threshold is an additional threshold applied to avoid collisions that might occur at high speeds.

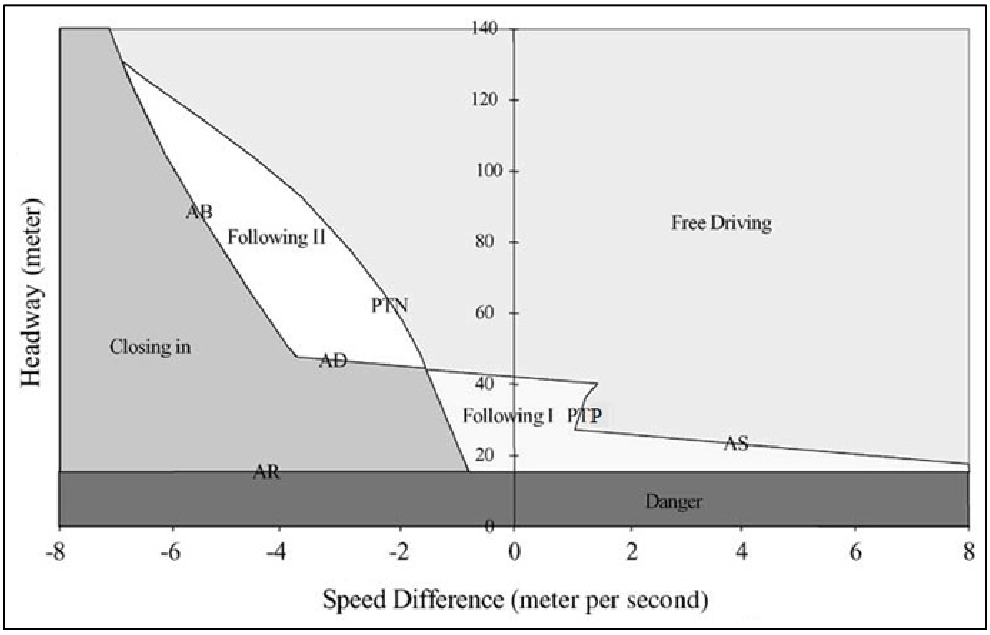

Figure 2.2 The CF phase diagram

(source: Fritzsche, 1994)

These six thresholds divide the phase space into five regions: Danger, Closing in, Following I, Following II, and Free Driving. According to the model, a follower will decelerate only when he/she is in either 'Danger' or 'Closing in' regions.

Brockfield et al. (2004) presented a calibration attempt for Fritzche (1994) model with vehicle trajectory data using a gradient-free optimization method known as "downhill simplex" (Lagarias et al., 1998). However, the estimation results are not reported.

Fancher and Bareket (1998) propose an extension of the psycho-physical model (Wiedemann, 1974) by introducing a comfort zone which is used when a driver is within ±12% of the desired spacing. Being unable to perceive the speed difference relative to the leader, the driver will try to maintain the current speed in this zone. The free-flow zone (or no-reaction zone) is outside the comfort zone where the desired speed is maintained by the driver.

2.3.2. Driving by visual angle (DVA)

Michaels (1963) points out that visual extent or size of the preceding vehicle contributes to a driver's perception of the driving situation. Later, Gray and Regan

(1998) show that human drivers are ill-suited to estimate longitudinal distances, absolute velocities, and accelerations of other objects in the scene. Rather, they are capable of accurately estimating time to collision (TTC) based on visual angles subtended by the preceding vehicle (that is, visual angle divided by rate of change of visual angle).

The basic assumption of the visual angle model is given by Michaels (1963) who states that when drivers are approaching a vehicle in front, they perceive the situation from the changes in the apparent size of the vehicle. More specifically, the relative speed is perceived through the changes in the visual angle subtended by the preceding vehicle. The visual angle (θ_n) can be calculated using Equation (2.25):

$$\theta_n(t) = 2\arctan\left(\frac{W}{2S_n(t)}\right) \approx \frac{W}{S_n(t)} \tag{2.25}$$

The angular velocity is found by differentiating this equation with respect to time *t*, as shown in Equation (2.26)

$$\frac{\mathrm{d}}{\mathrm{dt}}\theta_n(t) = -W\frac{\Delta V_n(t)}{(S_n(t))^2} \tag{2.26}$$

where W is the width of the preceding vehicle, S_n is the spacing between the preceding and the subject vehicles, measured from the front edge of the subject vehicle to the rear end of the preceding vehicle, and ΔV_n is the relative speed between the two vehicles.

Visual angle is used to replace relative spacing from the preceding vehicle, and angular velocity is used to replace relative velocity (or speed difference) in several Engineering CF models. As shown in Equation (2.27), Andersen and Sauer (2007) modified Helly's (1959) model by using visual angle as the stimuli. They call this model 'Driving by Visual Angle' (DVA)

$$a_n(t) = \alpha\left(\frac{1}{\theta_n(t)} - \frac{1}{\tilde{\theta}_n(t)}\right) + \lambda\frac{\mathrm{d}}{\mathrm{dt}}\theta_n(t) \tag{2.27}$$

where θ_n is the visual angle extent of the preceding vehicle; $\tilde{\theta}_n$ is the desired visual angle subtended by the preceding vehicle; $d\theta_n/dt$ is the rate of change in the visual angle; and α, λ are constants. The desired distance headway (or desired visual angle) should vary with speed, and is estimated by using the following formula

$$\tilde{\theta}_n(t) = 2\arctan\left(\frac{W}{\tilde{T}_n(t) \cdot V_n(t)}\right)$$

where $\tilde{T}_n$ is the desired time headway, and V_n is the speed of the subject vehicle. The simulation based on the DVA model produces similar speed and acceleration profiles, as observed from the actual driving situation. However, drivers' reaction time is ignored in the model, and a constant $\tilde{\theta}_n$ is used for simplicity in the simulation.

In a similar study, Jin et al. (2011) modified the full velocity difference (FVD) model (described in Section 2.2.4) using visual angle, as defined in Equation (2.28)

$$a_n(t) = \alpha[V_n^*(\theta_n(t)) - V_n(t)] - \lambda \frac{\mathrm{d}}{\mathrm{dt}} \theta_n(t) \tag{2.28}$$

where $d\theta_n/dt$ is the rate of change in the visual angle, α and λ are sensitivity coefficients. V_n^* is the optimal velocity a driver prefers based on the visual angle subtended by the preceding vehicle, and can be calculated as

$$V_n^*(\theta_n(t)) = V_1 + V_2 \tanh(C_1 S_n(t) - C_2)$$

where S_n is the spacing between the two vehicles; and V_1, V_2, C_1, C_2 are parameters. Basically, this model is a conversion of the original FVD model, using visual angle. The authors have used the same parameter values to calculate V_n^* as were used in the FVD model.

Selecting an appropriate visual angle threshold, however, can be challenging. According to Michaels and Cozan (1963), the visual angle threshold ranges between 0.0003 to 0.001 rad/sec, with an average of 0.0006 rad/sec. If we consider a preceding vehicle's width of 1.8m and a speed difference of 10 km/hr, a threshold value of 0.0006 rad/sec indicates that a driver can detect a change in angular velocity subtended by the preceding vehicle when the relative spacing is less than 91 meters. Ferrari (1989) assumes a fixed angular velocity threshold (i.e., 0.0003 rad/sec), with the minimum time headway between two successive vehicles of 1sec, for his traffic simulation model. However, in a study of 60 drivers, Hoffmann and Mortimer (1996) found that subjects were not able to perceive the relative velocity or to make reasonable estimations of TTC if the angular velocity was less than 0.003 rad/sec.

2.3.3. Driver risk-taking, distraction, and error

Drivers' risk-taking behavior, distraction, and error in crash-prone and other extreme situations are probably the least explored topics in the CF modeling literature. In this section, notable efforts to consider these factors in CF modeling are reviewed.

2.3.3.1. Use of Prospect Theory to model risk-taking behavior

The cognitive process of driving in risk-taking situations involves perception, judgment and execution of a particular decision strategy (for example, braking or lane-changing). This process can be treated as a human decision-making problem where variables such as surrounding traffic, the environment, and the nature of the drivers themselves (of varying age, gender, driving experience, and risk attitude) are likely to affect driving choices.

The expected utility theory (Neumann and Morgenstern, 1949) for decisions under risk is the basis for modern decision-making theories. However, inconsistency between the actual decisions made and the decisions predicted by the utility theory led to the need to develop more realistic models to describe actual decision processes. In particular, prospect theory by Kahneman and Tversky (1979) is a well-accepted descriptive model that captures human decision making when there is the possibility of risky outcomes.

Hamdar et al. (2008) and Hamdar et al. (2014) develop a driver behavior model based on Kahneman and Tversky's (1979) prospect theory. Specifically, their model considers driving as a sequential risk-taking task. In their model, Kahneman and Tversky's prospect theory provides the theoretical and operational basis for weighing a driver's alternatives. The main variable of interest in the model is the subjective probability ($p_{n,i}$) of being involved in a rear-end collision with the preceding vehicle. This probability depends on acceleration, spacing, and speed difference, as shown in Equation (2.29)

$$p_{n,i} \approx p_n(t + \hat{\tau}_n) = \phi\left(\frac{\Delta V_n(t)\hat{\tau}_n + 0.5a_n(\hat{\tau}_n)^2 - S_n(t)}{\sigma(V_{n-1})\hat{\tau}_n}\right) \tag{2.29}$$

where $\hat{\tau}_n$ is the anticipation time span, S_n denotes spacing from the preceding vehicle, and $\phi(z)$ is a cumulative distribution function for the standardized Gaussian.

The gains (or losses) in this model are expressed in terms of increase (or decrease) in speed from the previous acceleration instance, and are constrained by the maximum desired speed of the driver and non-negativity of speed. The value function explaining the gain or loss using prospect theory is defined as in Equation (2.30)

$$U_{PT}(a_n) = x[w + 0.5(1 - w)(\tanh(x) + 1)](1 + x^2)^{0.5(\gamma-1)} \tag{2.30}$$

where $x = a_n/a_0$; γ (non-negative) is the non-negative sensitivity parameter, a_0 is an acceleration normalizing factor (set to 1m/s^2), and w is the weight associated with negative acceleration. The driver sequentially evaluates candidate accelerations and eventually selects the one with the highest probability, using the following equation:

$$U(a_n) = \left(1 - p_{n,i}\right)U_{PT}(a_n) - p_{n,i}w_c k(V_n, \Delta V_n) \tag{2.31}$$

If driver n decides to accelerate at instance i, he could increase speed (considered as gain) or be involved in a rear end collision (considered as loss) with a probability of $p_{n,i}$. The loss in a probable collision is assumed to be related to two terms: a seriousness term $k(V_n, \Delta V_n)$ representing the expected consequence if a collision had occurred, and a weighting factor w_c (a higher w_c corresponds with conservative drivers, and a lower w_c with aggressive drivers). Finally, to reflect the stochasticity in drivers' responses, the selected acceleration is retrieved from the following probability density function

$$f(a_n) = \begin{cases} \dfrac{\exp[\beta \times U(a_n)]}{\int_{a_{\min}}^{a_{\max}} \exp[\beta \times U(a')]da'} & a_{\min} \leq a_n \leq a_{\max} \\ 0 & \text{otherwise} \end{cases} \tag{2.32}$$

where parameter $\beta > 0$ reflects the sensitivity of choice to the utility $U(a_n)$. It can also account for the experience of the driver, i.e. a higher number for more experienced drivers reflect more stable driving style than the style of the least experienced driver.

The proposed model allows risk-taking maneuvers when drivers are uncertain of the leader's future behavior and, consequently, crashes are possible. Talebpour et al. (2011) later extended this model to consider surrounding traffic conditions (especially congested and uncongested situations). A driver can have different preferences, and hence different responses, to the same situation because of different surrounding traffic conditions. For example, in free-flow conditions, higher acceleration rates result in higher utilities; however, in congested traffic, the perceived pressure usually discourages drivers from accelerating. Therefore, two behavioral regimes are proposed, with two different utility functions, as indicated in Equation (2.33)

$$U_{PT}(a_n) = P(C) \cdot U_{PT}^{C}(a_n) + (1 - P(C)) \cdot U_{PT}^{UC}(a_n) \tag{2.33}$$

where *P(C)* denotes the probability of a driver being in a congested regime, and depends on several factors such as speed, average spacing and average speed difference between the subject vehicle and the preceding vehicles in all lanes, and the average spacing and average speed difference between the subject vehicle and the following vehicles in all lanes; U_{PT}^{C} and U_{PT}^{UC} are utility functions for congested and uncongested traffic conditions respectively. The model was calibrated using Next-Generation Simulation (NGSIM) data (Alexiadis et al., 2004). The calibrated model shows consistency with observed phenomena in real traffic – phenomena such as: the probability of high acceleration rates decreases with an increase in density; higher spacing leads to higher acceleration rates; the higher the speed, the more a driver desires to reduce speed; and, in a congested situation, drivers maintain a speed closer to the average speed of the surrounding vehicles to avoid a crash.

2.3.3.2. CF models which consider driver error and distraction

Human drivers are prone to making driving errors, which are responsible for crash in most cases. 'Human error' is a broad term that has been used rather loosely to encompass almost all the unsafe acts that lead to crashes. Reason (1990) classifies unsafe acts into two distinct classes of behavior: errors and violations. An 'error' can be defined as the failure of planned actions to achieve the desired outcome, whereas a ‘violation’ is the deliberate infringement of some regulated or socially accepted code of behavior (Parker et al., 1995). Violation can be committed for a variety of reasons and can be distinguished through the issue of intentionality. Parker et al. (1995) found that the tendency to commit driving violations is a positive predictor of crash involvement, whereas no link between error-proneness and crash involvement was found. Stanton and Salmon (2009) further categorize driver errors into five groups: action errors, cognitive and decision-making errors, observation errors, information retrieval errors, and violations. CF can be affected by any of these errors; however, how and to what extent it is affected remains elusive and requires future research. This review focuses on driver errors – especially those caused by distractions.

‘Driver distraction’ can be defined as a diversion of attention away from activities critical for safe driving to a competing activity (Lee et al., 2008). ‘Distraction’ is also described as multi-task driving which reduces attention to driving itself. Studies have shown that multitasking while driving deteriorates driving performance, increases reaction time, and impacts lateral lane position and vision. This, in turn, poses serious safety hazards on the roads where 10% to 80% of reported crashes are related to distracted driving (McEvoy and Stevenson, 2007; Przybyla et al., 2012; Stutts, 2003). In a recent review of driver distraction, Young and Salmon (2012) explain how distraction could be responsible, at least to some extent, for most driver-related errors.

A major limitation of Engineering CF models is that they are designed to produce crash-free environments for the convenience of microscopic traffic simulations. However, crash-free environments are not always desirable, for example, for the study of extreme situations in safety analysis, and for the measurement of the effectiveness of in-vehicle active safety technology. Hamdar and Mahmassani (2008) explored six well-known Engineering CF models to observe their behaviors in crash-prone situations by relaxing their safety constraints. They simulated 3600 vehicles on a 10 km highway in a 2-hour period, and their findings are summarized in Table 2.1.

Table 2.1 Crash statistics of six CF models after relaxing safety constraints

(Source: Hamdar and Mahmassani, 2008)

Model	Modification of the safety constraint	Result
GHR model	The sensitivity term λ is treated as a random variable with a normal distribution ($\lambda_{mean} = C/\Delta X_n$; λ_{std} =0.1, where C is a constant). However, this modification alone did not cause any crashes. Crashes were created when ΔV_n was treated as a normally distributed random variable with mean as ΔV_n, and standard deviation of 0.5.	A complete flow break-down with the occurrence of 561 crashes
Gipps' model	Gipps' model has a safety constraint $x_{n-1} - s_{n-1} > x_n$, where s_{n-1} is the safety distance. A normally distributed random risk term D_n is subtracted from s_{n-1} so that the safety distance can be negative to allow crashes to occur.	The normally distributed random risk term $D_n$with mean 0.1 and std 0.1 created 42 crashes.
Continuous version of CA model (Krauss et al., 1996)	The safety constraint is relaxed by allowing $V_{max} = s_{gap}$, and by allowing speed to be equal to $s_{gap} + 0.1$meter.	29 crashes were produced. Unrealistically high deceleration rates were observed.
S-K model	V_{safe} in the S-K model is increased by 0.27 m/s; however, no crashes were generated until V_{safe} was increased to 0.45m/s.	A total of 2013 chain type crashes occurred, and occupied most of the 10 km highway.
IDM and IDMM	In the IDM model, the last term in the desired spacing $\frac{V_n(t)\Delta V_n(t)}{2\sqrt{a_{\max}a_{\mathrm{comf}}}}$ creates the safety buffer. The safety buffer was removed to create crashes.	A complete traffic breakdown with 1211 crashes for IDM and 674 crashes for IDMM were observed
Wiedmann model	The emergency braking mode is used to prevent crashes. This mode was replaced by a normal mode of deceleration, and the safety constraint was removed from the desired spacing threshold (BX) to generate crashes.	17 chain-type crashes were observed.

With these modifications, the Wiedemann, Gipps and CA models showed more stable behavior compared to the GHR, S-K and IDM/IDMM models, although the number of crashes is unrealistically high. These findings call for a richer representation of the cognitive process in the Engineering CF models, in order to produce realistic crash-causing behavior.

To more effectively incorporate human behavioral considerations into Engineering CF models, Van Winsum (1999) extended Helly's (1959) desired spacing model. The proposed model captures human behavior through the desired time headway, assuming that there could be substantial differences in the desired time headway between drivers that reflect variables such as driving conditions and mental effort. For example, less skilled drivers generally choose to drive with larger time headways to avoid collisions. Heino (1996) found that a driver's mental effort increases (as indicated by a reduction in heart rate variability) when the time headway is smaller than the preferred one. Van Winsum (1999) modified the desired spacing in Helly's model as

$$\widetilde{\Delta X}_n = \tilde{T}_n \cdot V_n$$

where $\tilde{T}_n$ denotes the desired time headway, which can be influenced by visual conditions (such as fog, rain and night driving), driver state (such as fatigue and inebriation), and the mental effort deployed in following the preceding vehicle. When the distance to the preceding vehicle is smaller than desired, the driver is assumed to decelerate until $\widetilde{D}_n$ is reached. Van Winsum (1999) also shows that, in response to the preceding vehicle's deceleration, the subject vehicle decelerates with a rate as shown in Equation (2.34)

$$b_n = \alpha.e.\left[\Delta X_n \Big/ \sqrt{2b_{n-1}\left(\widetilde{\Delta X}_n - \Delta X_n\right)}\right]^f + \beta + \varepsilon \tag{2.34}$$

where b_{n-1} is the deceleration of the preceding vehicle; ϵ is a random error term, and α, β, e, f are parameters. The use of the preceding vehicle's deceleration can be problematic and is rare in the CF literature because it is very difficult for the driver to measure it. Rather, Gipps (1981) uses the driver's estimated deceleration of the preceding vehicle. The model only covers the negative acceleration of the driver. An acceleration algorithm for the model is proposed by Wang et al. (2011), and is shown in Equation (2.35)

$$a_n = \alpha\left(\Delta X_n / \widetilde{\Delta X}_n\right) + \beta(\Delta V_n) + \lambda + \varepsilon \tag{2.35}$$

where α, β are constants; λ represents the influence of driving purpose and driving habit; other variables are the same as those for Equation (34). However, acceleration's direct dependency on distance can lead to unrealistic acceleration rates. The model has not been tested using real data.

Treiber et al. (2006) point out that the majority of Engineering CF models (such as OVM, FVD and IDM) produce unrealistic dynamics and crashes during simulation. Therefore, they compensate for the destabilizing effects of reaction times and estimation errors (in ΔV, TTC) by considering the spatial and temporal anticipations of the driver. More specifically, Treiber et al. (2006) propose four extensions to IDM: finite reaction times, estimation errors, spatial anticipation, and temporal anticipation. They call their model the 'Human Driver (meta-) Model' (HDM). In this model, the driver is aware of the surrounding traffic environment and can modify their driving behavior accordingly.

Przybyla et al. (2012) extend Newell's (2002) simplified CF model to accommodate the impact of distractions on driving. They assume that the distracted driver continues to drive at the constant speed (attained in the previous time step) throughout the distracted event. Their model divides the driver's trajectory into two types: the trajectory followed by a perfect driver (in other words, a perfect follower who can be described by Newell's model), and the trajectory followed by a distracted driver. However, they further assume that the driver is either distracted or not distracted for the entire trajectory. This could be problematic in representing actual behavior.

Bevrani and Chung (2012) improve Gipps' (1981) model by considering human imperfection in processing information and executing actions. More specifically, they include human perception limitations in detecting speed differences, extra delay in driving phase changes (assuming that reaction time increases after being in a fixed situation; that is, either in a constant speed or in an acceleration phase), and driver imperfection in adjusting speeds. However, human errors, such as distraction and risk taking, are omitted in their model.

An error-able CF model is proposed by Yang and Peng (2010). For the evaluation of active safety technologies (AST), they propose a stochastic CF model with an error mechanism derived from the Road-Departure Crash-Warning System Field Operational Test (RDCW), a large-scale naturalistic driving database. The model calculates the desired acceleration of the driver as a function of following distance, speed difference, and/or time headway. It also considers uncertainties in calculating the final acceleration, assuming that when the following distance is large, the driver cannot perceive accurately and has more room to deviate. The Yang and Peng (2010) model is represented by Equation (2.36)

$$\begin{aligned} \tilde{a}_n(t) &= f_{\tilde{a}_n}\left(\Delta X_n(t), \Delta V_n(t), T_n\right) \\ a_n(t) &= f\left(\tilde{a}_n(t), \sigma\right) \end{aligned} \tag{2.36}$$

where $\tilde{a}_n$ is the desired acceleration, and σ captures the deviation. The model's parameters are calculated from the RDCW database. Three major types of driving errors are introduced: perceptual limitation, time delay, and distraction. The human perception limitation is implemented based on the same method as the one described in Section 2.3.1: the introduction of the minimum threshold of speed difference that a driver can detect and will respond to. Time delay is estimated through a recursive least square identification process, and distraction is identified based on the statistical analysis of the RDCW data. The frequency and duration of distraction are also estimated. During distraction, the model continues to use the information from the previous time step without updating it.

2.4. Conclusions and discussions

This paper presents a review of the state-of-the-art of CF modeling from two different perspectives: the engineering perspective and the human factor perspective. Representative models of each perspective have been reviewed. The main features of these models (including their strength and weakness) are also summarized in Table 2.2 and Table 2.3, respectively. Compared with previous reviews of CF models, the paper is unique in that it provides a comprehensive review of notable attempts to incorporate human-factors in CF models through various approaches, such as visual angle-based models, and models that consider driver risk taking, distraction, and driver errors.

This review is an important step in advancing CF modeling, as the disregard of human factors (such as perceptional limitation, risk-taking behavior, error, and distraction) in the current CF models means that they are unrealistically over-simplified. Overall, the main limitation of the Engineering CF models is that they do not reflect the psychologically plausible characterization of how humans think about, and accomplish, driving tasks. For example, they do not capture the interdependencies among the decisions made by the same driver over time, or the effect of the surrounding environment (such as visibility and surrounding vehicle dynamics). The models represent instantaneous decision-making, which underestimates a driver's planning and anticipation capabilities, while overestimating their ability to evaluate all possible alternatives and to achieve an optimal level of driving performance. This, in turn, means that they are unsuited to the investigation of important issues which demand fine representations of driver behaviors. These issues include the analysis of crash-prone traffic conditions; the understanding of widely-reported puzzling phenomena such as capacity drop, stop-and-go oscillations, and traffic hysteresis; the microscopic analysis of traffic dynamics; and the development and evaluation of advanced vehicle control and safety systems.

Note that there are many (commercial or free) microscopic simulation software packages available based on various CF theories. For a detail review on popular microscopic simulation packages, see Barceló (2010). Although some of these simulation packages attempted to account for human behavior features (e.g., a reaction time distribution and perceptual thresholds are used in VISSIM and PARAMICS), many human factors which are crucial for describing human car-following (CF) behavior are, by and large, ignored (e.g., driving error, distraction, and risk-taking behavior).

To conclude this paper, common issues and research needs (in the authors' opinion) in data collection, model development, model calibration and validation in modeling CF are summarized below.

Data collection: Fully incorporating human factors into the Engineering CF models pose challenges in data collection. The primary data source used for developing CF models is loop detector data or trajectories at best, which can only provide basic vehicular information. Driver characteristics, which are critical for deciphering drivers' thinking processes during the CF procedure, cannot be extracted from this type of data. This serious data limitation often leads to the fact that human factors are usually over-simplified in the few CF models that indeed considered human factors. These models relied on only one or two parameters to indirectly capture the total impact of drivers' individual characteristics and cognitive features. Examples of these parameters are: perceptual thresholds, reaction time, visual angle, maximum desired speed, desired time headway, and etc. The model parameters related to human factors in most cases are unobservable in nature and, hence, are difficult to calibrate and validate using mainstream traffic data, which often leads to a further simplification of assuming these parameters to be constant across individuals ignoring driver heterogeneity. In our view, to obtain these model parameters, innovative data collection methods aiming to capture drivers' psychological disposition, perceptional performance, and cognitive function during CF are needed. For example, reaction time in different car-following circumstances can be observed from experiments using advanced driving simulator (see Haque and Washington (2014) as an example). Other human factors may also be obtained (completely or partially) by using driving simulator and/or from real driving experiments with instrumented vehicle. Of course, drivers in traffic flow may behave differently from what is observed from these experiments. Undesirable impact of such discrepancy can be minimized by employing advanced data analysis techniques. Unfortunately, in our extensive literature review we observed very few experiments designed for obtaining human factors critical for car-following modeling. More work in this regard is clearly needed. To get around the issue of a lack of human data, two common practices are: a) vehicle trajectory data are used to estimate some of these human factors (e.g., Brockfield et al., 2004; Park and Qi, 2006) with optimization technique; or even worse, b) values from the human factor literature or simply based on common sense are applied.

Model development: Overall, human-factor-oriented CF models are comparatively few in the literature, while Engineering CF models are predominant.

Some recent advances in CF modeling attempt to enhance the Engineering CF models by incorporating a few human psychological characteristics. However, future research on this front is in great need in this regard because many important psychological factors are still missing from these models (for example, error-able CF, distractions, driving needs, and interaction with other vehicles). To develop humanlike CF models, it is necessary to obtain a common understanding of the problem by seamlessly integrating the latest advances from both the Engineering and the human-factor-oriented CF models, bridging their gaps, and reconciling their inconsistencies. While a number of different psychological parameters are suggested by various researchers, no studies have ranked their importance in describing driver behavior in the CF situation, or attempted to accurately quantify their values. Consequently, many of the reported models simply take psychological parameters from the human factor literature without validating them within the context of CF. Meanwhile, although the need for incorporating human factors into CF models is great, adding these factors can dramatically increase the model's complexity, which underscores the importance of maintaining the balance between maximizing the model's predictive and explanatory power and minimizing the model's complexity. As recommended in Zheng (2014), factors considered in the model need to be behaviorally, empirically, and statistically justified for the target driver population. Another important and often-ignored issue in developing CF models is that the CF model should be able to be easily integrated into mainstream lane change modeling frameworks to provide a complete description of vehicular movements on road.

Calibration and validation: CF models often contain a wide range of variables, posing a significant challenge for model calibration and validation. Discussions on calibrating CF models are scattered in the literature (e.g., Brockfeld et al., 2004; Kesting and Treiber, 2008; Ossen and Hoogendoorn, 2008; Hoogendoorn and Hoogendoorn, 2010), however, guidance on the systematic and rigorous calibration and validation of traffic flow models is still lacking. The majority of the models were tested either numerically or by matching certain macroscopic traffic flow features (which, strictly speaking, can only invalidate microscopic CF models). This free-style approach causes substantial confusions, even cherry picking. In our view, a bi-level evaluation strategy should be generally preferred in developing a new CF model: at the macroscopic level, the model should be capable of explaining widely-observed traffic flow characteristics; at the microscopic level, vehicular movements should be close to actual observations (e.g., trajectories, speed profile, and acceleration profile). Furthermore, similar to lane changing models (Zheng 2014), vehicular data used for calibrating and validating CF models were mostly collected in developed countries where drivers are generally less aggressive than their counterparts in developing countries. To capture the full spectrum of CF, it is desirable to use data containing more diverse driving behaviors, particularly more aggressive driving behavior. Finally, calibrating and validating CF models containing human factors are even more challenging because of the difficulty in measuring these human factors, which often forces researchers to (over-)simplify the representations of the human factors in calibrating CF models, as discussed previously.

In summary, an improved and more comprehensive representation of human factors in CF models can lead to the next breakthrough in modeling vehicular movement on roadways. This comprehensive literature review of the state-of-the-art in the research field of human factor CF modeling is highly significant in providing a comprehensive knowledge base for this future work.

Table 2.2 Representative CF models: the engineering perspective

Model category	Model name (developers)	Model Equation	Strengths	Weakness and comments	Human factors[3] included
GHR model and their extensions	Linear CF model (Chandler et al., 1958)	$a_n(t) = \lambda.\Delta V_n(t-\tau_n)$	• Simplest model • The stability of the model is proved • Several functional form of λ is found, however the authors used λ = a as a constant.	• The model is too simple to describe actual traffic phenomena as the later models do.	• Reaction time
	Non-linear GHR model (Gazis et al. (1961)	$a_n(t) = \alpha V_n(t)^\beta \frac{\Delta V_n(t-\tau_n)}{\Delta X_n(t-\tau_n)^\gamma}$	• Simple and well-established model • Most studied model • Driver reaction time is considered • Model parameters can be easily estimated from either vehicle trajectory data or macroscopic data (using speed-density relationship) • Many estimations of the parameters are available	• Use of identical reaction time for all drivers does not capture inter-driver heterogeneity. • Human ability to perceive small changes in driving conditions are overestimated. • Model parameters do not consider behavioral differences between acceleration and deceleration.	• Reaction time

[3] Literature shows that human drivers are ill-suited to estimate longitudinal distance to preceding vehicle, absolute velocities, and accelerations of other objects in the scene (Gray and Regan, 1998). Therefore, these terms are omitted from human factors along with the speed and acceleration of the subject vehicle (these are elements of laws of motion). Similarly, maximum acceleration and deceleration are omitted as they are related to the subject vehicle's capability. All the other parameters that are to some extent related to human driving behavior are reported in this 'human factors' column.

Model category	Model name (developers)	Model Equation	Strengths	Weakness and comments	Human factors[3] included
				• The model is highly sensitive to velocity difference. When velocity difference is zero, any value of spacing is acceptable.	
	Lee (1966)	$a_n(t) = \int_0^t M(t-s)\Delta V_n(s)ds$	• Introduces memory function in the linear CF model. • The memory function makes the driver decisions consistent with the past driving profile, rather than creating instantaneous accelerations. • Removes unrealistic peaks in acceleration profile of the driver.	• The implementation of the model in traffic simulation is considerably more complex due to the need of maintaining an array of past conditions for each vehicle.	• Reaction time • Memory function to consider past driving experience
	Ahmed (1999)	See Equation (4)	• The model considers acceleration/deceleration asymmetry. • Two separate models are proposed for free flow and CF, separated by a headway threshold.	• Transition from free flow to CF and vice-versa are not smooth. • Human ability to perceive small changes in driving conditions are overestimated.	• Distribution of reaction time to consider driver heterogeneity • Acceleration/Decel

Model category	**Model name (developers)**	**Model Equation**	**Strengths**	**Weakness and comments**	**Human factors[3] included**
			• Traffic density is considered within 100m in front of the driver. • Driver heterogeneity is considered by distributing the reaction time over the driver population.		eration asymmetry • Driving condition in terms of traffic density
	Herman and Rothery (1965)	$a_n(t) = \sum_{i=1}^{m} \alpha_i \Delta V_{n,n-1}(t - \tau_n)$	• The model considers multi-vehicle interactions where driver follows more than one preceding vehicle.	• Linear CF model is used as a base model which has already been criticized for its simplicity	• Reaction time • Multi-vehicle interaction
Desired measures models	Helly's model (Helly, 1959)	$a_n(t) = \alpha_1 \Delta V_n(t - \tau_n) + \alpha_2 [\Delta X_n(t - \tau_n) - \widetilde{\Delta X}_n(t)]$	• The desired space headway creates a safety buffer which prevents collision. • The desired space headway is dependent on speed and acceleration of the subject vehicle.	• Direct dependency on following distance might create unrealistically high acceleration/deceleration. • Model parameters for desired space headway are difficult to estimate as it is unobservable in usual traffic data. • Desired space headway is not	• Reaction time • Desired space headway

Model category	Model name (developers)	Model Equation	Strengths	Weakness and comments	Human factors[3] included
				driver dependent.	
	Koshi et al. (1992) and Xing (1995)	$a_n(t) = \alpha_1 \frac{\Delta V_n(t-\tau_1)}{\Delta X_n(t-\tau_1)^l} + \alpha_2 \frac{[\Delta X_n(t-\tau_2) - \widetilde{\Delta X}_n(t)]}{\Delta X_n(t-\tau_2)^m} - \gamma \sin\varphi + \lambda[\tilde{V}_n - V_n(t-\tau_3)]$	• Direct dependency on following distance is solved. • The model has four stages: standard driving, acceleration from standing queue, effect of gradient and free flow acceleration.	• While the physical condition of the road in terms of gradient is considered, horizontal curvature effect is neglected. • No estimation effort is found.	• Reaction time • Desired space headway • Desired speed
	IDM (Treiber et al., 2000) IDMM (Treiber and Helbing, 2003) HDM (Treiber et al., 2006)	$a_n(t) = a_{\max}^{(n)}\left[1 - \left(\frac{V_n(t)}{\tilde{V}_n(t)}\right)^{\beta} - \left(\frac{\tilde{S}_n(t)}{S_n(t)}\right)^2\right]$	• This model considers both the desired speed and the desired space headway. • The desired space headway depends on speed, speed difference, minimum spacing, maximum acceleration, comfortable deceleration and desired time headway. • The model considers vehicle capacity. • Several attempts are found for calibration of the model.	• Reaction time is ignored in IDM. • Two extensions of IDM: IDMM and HDM are available. • IDMM considers driver's adaptation capability with surrounding environment to improve desired time headway calculation. • In HDM four extensions to IDM is proposed: finite reaction times,	*IDM and IDMM* • Desired space headway • Desired speed • Comfortable deceleration • Desired time headway *HDM* • Reaction time

Model category	Model name (developers)	Model Equation	Strengths	Weakness and comments	Human factors[3] included
			• The model is a combination of free-flow and CF model. • The transition between free-flow and CF model is smooth.	estimation errors, spatial anticipation, and temporal anticipation.	• TTC estimation error • Multi-vehicle interaction • Relative distance error
Safety distance models	Kometani and Sasaki (1959)	$\Delta X_n(t-\tau_n) = \alpha V_{n-1}^2(t-\tau_n) + \beta V_n^2(t) + \gamma V_n(t) + d$	• The model seeks to specify a safe following distance. • The model parameters are estimated. • The parameter d prevents the model from collision.	• Does not describe stimulus-response type function as most of the other models.	• Reaction time
	Newell (1961)	$V_n(t) = V_{\max}\left[1 - \exp\left(\frac{-\lambda(\Delta X_n(t-\tau_n)+d)}{V_{\max}}\right)\right]$	• It is a non-linear model and follows stimulus-response type function.	• Direct dependency on density might result in unrealistic accelerations or decelerations.	• Reaction time
	Gipps (1981)	Equation (13)	• The model use a safety distance which prevents collision • Separate model for free-flow and CF	• Although many behavioral parameters used, the model does not consider driver errors.	• Reaction time • Desired acceleration

Model category	Model name (developers)	Model Equation	Strengths	Weakness and comments	Human factors[3] included
			• The transition between free-flow and CF is smooth unless the preceding vehicle brakes harder than anticipated, preceding vehicle changes the lane or a new vehicle enters in front of the subject vehicle from adjacent lane. • It offers driver heterogeneity through distribution of behavioral parameters. • (Vehicle size + safety distance) follows a normal distribution.	• How the parameter values are estimated/selected is not explained	• Desired deceleration • Estimation of preceding vehicle's deceleration • Desired speed
Optimal velocity model	OV model (Bando et al., 1995) (Bando et al. (1998)	$a_n(t) = \alpha\left[V_n^*\left(\Delta X_n(t)\right) - V_n(t)\right]$ $a_n(t) = \alpha\left[V_n^*\left(\Delta X_n(t - \tau_n)\right) - V_n(t - \tau_n)\right]$	• The optimal velocity (OV) depends on the distance from the preceding vehicle. • The model was estimated by Helbing and Tilch (1998).	• Driver reaction time is ignored in this version but later introduced in Bando et al. (1998). • The model produces unrealistic acceleration and decelerations. • The model is unrealistically sensitive to reaction time.	• Reaction time

Model category	Model name (developers)	Model Equation	Strengths	Weakness and comments	Human factors[3] included
	GF model (Helbing and Tilch (1998)	$a_n(t) = \alpha\left[V_n^*\left(\Delta X_n(t)\right) - V_n(t)\right] + \lambda\left(\Delta V_n(t)\right) \cdot H\left(-\Delta V_n(t)\right)$	• Heaviside function (H) works at negative velocity difference and solves the problem of unrealistic deceleration that occurs in OV model. • Model parameters are estimated from real data.	• The model still produces unrealistic accelerations. • Driver reaction time is ignored.	NA
	FVD model (Jiang et al., 2001)	$a_n(t) = \alpha\left[V_n^*\left(\Delta X_n(t)\right) - V_n(t)\right] + \lambda\left(\Delta V_n(t)\right)$	• Velocity difference is included explicitly to overcome unrealistic accelerations/decelerations	• Having a single parameter for both acceleration and deceleration might lead to an unrealistic situation where the subject vehicle brakes insufficiently, even if the distance to the preceding vehicle is extremely short. • Driver reaction time is ignored • No estimation of the model parameters are found, neither the model is applied on real data.	NA

Model category	Model name (developers)	Model Equation	Strengths	Weakness and comments	Human factors[3] included
	AFVD model (Gong et al., 2008)	$a_n(t) = \alpha\left[V_n^*\left(\Delta X_n(t)\right) - V_n(t)\right] + \lambda_1\left(\Delta V_n(t)\right) \cdot H\left(-\Delta V_n(t)\right) + \lambda_2\left(\Delta V_n(t)\right) \cdot H\left(\Delta V_n(t)\right)$	• The model uses different responses in acceleration and deceleration as an improvement over FVD model.	• AFVD model takes longer time than FVD model to gain stability. • Numerical simulation is done but the model is not yet applied on real data and the parameters are not estimated.	NA
	Lenz et al. (1999)	$a_n(t) = \sum_{i=1}^{m} \alpha_i \left[V_n^*\left(\frac{\Delta X_{n,n-i}(t)}{i}\right) - V_n(t)\right]$	• The model considers multi-vehicle interactions which increases the model's stability.	• Driver reaction time is ignored • Numerical stability analysis is performed, but the model parameters are not estimated.	NA
	Davis (2003)	$a_n(t) = \alpha\left[V_n^*\left(\Delta X_n(t-\tau_n) + \tau_n \Delta V_n(t-\tau_n)\right) - V_n(t)\right]$	• The OV function is extended to consider the change in velocity difference as well as headway. • Unrealistic sensitivity to reaction time is solved.	• Although the OV function is measured at time $(t - \tau_n)$, the velocity is measured at time t, which needs a behavioral justification.	• Reaction time

Model category	Model name (developers)	Model Equation	Strengths	Weakness and comments	Human factors[3] included
Newell's simplified CF model	Newell (2002)	$x_n(t+T) = \min\begin{cases} x_n(t) + Tu, \\ x_{n-1}(t) - \delta \end{cases}$	• It is a parsimonious model (only two parameters are required). • The model can express macroscopic flow theory very well. • The model has been extended to capture traffic oscillation.	• The model is purely based on traffic flow theory. • No driver behavior parameters are available.	NA
Cellular Automata (CA) models	Nagel and Schreckenberg (1992) Krauss et al. (1996)	Equation (23)	• Randomness in speed is implemented to accommodate deceleration noise • The discrete version by Nagel and Schreckenberg (1992) was difficult to calibrate with real data, hence the continuous version is proposed by Krauss et al. (1996) as shown in the equation presented in this table.	• Unrealistic deceleration is observed at high densities. • Driver reaction time is ignored. • Although the discreteness of the model does not correspond directly to any property of real traffic, the model shows nontrivial and realistic behavior of traffic flow at the macroscopic level.	NA

Model category	**Model name (developers)**	**Model Equation**	**Strengths**	**Weakness and comments**	**Human factors[3] included**
	S-K model (Krauss and Wagner, 1997)	Equation (24)	• Unrealistic deceleration problem of Krauss et al.'s (1996) model is solved by replacing Sgap with Vsafe. • Vsafe is calculated based on maximum allowable deceleration. • S-K model outputs more realistic traffic characteristics at the macroscopic level than Krauss et al.'s (1996).	• Driver reaction time is ignored	NA

Table 2.3 Representative CF models: the human factor perspective

Model category	Model name (developers)	Model Equation	Strengths	Weakness and comments	Human factors included
Use of perceptual thresholds	Wiedemann (1974) Fritzsche (1994)	NA	• Perceptual thresholds selects minimum value of the stimulus a driver can perceive and will react to. • The thresholds are expressed as a function of speed difference and relative spacing. • They are different for acceleration and deceleration decisions. • The thresholds divides the driving plane to several decision zones, such as 'no reaction zone' (free-flow), 'closing in', 'danger' (must decelerate), and CF.	• The thresholds are simply obtained from the human factors literature. • The equations for different thresholds are undisclosed.	• Perceptual thresholds
Driving by visual angle	DVA model (Andersen and Sauer, 2007)	$a_n(t) = \alpha\left(\frac{1}{\theta_n(t)} - \frac{1}{\tilde{\theta}_n(t)}\right) + \lambda\frac{\mathrm{d}}{\mathrm{dt}}\theta_n(t)$	• Human driver are capable of accurately estimating time to collision (TTC) based on visual angles subtended by the preceding vehicle. • Visual angle is used to replace relative spacing from the preceding vehicle, and	• Driver reaction time is ignored. • A constant value for desired velocity is used for simplicity; thus, this model ignores driver heterogeneity.	• Visual angle • Angular velocity

Model category	Model name (developers)	Model Equation	Strengths	Weakness and comments	Human factors included
			angular velocity is used to replace relative velocity. • DVA model produces similar speed and acceleration profiles, as observed from the actual driving situation		
	Jin et al. (2011)	$a_n(t) = \alpha[V_n^*(\theta_n(t)) - V_n(t)] - \lambda \frac{\mathrm{d}}{\mathrm{dt}} \theta_n(t)$	• It is the FVD model using visual angle.	• The authors used same parameter values as used for FVD model. • Driver reaction time is ignored	• Visual angle • Angular velocity
Use of Prospect Theory to model risk-taking behavior	Hamdar et al. (2008)	Equation (29), (30), (31) and (32)	• The subjective probability of being involved in a rear-end collision depends on acceleration, spacing and speed difference. • The gains (or losses) in this model are expressed in terms of increase (or decrease) in speed from the previous	• The probabilistic nature may create more acceleration noise than other models such as GHR, Gipps and IDM.	• Risk-taking behavior • Maximum desired speed • Anticipation time • Uncertainties of the preceding vehicle's

Model category	Model name (developers)	Model Equation	Strengths	Weakness and comments	Human factors included
			acceleration instance. • Final acceleration is retrieved from a probability density function to reflect stochasticity in driver's response. • The model allows risk-taking maneuvers when drivers are uncertain of the leader's future behavior and, consequently, crashes are possible.		speed • Uncertainties of the spacing • Random components of the subjective utility function • Reaction time (not explicitly included)
CF models which consider driver error and distraction	Van Winsum (1999)	$b_n =$ $\alpha . e . \left[\Delta X_n / \sqrt{2 b_{n-1} (\widetilde{\Delta X}_n} \right.$ $\beta + \varepsilon$ $\widetilde{\Delta X}_n = \tilde{T}_n \cdot V_n$	• The model assumes that the driving conditions and mental effort can make substantial difference in desired time headway. • The desired time headway can be influenced by visual conditions (such as fog, rain and night driving), driver state (such as fatigue and inebriation), and the mental effort deployed in following the	• The model use preceding vehicle's deceleration as a parameter which is really difficult to measure accurately for a human driver. Rather, Gipps (1998) uses an estimate to preceding vehicle's deceleration. • The model parameters are not	• Desired time headway • Driver reaction time • Driving condition

Model category	Model name (developers)	Model Equation	Strengths	Weakness and comments	Human factors included
			preceding vehicle.	estimated • The model is not yet tested with real data	
	Yang and Peng (2010)	$\tilde{a}_n(t) = f_{\tilde{a}_n}\left(\Delta X_n(t), \Delta V_n(t),\right.$ $a_n(t) = f\left(\tilde{a}_n(t), \sigma\right).$	• It is a stochastic CF model. • Driver error mechanism is developed from a large scale naturalistic driving database • Three major types of driver errors are introduced: perceptual limitation, time delay, and distraction.	• The effect of distraction is hypothesized as no change in driving condition during distracted period. No real experiment is done to prove the assumption. • Homogenous driving population used	• Driver reaction time • Driver distraction • Perceptual thresholds • Stochastic error behavior

References

Ahmed, K.I., 1999. Modeling drivers' acceleration and lane changing behavior. Massachusetts Institute of Technology.

Alexiadis, V., Colyar, J., Halkias, J., Hranac, R., McHale, G., 2004. The next generation simulation program. ITE Journal 74 (8), 22-26.

Andersen, G.J., Sauer, C. W., 2007. Optical information for car following: The driving by visual angle (DVA) model. Human Factors: The Journal of the Human Factors and Ergonomics Society 49 (5), 878-896.

Bando, M., Hasebe, K., Nakanishi, K., Nakayama, A., 1998. Analysis of optimal velocity model with explicit delay. Physical Review E 58 (5), 5429-5435.

Bando, M., Hasebe, K., Nakayama, A., Shibata, A., Sugiyama, Y., 1995. Dynamical model of traffic congestion and numerical simulation. Physical Review E 51 (2), 1035-1042.

Barceló, J., 2010. Fundamentals of traffic simulation. Springer.

Barceló, J., Casas, J., 2005. Dynamic network simulation with AIMSUN Simulation Approaches. In: Kitamura, R., Kuwahara, M. (Ed.), Simulation Approaches in Transportation Analysis. Springer, pp. 57-98.

Bevrani, K., Chung, E., 2012. A safety adapted car following model for traffic safety studies. In: Stanton, N. A. (Ed.), Advances in Human Aspects of Road and Rail Transportation. CRC Press, USA, pp. 550-559.

Boer, E.R., 1999. Car following from the driver's perspective. Transportation Research Part F: Traffic Psychology and Behaviour 2 (4), 201-206.

Boer, E.R., Hoedemaeker, M., 1998. Modeling driver behavior with different degrees of automation: A hierarchical decision framework of interacting mental models. In: Proceedings of the 17th European Annual Conference on Human Decision Making and Manual Control, Valenciennes, France.

Brackstone, M., McDonald, M., 1999. Car-following: a historical review. Transportation Research Part F: Traffic Psychology and Behaviour 2 (4), 181-196.

Brackstone, M., McDonald, M., Wu, J., 1998. Lane changing on the motorway: Factors affecting its occurrence, and their implications. In: 9th International Conference on Road Transport Information and Control, London, UK.

Brackstone, M., Sultan, B., McDonald, M., 2002. Motorway driver behaviour: studies on car following. Transportation Research Part F: Traffic Psychology and Behaviour 5 (1), 31-46.

Brockfeld, E., Kühne, R.D., Wagner, P., 2004. Calibration and validation of microscopic traffic flow models. Transportation Research Record 1876 (1), 62-70.

Chandler, R.E., Herman, R., Montroll, E.W., 1958. Traffic dynamics: studies in car following. Operations research 6 (2), 165-184.

Chen D., Laval J., Zheng Z., Ahn S., 2012. A behavioral car-following model that captures traffic oscillations. Transportation Research Part B: Methodological 46 (6), 744-761.

Chen D., Laval J., Ahn S., Zheng Z., 2012. Microscopic traffic hysteresis in traffic oscillations: A behavioral perspective. Transportation Research Part B: Methodological 46 (10), 1440-1453.

Chen D., Ahn S., Laval J., Zheng Z., 2014. On the periodicity of traffic oscillations and capacity drop: The role of driver characteristics. Transportation Research Part B: Methodological 59, 117-136.

Davis, L., 2003. Modifications of the optimal velocity traffic model to include delay due to driver reaction time. Physica A: Statistical Mechanics and its Applications, 319, 557-567.

Edie, L.C., 1961. Car-following and steady-state theory for noncongested traffic. Operations research, 9 (1), 66-76.

Fancher, P.S., Bareket, Z., 1998. Evolving model for studying driver-vehicle system performance in longitudinal control of headway. Transportation Research Record: Journal of the Transportation Research Board 1631 (1), 13-19.

Farah, H., Koutsopoulos, H.N., Saifuzzaman, M., Kölbl, R., Fuchs, S., Bankosegger, D., 2012. Evaluation of the effect of cooperative infrastructure-to-vehicle systems on driver behavior. Transportation Research Part C: Emerging Technologies 21 (1), 42-56.

Fellendorf, M., Vortisch, P., 2010. Microscopic traffic flow simulator VISSIM. In: Barceló, J. (Ed.), Fundamentals of Traffic Simulation, Springer, New York, pp. 63-93.

Ferrari, P., 1989. The effect of driver behaviour on motorway reliability. Transportation Research Part B: Methodological 23 (2), 139-150.

FHWA, 1985. Freeway data collection for studying vehicle interactions. Technical Report FHWA/RD-85/108, Federal Highway Administration, US Department of Transportation, McLean, VA.

Fritzsche, H.T., 1994. A model for traffic simulation. Traffic Engineering and Control 35 (5), 317-321.

Gazis, D.C., Herman, R., Rothery, R.W., 1961. Nonlinear follow-the-leader models of traffic flow. Operations research 9 (4), 545-567.

Gipps, P.G., 1981. A behavioural car-following model for computer simulation. Transportation Research Part B: Methodological 15 (2), 105-111.

Goldberg, D.E., 1989. Genetic algorithms in search, optimization, and machine learning. Addison-Wesley Publishing Co., Inc., Reading, MA.

Gomes, G., May, A., Horowitz, R., 2004. Calibration of VISSIM for a congested freeway. California Partners for Advanced Transit and Highways (PATH).

Gong, H., Liu, H., Wang, B.H., 2008. An asymmetric full velocity difference car-following model. Physica A: Statistical Mechanics and its Applications 387 (11), 2595-2602.

Gray, R., Regan, D., 1998. Accuracy of estimating time to collision using binocular and monocular information. Vision research 38 (4), 499-512.

Greenshields, B.D., Bibbins, J., Channing, W., Miller, H., 1935. A study of traffic capacity. In: Proceedings of the Highway research board, volume 14, pp. 448-477.

Hamdar, S., 2012. Driver behavior modeling, In: Eskandarian, A. (Ed.), Handbook of Intelligent Vehicles, Springer, pp. 537-558.

Hamdar, S.H., Mahmassani, H. S., 2008. From existing accident-free car-following models to colliding vehicles: exploration and assessment. Transportation Research Record: Journal of the Transportation Research Board 2088 (1), 45-56.

Hamdar, S. H., Mahmassani, H. S., Treiber, M., 2014. From behavioral psychology to acceleration modeling: Calibration, validation, and exploration of drivers cognitive and safety parameters in a risk-taking environment. arXiv preprint arXiv:1403.4980.

Hamdar, S.H., Treiber, M., Mahmassani, H. S., Kesting, A., 2008. Modeling driver behavior as sequential risk-taking task. Transportation Research Record: Journal of the Transportation Research Board 2088 (1), 208-217.

Hancock, P., 1999. Is car following the real question–are equations the answer?. Transportation Research Part F: Traffic Psychology and Behaviour 2 (4), 197-199.

Haque, M. M., Washington, S., 2014. A parametric duration model of the reaction times of drivers distracted by mobile phone conversations. Accident Analysis & Prevention 62, 42-53.

Helbing, D., Tilch, B., 1998. Generalized force model of traffic dynamics. Physical Review E, 58 (1), 133-138.

Helly, W., 1959. Simulation of bottlenecks in single-lane traffic flow. In: Proceedings of the Symposium on Theory of Traffic Flow, Research Laboratories, General Motors, New York.

Herman, R., Montroll, E.W., Potts, R.B., Rothery, R.W., 1959. Traffic dynamics: analysis of stability in car following. Operations research 7 (1), 86-106.

Herman, R., Rothery, R.W., 1965. Car following and steady-state flow. In: Proceedings of the 2nd International Symposium on the Theory of Traffic Flow, OECD, Paris.

Hoffmann, E.R., Mortimer, R.G., 1996. Scaling of relative velocity between vehicles. Accident Analysis & Prevention 28 (4), 415-421.

Hoogendoorn, S.P., Hoogendoorn, R., 2010. Generic calibration framework for joint estimation of car-following models by using microscopic data. Transportation Research Record 2188, 37-45.

Hoogendoorn, S.P., Ossen, S., 2005. Parameter estimation and analysis of car-following models. In: Proceedings of the 16th International Symposium on Transportation and Traffic Theory, University of Maryland, College Park, USA.

Ištoka Otković, I., Tollazzi, T., Šraml, M., 2013. Calibration of microsimulation traffic model using neural network approach. Expert systems with applications 40 (15), 5965-5974.

Jin, S., Wang, D.H., Huang, Z.Y., Tao, P.F., 2011. Visual angle model for car-following theory. Physica A: Statistical Mechanics and its Applications 390 (11), 1931-1940.

Kahneman, D., Tversky, A., 1979. Prospect theory: an analysis of decision under risk. Econometrica 47 (2), 263-291.

Kesting, A., Treiber, M., 2008. Calibrating car-following models using trajectory data: methodological study. Transportation Research Record 2088, 148-156.

Kikuchi, S., Chakroborty, P., 1992. Car-following model based on fuzzy inference system. Transportation Research Record: Journal of the Transportation Research Board 1365, 82-91.

Kometani, E., Sasaki, T., 1959. Dynamic behaviour of traffic with a non-linear spacing-speed relationship. In: Proceedings of the Symposium on Theory of Traffic Flow, Research Laboratories, General Motors, New York.

Koshi, M., Kuwahara, M., Akahane, H., 1992. Capacity of sags and tunnels on Japanese motorways. ITE Journal 62 (5), 17-22.

Koutsopoulos, H.N., Farah, H., 2012. Latent class model for car following behavior. Transportation Research Part B: Methodological 46 (5), 563-578.

Krauss, S., Wagner, P., 1997. Metastable states in a microscopic model of traffic flow. Physical Review E 55 (5), 5597-5602.

Krauss, S., Wagner, P., Gawron, C., 1996. Continuous limit of the Nagel-Schreckenberg model. Physical Review E 54 (4), 3707-3712.

Lagarias, J.C., Reeds, J.A., Wright, M.H., Wright, P.E., 1998. Convergence properties of the Nelder-Mead Simplex method in low dimensions. SIAM Journal of Optimization 9 (1), 112-147.

Laval, J.A., Leclercq, L., 2010. A mechanism to describe the formation and propagation of stop-and-go waves in congested freeway traffic. Phil. Trans. R. Soc. A 368 (1928), 4519-4541.

Lee, G., 1966. A generalization of linear car-following theory. Operations research 14 (4), 595-606.

Lee, J.D., Young, K.L., Regan, M.A., 2008. Defining driver distraction. In: Regan, M.A., Lee, J.D., Young, K.L. (Ed.), Driver Distraction: Theory, Effects, and Mitigation. CRC Press, USA, pp. 31–40.

Lenz, H., Wagner, C., Sollacher, R., 1999. Multi-anticipative car-following model. The European Physical Journal B - Condensed Matter and Complex Systems 7 (2), 331-335.

Lighthill, M.J., Whitham, G.B., 1955. On kinematic waves. II. A theory of traffic flow on long crowded roads. In: Proceedings of the Royal Society of London. Series A. Mathematical and Physical Sciences, 229 (1178), 317-345.

Lownes, N.E., Machemehl, R.B., 2006. Sensitivity of simulated capacity to VISSIM driver behavior parameter modification. Transportation Research Record, 1988, 102–110

Maerivoet, S., De Moor, B., 2005. Cellular automata models of road traffic. Physics Reports 419 (1), 1-64.

McEvoy, S., Stevenson, M., 2007. An exploration of the role of driver distraction in serious road crashes. In: Proceedings of the International conference on the distractions in driving, Sydney, Australia.

Michaels, R., 1963. Perceptual factors in car following. In: Proceedings of the 2nd International Symposium on the Theory of Road Traffic Flow, OECD, London, UK.

Michaels, R., Cozan, L., 1963. Perceptual and field factors causing lateral displacement. Highway Research Record (25), 1-13.

Muhrer, E., Vollrath, M., 2011. The effect of visual and cognitive distraction on driver’s anticipation in a simulated car following scenario. Transportation Research Part F: Traffic Psychology and Behaviour 14 (6), 555-566.

Nagel, K., Schreckenberg, M., 1992. A cellular automaton model for freeway traffic. Journal de Physique I 2 (12), 2221-2229.

Neumann, J., (1948). The general and logical theory of automata, In: Jeffress, L.A. (Ed.), Cerebral Mechanisms in Behavior, Wiley, New York, pp. 1-41.

Newell, G.F., 1961. Nonlinear effects in the dynamics of car following. Operations research 9 (2), 209-229.

Newell, G.F., 2002. A simplified car-following theory: a lower order model. Transportation Research Part B: Methodological 36 (3), 195-205.

Olstam, J.J., Tapani, A., 2004. Comparison of car-following models. Swedish National Road and Transport Research Institute.

Ossen, S., Hoogendoorn, S.P., 2008. Validity of trajectory-based calibration approach of car-following models in presence of measurement errors. Transportation Research Record 2088, 117-125.

Ossen, S., Hoogendoorn, S.P., 2011. Heterogeneity in car-following behavior: Theory and empirics. Transportation Research Part C: Emerging Technologies 19 (2), 182-195.

Panwai, S., Dia, H., 2005. Comparative evaluation of microscopic car-following behavior. IEEE Transactions on Intelligent Transportation Systems 6 (3), 314-325.

Park, B., Qi, H., 2006. Microscopic simulation model calibration and validation for freeway work zone network-a case study of VISSIM. In: Intelligent Transportation Systems Conference. ITSC'06. IEEE pp. 1471-1476.

Parker, D., Reason, J.T., Manstead, A.S.R., Stradling, S.G., 1995. Driving errors, driving violations and accident involvement. Ergonomics 38 (5), 1036-1048.

Peng, G., Sun, D., 2010. A dynamical model of car-following with the consideration of the multiple information of preceding cars. Physics Letters A 374 (15), 1694-1698.

Pipes, L.A., 1953. An operational analysis of traffic dynamics. Journal of applied physics 24 (3), 274-281.

Przybyla, J., Taylor, J., Jupe, J., Zhou, X., 2012. Simplified, data-driven, errorable car-following model to predict the safety effects of distracted driving. In: Proceedings of the 15th International IEEE Conference on Intelligent Transportation Systems, Alaska, USA, pp. 1149 – 1154.

Reason, J., 1990. Human error. Cambridge University press.

Reuschel, A., 1950. Fahrzeugbewegungen in der Kolonne. Oesterreichisches Ingenieur-Archiv 4 (3/4), 193-215.

Rhodes, N., Pivik, K., 2011. Age and gender differences in risky driving: The roles of positive affect and risk perception. Accident Analysis & Prevention 43 (3), 923-931.

Richards, P.I., 1956. Shock waves on the highway. Operations research 4 (1), 42-51.

Ross, T.J., 2010. Fuzzy logic with engineering applications. John Wiley & Sons.

Siuhi, S., Kaseko, M.S., 2010. Parametric study of stimulus-response behavior for car-following models. In: Proceedings of the Transportation Research Board 89th Annual Meeting, USA.

Stanton, N.A., Salmon, P.M., 2009. Human error taxonomies applied to driving: A generic driver error taxonomy and its implications for intelligent transport systems. Safety Science 47 (2), 227-237.

Stutts, J.C., 2003. Distractions in everyday driving. AAA Foundation for Traffic Safety, Washington, DC.

Subramanian, H., 1996. Estimation of car-following models. Massachusetts Institute of Technology.

Talebpour, A., Mahmassani, H. S., Hamdar, S. H., 2011. Multiregime Sequential Risk-Taking Model of Car-Following Behavior. Transportation Research Record: Journal of the Transportation Research Board 2260 (1), 60-66.

Toledo, T., 2007. Driving behaviour: models and challenges. Transport Reviews 27 (1), 65-84.

Treiber, M., Helbing, D., 2003. Memory effects in microscopic traffic models and wide scattering in flow-density data. Physical Review E 68 (4), 046119-1-046119-8.

Treiber, M., Hennecke, A., Helbing, D., 2000. Congested traffic states in empirical observations and microscopic simulations. Physical Review E 62 (2), 1805.

Treiber, M., Kesting, A., 2013. Traffic flow dynamics: Data, models and simulation, ISBN 978-3-642-32459-8. Springer-Verlag Berlin Heidelberg.

Treiber, M., Kesting, A., Helbing, D., 2006. Delays, inaccuracies and anticipation in microscopic traffic models. Physica A: Statistical Mechanics and its Applications 360 (1), 71-88.

Van Winsum, W., 1999. The human element in car following models. Transportation Research Part F: Traffic Psychology and Behaviour 2 (4), 207-211.

Von Neumann, J., Morgenstern, O., 1949. Theory of games and economic behavior. Princeton University Press.

Wang, W., Zhang, W., Guo, H., Bubb, H., Ikeuchi, K., 2011. A safety-based approaching behavioural model with various driving characteristics. Transportation Research Part C: Emerging Technologies 19 (6), 1202-1214.

Wiedemann, R., 1974. Simulation des StraBenverkehrsflusses. In: Proceedings of the Schriftenreihe des tnstituts fir Verkehrswesen der Universitiit Karlsruhe, Germany.

Wolfram, S., 1983. Statistical mechanics of cellular automata. Reviews of modern physics 55 (3), 601-644.

Wu, J., Brackstone, M., McDonald, M., 2000. Fuzzy sets and systems for a motorway microscopic simulation model. Fuzzy sets and systems 116 (1), 65-76.

Xing, J., 1995. A parameter identification of a car following model. In: Steps Forward. Intelligent Transport Systems World Congress, Yokohama, Japan, pp. 1739-1745 .

Yang, H.H., Peng, H., 2010. Development of an errorable car-following driver model. Vehicle System Dynamics 48 (6), 751-773.

Young, K.L., Salmon, P.M., 2012. Examining the relationship between driver distraction and driving errors: A discussion of theory, studies and methods. Safety Science 50 (2), 165-174.

Zheng, Z., 2014. Recent developments and research needs in modeling lane changing. Transportation Research Part B: Methodological 60, 16-32.

Zheng, Z., Ahn, S., Chen, D., Laval, J., 2013. The effects of lane-changing on the immediate follower: Anticipation, relaxation, and change in driver characteristics. Transportation Research Part C: Emerging Technologies 26, 367-379.

Zheng Z., Ahn S., Chen D., Laval J., 2011a. Applications of wavelet transform for analysis of freeway traffic: Bottlenecks, transient traffic, and traffic oscillations. Transportation Research Part B: Methodological 45 (2), 372-384.

Zheng Z., Ahn S., Chen D., Laval J., 2011b. Freeway traffic oscillations: Microscopic analysis of formations and propagations using Wavelet Transform. Transportation Research Part B: Methodological 45 (9), 1378-1388.

Chapter 3

Impact of mobile phone use on car-following behavior for young drivers

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Impact of mobile phone use on car-following behavior for young drivers

Mohammad Saifuzzaman[1], Md. Mazharul Haque[1, 2], Zuduo Zheng[1], Simon Washington[1, 2]

[1] School of Civil Engineering & Built Environment, Science and Engineering Faculty, Queensland University of Technology (QUT), Brisbane, Australia

[2] Centre for Accident Research and Road Safety (CARRS-Q), Faculty of Health, Queensland University of Technology (QUT), Brisbane, Australia

Publication status: This article is published in *Accident Analysis and Prevention.* Volume: 82, pages: 10-19, published: September, 2015. doi: 10.1016/j.aap.2015.05.001

Journal quality: The journal in which this paper appears is a peer-reviewed publication with an international readership. The journal's Impact Factor is 2.070, and ranks Q1, 4/29 (Human Factors and Ergonomics) according to the SCImago Journal Rank.

Foreword: This chapter (article) investigates the effect of human factors on CF behavior from a carefully designed driving simulator experiment about mobile phone distraction and young driver's safety. It provides the basic understanding about human factor's impact on CF behavior which is used in the following chapter to build up a framework for human-like CF models. This article addresses the second objective of this thesis as stated in Section 1.2 of Chapter 1.

Statement of contribution of co-authors for thesis by published paper

Publication title: Impact of mobile phone use on car-following behavior for young drivers

The authors listed below have certified that:

- They meet the criteria for authorship in that they have participated in the conception, execution, or interpretation, of at least that part of the publication in their field of expertise;
- They take public responsibility for their part of the publication, except for the responsible author who accepts overall responsibility for the publication;
- There are no other authors of the publication according to these criteria;
- Potential conflicts of interest have been disclosed to (a) granting bodies, (b) the editor or publisher of journals or other publications, and (c) the head of the responsible academic unit, and
- They agree to the use of the publication in the student's thesis and its publication on the Australasian Digital Thesis database consistent with any limitations set by publisher requirements.

Each author's contributions are listed below:

Contributor	*Statement of contribution*
Mohammad Saifuzzaman Signature: Saifuzzaman Date: 23/06/2016	Conducted data analysis, and wrote the manuscript. The candidate was also responsible for any revisions made at the suggestions of journal reviewers.
Md. Mazharul Haque	Supplied the data, provided guidance in data processing and to the choice of statistical models, and answered some of the questions asked by the journal reviewers.
Zuduo Zheng	Supervised the research, reviewed the manuscript and played the role of the corresponding author.
Simon Washington	Provided guidance in interpreting model outcomes and reviewed the manuscript.

Principal Supervisor Confirmation:

I have sighted email or other correspondence from all co-authors confirming their certifying authorship.

Dr. Zuduo Zheng		23.06.2016
(Name)	(Signature)	(Date)

Impact of mobile phone use on car-following behavior for young drivers

Mohammad Saifuzzaman, Md. Mazharul Haque, Zuduo Zheng, Simon Washington

Abstract

Multitasking, such as the concurrent use of a mobile phone and operating a motor vehicle, is a significant distraction that impairs driving performance and is becoming a leading cause of motor vehicle crashes. This study investigates the impact of mobile phone conversations on car-following behavior. The CARRS-Q Advanced Driving Simulator was used to test a group of young Australian drivers aged 18 to 26 years on a car-following task in three randomised phone conditions: baseline (no phone conversation), hands-free and handheld. Repeated measure ANOVA was applied to examine the effect of mobile phone distraction on selected car-following variables such as driving speed, spacing, and time headway. Overall, drivers tended to select slower driving speeds, larger vehicle spacings, and longer time headways when they were engaged in either hands-free or handheld phone conversations, suggesting possible risk compensatory behavior. In addition, phone conversations while driving influenced car-following behavior such that variability was increased in driving speeds, vehicle spacings, and acceleration and decelerations. To further investigate car-following behavior of distracted drivers, driver time headways were modelled using Generalized Estimation Equation (GEE). After controlling for various exogenous factors, the model predicts an increase of 0.33 seconds in time headway when a driver is engaged in hands-free phone conversation and a 0.75 seconds increase for handheld phone conversation. The findings will improve the collective understanding of distraction on driving performance, in particular car following behavior which is most critical in the determination of rear-end crashes.

3.1. Introduction

3.1.1. Distracted driving induced by mobile phone use

Driver distraction can be defined as a diversion of attention away from activities critical for safe driving to a competing activity (Lee *et al.* 2009). *Distraction* is also described as multi-task driving which reduces attention and cognitive resources allocated to the driving task. Studies have shown that multitasking while driving deteriorates driving performance, increases reaction time, and impacts lateral lane position and vision. This, in turn, poses serious safety concerns on the roads. A naturalistic driving study with 43000 hours of driving data from 241 drivers showed that the use of mobile phone while driving is associated with a higher number of crashes and incidents than driver interactions with any other source of distraction (Neale *et al.* 2005).

An extensive literature has empirically documented the risks associated with mobile phone use while driving (see Drews and Strayer (2009) for a detail review). Driving with phone conversation is considered as multitasking where a part of brain is occupied for the processing of the auditory sentences. An analysis using functional magnetic resonance imaging (fMRI) showed that, mobile phone distraction requiring the processing of auditory sentences decreases the brain activity by as much as 37% of the critical tasks associated with driving (Just *et al.* 2008). The increased cognitive load might cause a withdrawal of attention from the visual scene where not all the information a driver sees is processed; this phenomena is known as inattention blindness (Strayer *et al.* 2003).

Mobile phone use while driving is one of the most common distractions that motor vehicle drivers engage. In 2012 the National Highway Transportation Safety Administration estimates that 9% of drivers on the roadway at any given daylight moment are using some type of phone (either handheld or hands-free); for handheld phone use in particular, this estimate was 5% (NHTSA 2014). White *et al.* (2010) observed 796 Australian drivers aged 17–76 years who owned mobile phones, and found that 43% of them reported answering calls while driving on a daily basis, followed by making calls (36%), reading text messages (27%), and sending text messages (18%). Mobile phone use while driving is more prevalent among young (and less experienced) drivers, who generally possess an elevated crash risk. A recent survey reported that almost one in two Australian drivers aged between 18 to 24 years used a handheld mobile phone while driving, nearly 60% of them sent text messages, and about 20% of them read emails and surfed the internet (AAMI 2012).

In a naturalistic driving study Fitch *et al.* (2013) investigated the effects of distraction from the use of mobile phones while driving on 204 drivers. On average drivers were estimated to be talking on a mobile phone 10.6 percent of the time when they were driving with a mean call duration of 4.02 minutes. The study identifies that mobile phone subtask (locating, answering, dialing, browsing, text messaging and ending the call) can take driver's eyes off the forward roadway for up to 33.1 to 71.5 percentage of time. Furthermore, locating/answering a handheld mobile phone was found to be associated with an increased safety risk (crash or near crash).

To reduce the negative effect of mobile phone use while driving, hands-free technology is widely used. However, conversation using both hands-free and handheld mobile phones has adverse effect on driving. A meta-analysis by Caird *et al.* (2008) reveals that the effect of hands-free versus handheld phone studies did not differ appreciably from one another in terms of reaction time of the driver. Overall, a mean increase in reaction time of 0.25 seconds was reported for all phone-related tasks. A recent simulator study reported that both hands-free and handheld phone conversations are associated with about 40% increase in reaction times of drivers to peripheral traffic events (Haque and Washington 2014). Overall, studies did not find any significant difference in relative risk of a crash for handheld and hands-free phones, both options individually associated with a fourfold increase in crash risk (McEvoy *et al.* 2005).

3.1.2. Impact of distracted driving on car-following

A few studies specifically have targeted to capture the adverse effect of mobile phone use on car-following behavior. Car-following refers to the behavior of a driver to follow a leading vehicle longitudinally. It is the most common routine driving situation and an important requirement for the safe driving (see Saifuzzaman and Zheng (2014) for the latest review).

In a driving simulator study Alm and Nilsson (1995) observed the effects of hands-free mobile phone conversation on car-following behavior. In their study, 40 participants drove a simulator vehicle for 80km where a total of 16 car-following events occurred randomly. The participants were randomly exposed to a phone conversation task in 8 of these car-following situations. They observed an increased reaction time for phone conversation while driving. Furthermore, the participants did not compensate for their increased reaction time by increasing their headway during the phone task. However, later studies reported reduction in speed when driving with phone conversation, a behavior known as risk compensation (Törnros and Bolling 2006). For example, Ranney *et al.* (2004) observed higher reduction of speed when driving with handheld phone conversation compared to other types of phone conversations (headset hands-free and voice dialing speaker kit hands-free) and baseline (no phone). Furthermore, drivers were found to increase their time headways during all types of phone conversations.

Drews and Strayer (2009) in their detail review about effect of mobile phone use on driving also reported increased reaction time and reduction of speed. Furthermore, an increase in lane deviation and fluctuation of speed are also reported which indicates less control over driving due to distraction caused by mobile phone use. A recent study by Stavrinos *et al.* (2013) also supports these findings by reporting significantly greater variability in driving speed, lower lane change frequency and higher lane deviations in distracted driving compared to baseline (no phone use while driving).

Strayer *et al.* (2011) in their study asked the participants to follow a pace car that was programmed to brake at 32 randomly distributed locations over a 24-mile multi-lane highway. They observed a slower brake reaction time for driver with mobile phone conversation compared to no phone driving. The distracted drivers also took longer time to recover their speed that was lost following braking. The drivers conversing on mobile phones tended to have a more cautious driving profile in terms of speed and following distance (i.e. maintaining lower speed and higher spacing) than non-distracted driving. However, crash rate was still higher compared to driving with no phone conversation. No significant difference was observed between driving with handheld and hands-free phone conversations.

Driver reaction time, speed, and following distance are considered key variables in describing the stability and flow of traffic. Driver engaging in phone conversations while driving can significantly influence these variables, thus, performs poorly in following the preceding vehicle. Although aforementioned studies have attempted to document the risk of mobile phone use in car-following situation, overall the literature is scarce, and our understanding on this important issue remains elusive. For instance, fluctuations in speed and spacing and acceleration noise have been seldom measured, which could give valuable insight about driver's control over car-following in distracted situations. Driver demographics could also influence car-following behavior in distracted situation, which needs to be explored.

3.1.3. Research objective

This study aims to investigate the effect of both hands-free and handheld mobile phone conversation on car-following behavior of young drivers. A simulator experiment was designed where a participant drove a simulator vehicle in three different phone conditions: baseline (no-phone conversation), hands-free phone conversation and handheld phone conversation. A wide range of variables (such as driving speed, spacing, speed difference, time headway and acceleration noise) were considered to examine car-following behavior of distracted drivers. The effects of distraction on the car following behavior were mainly identified by comparing the driving performances in distracted and non-distracted (no-phone conversation) conditions. In addition, driver's time headway was modelled using the Generalized Estimation Equation (GEE) to develop further insights into the car-following behavior of distracted drivers.

3.2. Driving simulator experiment

3.2.1. Driving simulator

To accomplish this study, an experimental driving simulator study was conducted at the Centre for Accident Research and Road Safety – Queensland (CARRS-Q), Queensland University of Technology (QUT). In this experiment a group of distracted drivers were exposed to a number of traffic events using the CARRS-Q Advanced Driving Simulator[4].

The simulator incorporates a complete Holden Commodore vehicle with working controls and instruments. When seated in the simulator vehicle, the driver and passengers are immersed in a virtual environment that includes a 180 degree front field of view (using three front-view projectors), simulated rear view mirror images, surround sound for engine and environment noise, real car cabin and simulated vehicle motion. Road images are displayed onto the front view projector, the wing mirrors and the rear view mirror at 60 Hz to create a photorealistic virtual environment. The simulator was capable of accurately reproducing motion cues for sustained acceleration, braking manoeuvers, cornering and interaction with varying road surfaces. The simulator used SCANeR™ studio software. Driving performances data like position, speed, acceleration and braking were recorded at rates up to 20 Hz.

3.2.2. Participants

Thirty-two volunteers were recruited by disseminating recruitment flyers using university student email addresses or university social media and distributing recruitment flyers inside the campus. An eligible participant should meet the following conditions: 1) be aged between 18 and 26 years, 2) hold either a provisional or open Australian issued driver's licence, 3) not had a history of motion sickness and epilepsy, and 4) not be pregnant. The participants were reimbursed upon completion of the study. The participants also filled a survey questionnaire about their driving history, mobile phone use, and driving behavior.

Descriptive statistics of the participants are presented in Table 3.1. The participants were on average 21.47 (SD 1.98) years old and split evenly by gender. About 66% of the participants held open (non-restricted) licenses and the rest has provisional licenses. Note that in Queensland, Australia, a newly licensed driver is required to hold a provisional license for up to 3 years before obtaining an open

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[4]Detail about the simulator can be found at http://www.carrsq.qut.edu.au/simulator/

license. Average driving experience was 4.2 (SD 1.87) years where the provisional and open license holders had 2.64 (SD 0.75) and 5.01 (SD 1.79) years of average driving experience, respectively. In terms of vehicle kilometre travelled about 44% drove less than 10,000km, 47% drove in between 10,000 to 20,000km, and the rest drove more than 20,000km in a typical year.

Table 3.1 Descriptive statistics of the participants

Driver characteristics	Mean	SD	Count	Percentage
Driver’s age (years)	21.47	1.98	-	
Gender				
Male	-	-	16	50.00
Female	-	-	16	50.00
License type				
Open	-	-	21	65.63
Provisional	-	-	11	34.38
Years of driving	4.20	1.87	-	
Kilometres driven in a typical year				
0–10,000 km	-	-	14	43.75
10,000–20,000 km	-	-	15	46.88
>20,000 km	-	-	3	9.38
General mobile phone usage history				
Calls (in a typical week)	65.34	43.41		
Text message (in a typical week)	260.66	198.66		
Frequency of mobile phone use while driving				
at least once in a day	-	-	11	34.38
once or twice in a week	-	-	15	46.88
once or twice in a month or year	-	-	6	18.75
Usage of handheld phone while talking and driving				
0-25%	-	-	17	53.13
26-50%	-	-	6	18.75
51-75%	-	-	4	12.50
76-100%	-	-	5	15.63

Table 3.1 also presents the mobile phone use history of the participants. On average a participant made (or received) 65 (SD 43) calls and sent (or received) 261 (SD 199) text messages in a typical week. More interestingly, the scenario about mobile phone uses while driving showed that, about 34% of the sample used it at least once in a day; 47% of used once or twice in a week; and the rest used mobile phones while driving only once or twice in a month or year. About the type of mobile phone use while talking and driving 53% of the participants reported using a hand-held phone 0–25% of the time, 19% reported 25–50%, 12% reported 50–75%, and the remaining 16% reported using a handheld phone 76–100% of the talking time whilst driving.

3.2.3. Experimental setup

The simulated route in the experiment was 7km long that went through Brisbane CBD (central business district of Brisbane, Australia) and a hypothetical suburban area. Various traffic events were programmed to occur in the course of the simulated driving such as car-following, overtaking, pedestrian crossing and sudden breaking of a lead vehicle. A part of the experimental data have been used in Haque and Washington (2013) and Haque and Washington (2014) to observe the effect of distraction on reaction time. However, in this study the data from car-following event is used which has not been applied before[5]. Details of the participant testing protocol can be found in Haque and Washington (2014).

The car-following event was occurred along urban roads, where the speed limit was 40 km/h. A detail of the car-following scenario is shown in Figure 3.1. The odd number in this figure represents intersection and the even number represents the roadway between two intersections. The roadway has four lanes with unidirectional traffic flow. Lane 1 and lane 4 had parked vehicles, leaving only lane 2 and lane 3 available for driving.

[5] The data used by Haque and Washington (2014) covered the traffic event where a pedestrian entered a zebra crossing from the sidewalk. Haque and Washington (2013) used data from the traffic event where a lead car breaks suddenly. In contrast, the data used in this paper were collected from a different road segment which was designed for the car-following event only. In addition, the methodology applied in this paper differs from those in the past two studies.

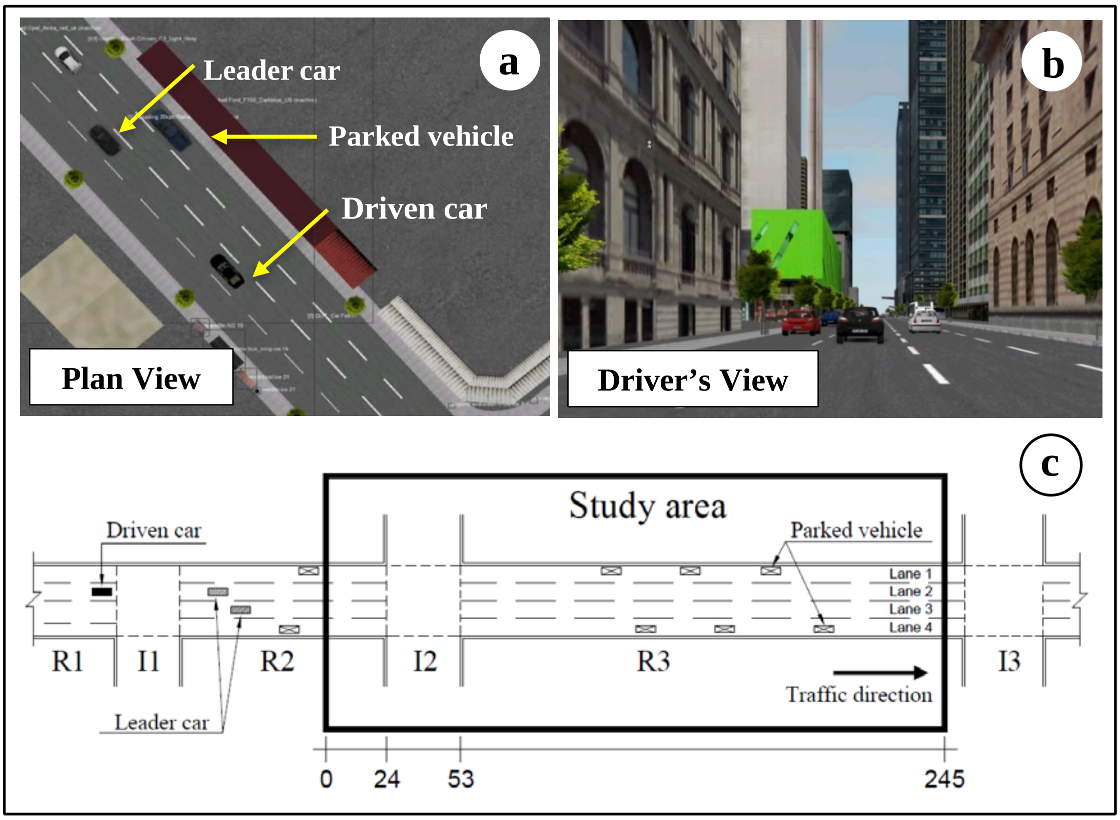


Figure 3.1 (a) plan view showing driven and leader vehicles; (b) driver's view showing leader vehicles and occupied adjacent lanes; (c) detail of the study area

In this car-following scenario, when the driven vehicle (shown as the black rectangle in Figure 3.1) stops at the signalized intersection I1, two lead vehicles appear on the two lanes of road section R2 (shown as rectangle with hatched lines). They were pre-programmed with selected speeds. When the signal at the intersection I1 turns green, the two lead vehicles start moving slowly at same speed. No other cars were present in between the driven vehicle and the lead vehicles. Driven vehicle will be referred as subject vehicle in rest of this paper. When the spacing between the subject and the lead vehicle reached 60m, the speed of both lead vehicles increased up to 20km/h. When the spacing was 30m or less, lead vehicles increased the speed to 35km/h with an acceleration of about 4.0 m/s^2 and maintained that speed until the end of the car-following event. Both lead vehicles run with same speed so that the driver neither could overtake nor benefit by changing lane. The signal at intersection I2 was kept green to provide uninterrupted flow from section R2 to R3.

Each participant was required to drive in three phone conditions: a baseline condition (without any phone conversation), and hands-free and handheld phone conditions on the same road. Three route starting points were designed to reduce learning effects. The driving conditions were counterbalanced across participants to control for carry-over effects. Before participating in the experimental drive, each participant performed a practice drive of 5-6 minutes to become familiar with the driving simulator. The participants in this study did not go through acuity or colour deficiency testing. The details of the participant testing protocol can be found in Haque and Washington (2014).

3.2.4. Mobile phone task

A Nokia 500 phone was used in this study which had dimensions of 111.3 x 53.8 x 14.1mm. The participants talked through a Bluetooth headset in the hands-free condition, and were required to hold the phone to their ear for the duration of the conversation in the handheld condition. The experimenter called the participant before the start of the drive and the call continued until the end of the drive. The experimenter was neither able to observe the driving of a participant, nor receive any clues regarding route progress.

The phone conversation was cognitive in nature, which required simultaneous storage and processing of information, and thus distracted the drivers by increasing their cognitive load. Conversation dialogues were modified from Burns *et al.* (2002). The participants were required to provide an appropriate response after hearing a complete question, solving a verbal puzzle, or solving a simple arithmetic problem.

3.3. Data and analysis

3.3.1. Dataset for analysis

There was no geographically fixed point where the car-following started, as it depended on the speed of the subject vehicle. To observe car-following behaviors from all the participants, a roadway segment of 245m length was selected as shown with a thick border in Figure 3.1. The car-following duration within the study area is ranged between 22 to 39 seconds. Similar length of the CF duration is reported in the literature (e.g., Muhrer and Vollrath, 2011; and He et al., 2014).

The final dataset contained vehicle trajectory data for 32 participant drivers in three phone conditions. Hence, a total of 96 car-following trajectories were obtained from the simulator experiment. The simulator recorded different driving related variables such as speed of the subject vehicle, spacing between the subject and the lead vehicle in the same lane of the driver, position of the vehicles, acceleration and braking of the subject vehicle, and speed difference between the subject and the lead vehicle. Driver demographic variables like age, gender, licence type, and driving history were collected from the questionnaire filled up by each participant before starting the simulator drives

3.3.2. Statistical analysis

A wide range of car-following related variables is identified in literature. The following variables were considered to examine the effect of distraction on car-following behavior:

a) Average speed of the subject vehicle n [$\mu(V_n)$],
b) Average spacing from the lead vehicle [$\mu(\Delta X_n)$],
c) Average speed difference [$\mu(\Delta V_n)$, $\Delta V_n = V_{n-1} - V_n$],
d) Average time headway [$\mu(\Delta T_n)$, $\Delta T_n = \Delta X_n / V_n$],
e) Fluctuation in speed [$\sigma(V_n)$],
f) Fluctuation in spacing [$\sigma(\Delta X_n)$],
g) Acceleration noise.

Acceleration noise (AN) is the least used variable among the above mentioned ones. Acceleration noise is defined as the standard deviation of acceleration/deceleration of a vehicle. It was first proposed by Herman *et al.* (1959) to describe the driver–car–road interaction under diverse conditions. In free flowing traffic and in steady driving acceleration noise is relatively small. However, it may increase for various reasons for example when the roadway conditions deteriorate, and the level of traffic and congestion increases (Taylor et al. 2000). A reckless driver, who drives fast and applies sudden breaks, will have a larger acceleration noise than the one who drives smoothly (Jones and Potts, 1962). Farah et al. (2012) used acceleration noise to see if drivers' acceleration behaviors have improved when driving with cooperative systems. Belzet al. (2011) found that young drivers (i.e., 21-35years) have higher acceleration noise than old drivers (i.e., above 70 years old) in high speed and on grades. Studies (e.g., Jones and Potts, 1962) suggest that higher acceleration noise indicates potentially dangerous situations.

The above-mentioned variables were calculated for each driver in three driving situations. The dataset represents a panel data where each variable was measured in three different driving conditions. One-way repeated measures ANOVA test was performed to observe the effect of distraction on selected dependent variables. Later, a pairwise t-test with adjusted *p*-value was used as post hoc test to see which driving conditions were significantly different. Holm–Bonferroni (Holm 1979) method had been applied for *p*-value adjustment.

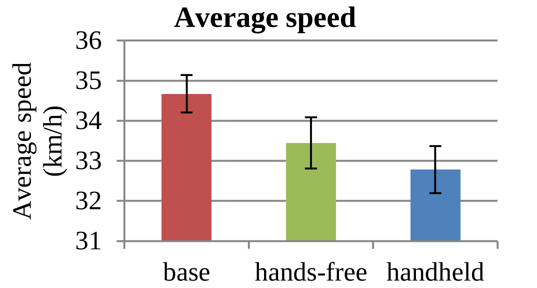
Finally, Generalized Estimation Equation (GEE) (Liang and Zeger 1986) was applied to model driver's time headway as a function of various independent variables. GEEs represent an extension of the Generalized Linear Models (GLM; Nelder and Baker 1972) to accommodate correlated data where the correlation is a result of repeated observations of the same participant. GLM is based on the maximum likelihood theory (McCullagh and Nelder, 1989) for independent observations. GEE is based on quasi-likelihood theory (Wedderburn, 1974) where no assumption needs to be made about the distribution of the response observations, and the response observations do not necessarily have to be independent. In the context of this study, time headways of the same driver were observed in three phone conditions, and hence GEE is a suitable modeling technique to account for possible correlation arising from multiple observations across individuals. While the GEE analysis can accommodate various correction structures, this study adopted an exchangeable correlation structure which assumes a constant correlation coefficient among multiple observations from an individual.

Since GEE models are particularly suitable for panel data where residuals are not independent, common likelihood based methods and other measures of model fit of ordinary linear regression are not applicable here. Pan (2001) proposed quasi-likelihood under independence model criteria (QIC) to select best working correlation structure. Zheng (2000) introduced a simple extension of R^2 statistics for GEE models and named as Marginal R^2 to be used as a fitness measure. In this study, the QIC and Marginal R^2 value were used to measure goodness of fit of the model.

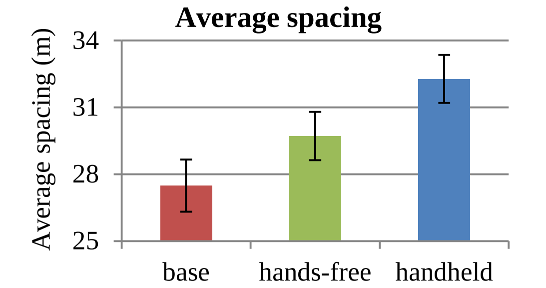
3.4. Results

3.4.1. *Driving performances of distracted drivers in CF situation*

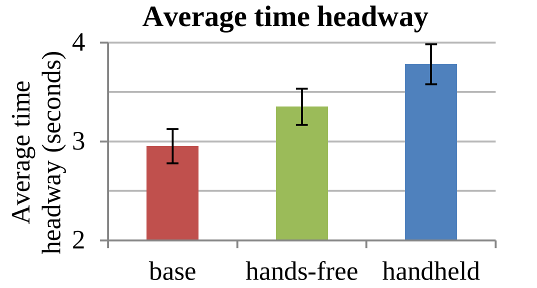
To examine the effect of mobile phone use while car-following, bar chart with mean value and standard error (SE) for selected CF variables are presented in Figure 3.2.



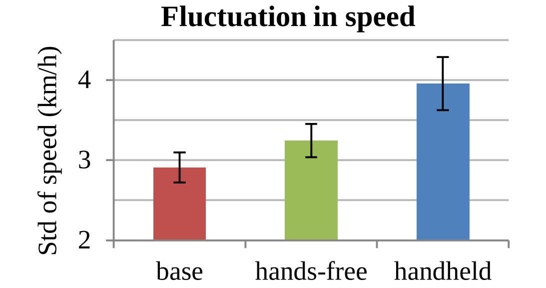
Average	34.67	33.45	32.78
SE	0.47	0.64	0.59
$F_{2,62} = 6.90$		$p = 0.002$	



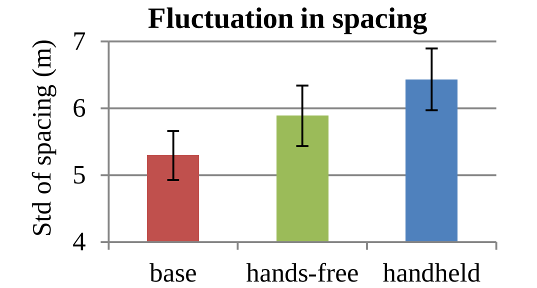
Average	27.49	29.72	32.28
SE	1.17	1.08	1.08
$F_{2,62} = 12.43$		$p = 0.000$	



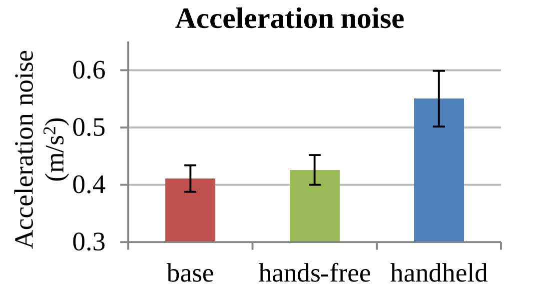
Average	2.95	3.35	3.78
SE	0.17	0.18	0.20
$F_{2,62} = 12.82$		$p = 0.000$	



Average	2.91	3.24	3.95
SE	0.19	0.21	0.33
$F_{2,62} = 6.27$		$p = 0.003$	



Average	5.30	5.89	6.43
SE	0.37	0.45	0.46
$F_{2,62} = 3.56$		$p = 0.034$	



Average	0.41	0.43	0.55
SE	0.02	0.03	0.05
$F_{2,62} = 7.59$		$p = 0.001$	

Figure 3.2 Effect of distraction on CF variables (error bar represents SE)

Average speed

It is the average of speeds obtained from car-following trajectories. Figure 2 shows that the average speed of the subject vehicle reduces with distraction level. A significant effect of distraction on speed selection is found from the repeated measures ANOVA test ($F_{2,62}=6.90$, $p=0.002$). Post hoc test further suggests that the difference in baseline vs handheld phone condition is most significant ($p=0.004$) and baseline vs hands-free are least significant ($p=0.029$). In general the average speed was 5.5% and 3.5% slower from baseline when drivers were distracted by a handheld and hands-free phone conversation respectively.

Average spacing

Average spacing is the mean distance the subject vehicle maintained from the lead vehicle while car-following. A significant increase in spacing choice is observed as an effect of distraction ($F_{2,62}=12.43$, $p=0.000$). Average spacing was 17.4% ($p=0.000$) higher in handheld and 8.1% ($p=0.045$) higher in hands-free compared to baseline condition.

Average speed difference

It is the mean speed difference between the subject and lead vehicle during the car-following event. No significant difference is observed in average speed difference ($F_{2,62}=0.51$, $p=0.604$), and standard deviation of speed difference ($F_{2,62}=1.90$, $p=0.158$) in distracted situation. A driver in car-following situation continuously attempts to match their speed with the lead vehicle. Hence, it is expected that the speed difference would be similar in all three driving conditions.

Average time headway

Time headway for driver *n* at an instant *t* is defined as the elapsed time between the front of the lead vehicle passing a point on the roadway and the front of the following vehicle passing the same point (Evans 1991). A significant effect of distraction on average time headway during car-following is observed ($F_{2,62}=12.82$, $p=0.000$). The mean values suggest that time headway increases with distraction level. Compared to baseline condition the average time headway was 28.0%

($p=0.000$) higher for handheld and 13.5% ($p=0.018$) for hands-free phone conversation while driving.

Fluctuation in speed

It is the standard deviation of speed of the driven vehicle during car-following. A significant effect of distraction on fluctuation in speed is observed ($F_{2,62}=6.27$, $p=0.003$). The mean suggest that fluctuation in speed increases with distraction level. The fluctuation in speed was 35.9% ($p=0.022$) higher when driving with handheld phone conversation compared to baseline condition. The difference between hands-free and baseline was not statistically significant ($p=0.232$).

Fluctuation in spacing

It is the standard deviations of spacing between the subject and lead vehicle during car-following. Similar to fluctuation in speed, a significant effect of distraction on fluctuation in spacing is observed ($F_{2,62}=3.56$, $p=0.034$). Figure 3 suggests that fluctuation in spacing increases with distraction level. The fluctuation in spacing was 21.5% ($p=0.023$) higher when driving with handheld phone conversation compared to baseline. The difference between hands-free and baseline was not statistically significant ($p=0.378$).

Acceleration noise

It is the standard deviation of acceleration of the subject vehicle. A significant increase in acceleration noise is observed as an effect of distraction ($F_{2,62}=7.59$, $p=0.001$). The bar chart in Figure 3 and Post hoc test suggest that the distraction effect is not significant for hands-free driving ($p=0.557$), but acceleration noise was significantly higher (33.9%, $p=0.015$) when driving with handheld phone conversation compared to the baseline condition. Acceleration noise is an indicator of driving smoothness. An increased acceleration noise in handheld condition explains less control over driving.

3.4.2. Speed, spacing and time headway profile

To observe the car-following behavior along the road segment, four most important car-following variables were considered. They were speed, spacing, time headway and speed difference. The average values of these variables were plotted against distance travelled. The variable values are averaged over every 4m segment (which is the size of the driven car) using the formula shown in Equation (3.1):

$$X_{ij} = \frac{1}{32}\sum_{1}^{n=32} X_{nij} \quad ; \quad where \begin{cases} i = segment\ id\ [1{:}61] \\ j = [base, handsfree, handheld] \end{cases} \tag{3.1}$$

where X denotes the variable value, i is the segment id and j is the phone condition. The profiles are shown in Figure 3.3.

The speed, spacing and time headway profile shows clear difference between the three driving conditions. In general, distracted drivers tend to select a slower driving speed and maintain a higher spacing and longer time headways with the lead vehicle throughout the length of the road where car-following situation existed. Maximum difference is observed between baseline condition and driving with handheld phone conversation. No clearly noticeable difference is observed in speed difference since drivers were exposed in a car-following situation. As a result, drivers appear to match their speed with the lead vehicle which was maintaining a constant speed.

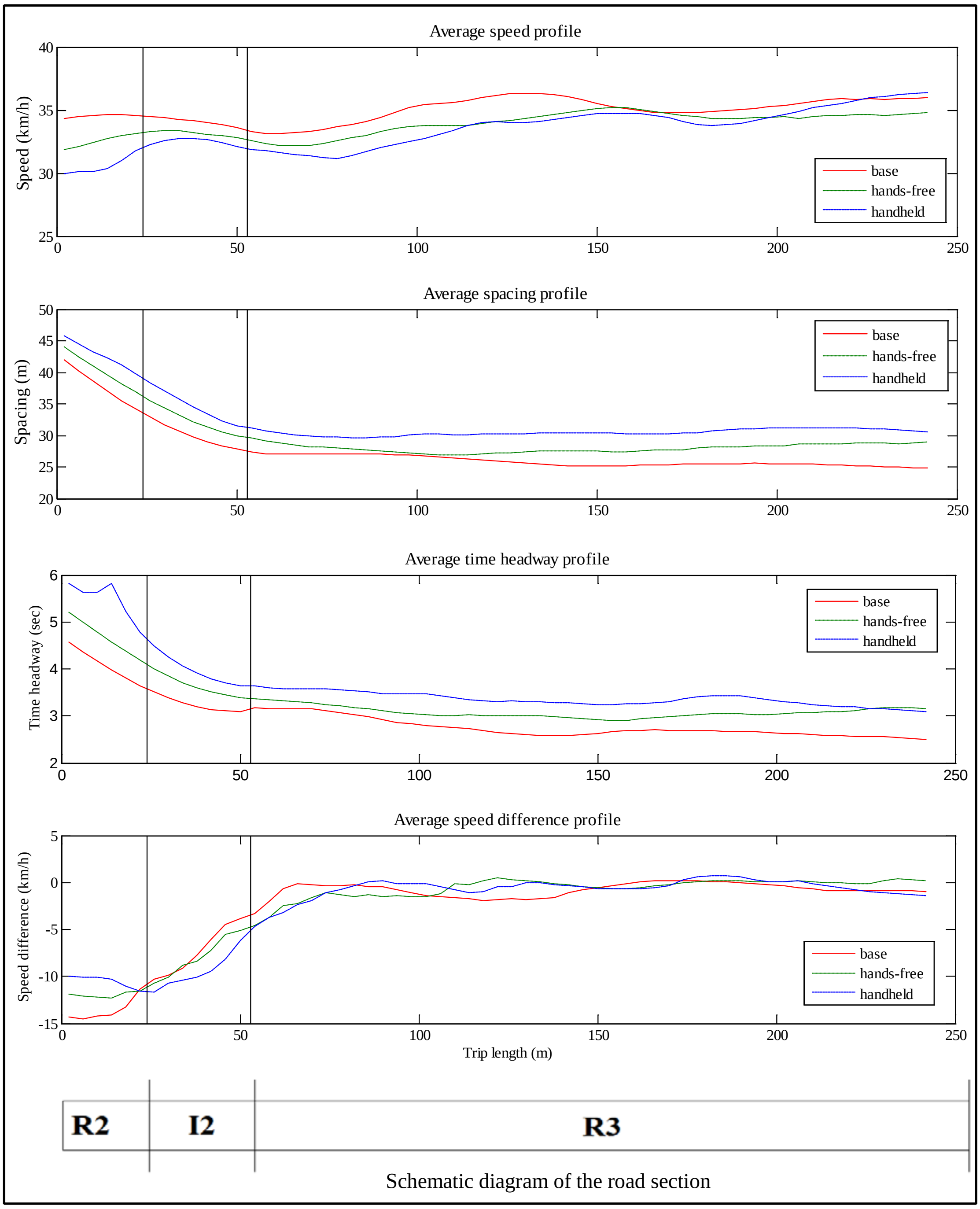


Figure 3.3 Profile for speed, spacing, time headway and velocity difference

3.4.3. GEE analysis

GEE was applied to model driver's time headway as a function of various independent variables. The analysis will identify what factors may affect driver's time headway selection. Time headway was selected as the dependent variable because it considers both the speed and spacing together. The potential explanatory variables for the statistical model included phone condition, driver demographics (age, gender, license type and driving experience) and average speed difference with the lead vehicle. Descriptive statistics of these variables are presented in Table 3.2. Data from all 32 drivers are available in three phone conditions, which created a balanced panel data with 3 observations per driver.

Table 3.2 Descriptive statistics of variables for GEE

Variable name	Description of variables	Min	Max	Mean	SD	Count
Phone condition						
Base	No phone conversation = 1, else = 0	-	-	-	-	32
Hands-free	Hands-free conversation = 1, else = 0	-	-	-	-	32
Handheld	Handheld conversation = 1, else = 0	-	-	-	-	32
Driver’s age	Continuous variable	18	26	21.47	1.98	-
Gender						
Male	If a driver was male = 1, else = 0	-	-	-	-	16
Female	If a driver was female = 1, else = 0	-	-	-	-	16
License type						
Open	If a driver held an open license = 1, else = 0	-	-	-	-	21
Provisional	If a driver held a provisional license = 1, else = 0	-	-	-	-	11
Years of driving	Continuous variable	1	9	4.20	1.87	-
Average time headway	Continuous variable	1.23	6.36	3.36	1.10	-
Average speed difference	Continuous variable	-5.93	3.10	-2.46	1.68	-

Time headway selections of drivers were modelled with a Generalized Estimation Equation with exchangeable correlation structure. The model results are presented in Table 3.3. The best-fit model was derived from a set of models with all possible independent variables following Marginal R^2 and QIC criteria. This model produced the smallest QIC value from a set of alternative models with different independent variables and correlation structures. Smallest QIC value ensures the selection of best working correlation structure (exchangeable in this case). The model also estimated a value of 0.50 for the exchangeable correlation parameter, which indicates a significant correlation among observations of each driver and thus further ensures the appropriateness of the GEE model. This model produced highest Marginal R^2 value among the tested models. The Marginal R^2 value suggests that the model can explain 49% of the variability in the dataset. In this model, all parameters are significant. The best-fit model retained four significant variables including phone condition, average speed difference, driver gender and driver license type.

Table 3.3 GEE Model Estimates for average time headway*

Variable	Estimate	SE	Wald statistic	*p*-value
Constant	3.77	0.21	308.32	<0.001
Phone Condition				
Hands-free	0.33	0.13	6.54	0.011
Handheld	0.75	0.16	21.63	<0.001
Average speed difference	0.29	0.03	92.47	<0.001
Gender				
Female	-0.68	0.28	5.66	0.017
Licence Type				
Provisional	0.81	0.30	7.24	0.007
Estimated scale parameters	0.61	0.11		
Estimated Correlation Parameters	0.50	0.12		
QIC	-30.84			
Quasi-Likelihood	-29.47			
Marginal R^2	0.49			
Number of Observations	96			
Number of clusters	32			
Maximum cluster size	3			

*Model equation: Average time headway = $b_0 + b_1$ * Phone condition + b_2 * Average speed difference + b_3 * Gender + b_4 * Licence type

The parameters for both phone conditions have been found to be positive and significant at 5% significance level in the GEE model. Results clearly indicate that distracted driving influences the time headway selection of drivers in car-following situation. Parameter estimates suggest that distracted drivers, on average, tend to keep 0.33 seconds more headways when engaged in hands-free phone conversation compared to baseline driving. The corresponding headway difference for handheld phone driving condition was about 0.75 seconds. The effects of distraction are higher in driving with handheld phone conversation since this condition has both cognitive and manual distraction. Consequently, handheld driving may be associated with the highest time headway among the three driving scenarios.

Average speed difference, which represents the speed difference between the subject and lead vehicle, has also been significant and positive in the GEE model of time headways in car-following situation. Results suggest that time headway increases with the increase in speed differences. A 1 km/h increase in speed differences leads to about 0.29 seconds increase in time headways. Speed difference can have both positive and negative values. When a lead vehicle is travelling faster than the subject vehicle, the speed difference is positive and the corresponding time headway increases. On the other hand, when the subject vehicle is approaching to a slower vehicle, the speed difference is negative and the corresponding time headway decreases.

It is interesting to notice that female drivers keep less time headway than male drivers. The parameter associated with gender suggests that in general female drivers keep 0.68 seconds less time headway than a male driver in same car-following situation. Driving experience seems to have an impact on time headway selection as the model shows that 'provisional' license holders (less experienced driver) prefer to keep longer time headway than 'open license holders (experienced driver). The effect is even higher than gender. According to the model, a provisional licence holder will keep 0.81 seconds longer time headway than an open licence holder in car-following situation. It is understandable as provisional drivers might have less confidence on their driving ability and thus drive with longer time headway.

3.5. Discussion

Types of phone conversation (hands-free or handheld) affect the car following behavior differently. When driving with hands-free phone conversation the car-following performance did not deteriorate significantly from the baseline. As a result no significant difference was observed for variables like average spacing, fluctuation in spacing and speed, and acceleration noise. This can be partially explained by the prevalence of mobile phone use among the young participants (on average the participants reported to make 65 calls and send 260 text messages in a typical week). However, similar tests on older drivers are needed to confirm this finding.

The findings were different for drivers engaged in handheld phone conversations, with the additional physical constraint of holding the phone. This multitasking configuration increased the workload to the highest level among the three phone conditions. The handheld condition placed an additional manual load on the driver, which together with the mental demand, leads to a greater distraction effect on drivers during the two phone conversations (Higher workload in handheld phone condition was also reported in Matthews et al. (2003) who discovered no difference in mental demand between hands-free and handheld phone conversation, however, physical demand was higher for handheld phone). As a result, the car-following performance was significantly deteriorated. The largest difference between driving conditions was the fluctuation in speed between handheld and baseline driving condition. The second largest difference was acceleration noise between the handheld and baseline conditions. Compared to the baseline condition, a 35.9% increase in speed fluctuation along with 33.9% increase in acceleration noise revealed a significant impact of distracted behavior caused by handheld phone conversations. Increased fluctuation in speed and acceleration explains less control over driving situation in handheld situation compared to baseline. However, drivers have perceived the risk associated with distraction caused by phone conversation while driving. To compensate the risk they showed risk compensatory behavior by increasing spacing and decreasing speed from baseline condition. The risk compensatory behavior is observed in both phone conditions. However, the magnitude is highest for handheld phone conversation which is most likely caused by highest perception of risk in this situation.

Fluctuation of spacing increased when driving with handheld phone conversation compared to baseline. However, in Figure 3 the spacing profiles become fairly stable in all three conditions after about 70m from the start point of car-following. Additional descriptive analysis is performed on car-following data within 70-245m road section. The new analysis shows similar conclusion for all variables except that the difference in fluctuation of spacing becomes insignificant

($F_{2,62}=0.618$, $p=0.541$). It appears that distracted drivers have more variations in spacing when they try to achieve their desired spacing for car-following. Once the desired spacing is reached, drivers try to maintain that unless any change occurs in driving environment.

The time headway selection of drivers was modelled using GEE. The model shows that a typical driver increases the time headway by 0.33 seconds when conversing using hands-free devices and by 0.75 seconds when using handheld mobile phones. In general, female drivers maintain shorter time headways than male drivers. Less experienced drivers (provisional license holders) maintain greater time headways than experienced drivers (open license holder) on average. Female drivers with open driving licenses maintain the shortest time headways in this model, while male drivers with provisional licences maintain the longest time headways. Distraction further increases time headways for all drivers.

3.6. Conclusion

This study investigates car-following behavior of drivers distracted by mobile phone conversations. Participants were exposed to a car-following task in a motion-based driving simulator where the lead vehicle maintained a predefined speed profile depending on the spacing between the driver and the lead vehicle. Focus was given to the behavior of young drivers only with an age cohort between 18 to 26 years. The sample size was good enough to identify some patterns and factors affecting the car-following behavior of young drivers, although a larger sample size may increase the statistical reliability of the results. A set of variables were selected to capture car-following behavior. Repeated measures ANOVA tests were implemented to identify the effect of mobile phone distraction on the selected car-following variables. The study finds evidence of a significant effect of distraction on speed selection, vehicle spacing, and time headways. Overall, drivers maintained lower speeds, larger vehicle spacings, and longer time headways when engaged in phone conversations compared to baseline without phone conversations. This finding may indicate the presence of risk-compensatory behavior, which has been elsewhere observed and reported in the literature (Ranney *et al.* 2004, Strayer *et al.* 2011).

The repeated measures ANOVA test also revealed significant effects of distraction on fluctuation in speed and spacing, and acceleration noise. These increases suggest that distracted driving results in less consistent control in maintaining speed and vehicle spacing in car-following situations. The reduction in speed and increase in vehicle spacing could reflect drivers' attempts to compensate for the increased risk associated with the mobile phone conversations, or could be an artefact of the distraction itself. If the reduction reflects risk compensation, there is insufficient evidence to assess whether the reduction in crash risk would offset the increased crash risk arising from distraction. Other evidence on crash risk while distracted suggests that crash risk overall is increased while distracted. For example, both hands-free and handheld phone uses while driving are associated with a fourfold increase in accident risk (McEvoy*et al.* 2005, Redelmeier and Tibshirani1997). These findings suggest that observed risk compensation is insufficient to offset risk increment caused by cognitive distraction.

These results can foster a better understanding of the consequence of distracted driving on road crashes, and shed light on the complexity involved with modeling driving behavior. Driving behavior modeling is one of the oldest and most studied topics in Traffic Engineering. Many models have been developed to describe two primary driving tasks: car following (see Saifuzzaman and Zheng (2014) for the latest review) and lane changing (see Zheng (2014) for a comprehensive review). Despite notable progress in the last few decades on this important topic, efforts to incorporate human factor effects are limited. For most driving behavior models, information on vehicular movements is the only input. The potential complexity introduced by human drivers is by and large ignored. This omission is not surprising due to our limited understanding on human factor issues. More specifically, there is a clear need to comprehensively investigate and accurately quantify how drivers perform when distracted because of its importance to both road safety and driver behavior modeling. This research gap partially motivated this study. The findings clearly show that drivers behave differently when distracted by hand-held phone conversations. Unfortunately, most of the existing car-following models do not consider such impacts on driving because they are developed for normal (i.e., non-distracted) driving situations (Saifuzzaman and Zheng 2014). Recently, researchers in the traffic flow community have realized the importance of improved and more comprehensive reflection of human factor dimensions in car-following models, and have started exploring new ideas (e.g., Hamdar and Mahmassani (2008)). We believe that empirical evidence on how distracted driving influences car-following behavior (e.g., speed, spacing, and time headway) revealed in this study can facilitate such efforts. In keeping, the authors are working currently on improving car-following model performance by incorporating behavioral differences caused by distraction.

Current study did not address reaction time differences arising from distracted driving, as this topic is covered in Haque and Washington (Haque and Washington 2013, Haque and Washington 2014). This study is focused on car-following behavior of young drivers only; further study is required to investigate the effect of mobile phone distraction in a wider range of driver ages to compare the car-following behavior across different age groups. Future studies are also required to investigate distracted car-following behavior in other scenarios, for example, on longer road section, with different speed limits, and on curve segments. Influence of other type of human factors (for example, fatigue, drowsiness, alcohol and drug use, emotion and stress) on car-following behavior should also be investigated in future to obtain a better picture about human car-following behavior in different circumstances.

References

Aami, 2012. 11th aami young drivers index. Retrieved at: http://www.aami.com.au/sites/default/files/fm/news/11th_aami_young_drivers_index.pdf.

Alm, H., Nilsson, L., 1995. The effects of a mobile telephone task on driver behaviour in a car following situation. Accident Analysis & Prevention 27 (5), 707-715.

Belz, N.P., Aultman-Hall, L., 2011. Analyzing the effect of driver age on operating speed and acceleration noise. Transportation Research Record: Journal of the Transportation Research Board 2265 (1), 184-191.

Burns, P., Parkes, A., Burton, S., Smith, R., Burch, D., 2002. How dangerous is driving with a mobile phone? Benchmarking the impairment to alcohol. TRL Report 547. Transportation Research Labratory, Berkshire.

Caird, J.K., Willness, C.R., Steel, P., Scialfa, C., 2008. A meta-analysis of the effects of cell phones on driver performance. Accident Analysis & Prevention 40 (4), 1282-1293.

Drews, F.A., Strayer, D.L., 2009. Cellular phones and driver distraction. In: Regan, M.A., Lee, J.D., Young, K.L. eds. Driver distraction: Theory, effects, and mitigation. CRC Press, pp. 169-190.

Evans, L., 1991. Traffic safety and the driver. Van Nostrand Reinhold, New York.

Farah, H., Koutsopoulos, H.N., Saifuzzaman, M., Kölbl, R., Fuchs, S., Bankosegger, D., 2012. Evaluation of the effect of cooperative infrastructure-to-vehicle systems on driver behavior. Transportation Research Part C: Emerging Technologies 21 (1), 42-56.

Fitch, G.M., Soccolich, S.A., Guo, F., Mcclafferty, J., Fang, Y., Olson, R.L., Perez, M.A., Hanowski, R.J., Hankey, J.M., Dingus, T.A., 2013. The impact of hand-held and hands-free cell phone use on driving performance and safety-critical event risk. Report No. DOT HS 811 757. National Highway Traffic Safety Administration, Washington, DC.

Hamdar, S.H., Mahmassani, H.S., 2008. From existing accident-free car-following models to colliding vehicles: Exploration and assessment. Transportation Research Record: Journal of the Transportation Research Board 2088 (1), 45-56.

Haque, M., Washington, S., 2013. Effects of mobile phone distraction on drivers' reaction times. Journal of the Australasian College of Road Safety 24 (3), 20-29.

Haque, M.M., Washington, S., 2014. A parametric duration model of the reaction times of drivers distracted by mobile phone conversations. Accident Analysis & Prevention 62, 42-53.

Herman, R., Montroll, E.W., Potts, R.B., Rothery, R.W., 1959. Traffic dynamics: Analysis of stability in car following. Operations research 7 (1), 86-106.

Holm, S., 1979. A simple sequentially rejective multiple test procedure. Scandinavian journal of statistics, 65-70.

He, J., Chaparro, A., Nguyen, B., Burge, R.J., Crandall, J., Chaparro, B., Ni, R., Cao, S., 2014. Texting while driving: Is speech-based text entry less risky than handheld text entry? Accident Analysis & Prevention 72, 287-295.

Jones, T.R., Potts, R.B., 1962. The measurement of acceleration noise-a traffic parameter. Operations Research 10 (6), 745-763.

Just, M.A., Keller, T.A., Cynkar, J., 2008. A decrease in brain activation associated with driving when listening to someone speak. Brain research 1205, 70-80.

Lee, J.D., Young, K.L., Regan, M.A., 2009. Defining driver distraction. In: Lee, J.D., Young, K.L., Regan, M.A. eds. Driver distraction: Theory, effects, and mitigation. CRC Press, pp. 31-40.

Liang, K.-Y., Zeger, S.L., 1986. Longitudinal data analysis using generalized linear models. Biometrika 73 (1), 13-22.

McCullagh, P., Nelder, J. A., 1989. Generalized Linear Models. 2nd ed. London: Chapman& Hall.

McEvoy, S.P., Stevenson, M.R., Mccartt, A.T., Woodward, M., Haworth, C., Palamara, P., Cercarelli, R., 2005. Role of mobile phones in motor vehicle crashes resulting in hospital attendance: A case-crossover study. BMJ 331, 428-430.

Muhrer, E., Vollrath, M., 2011. The effect of visual and cognitive distraction on driver's anticipation in a simulated car following scenario. Transportation Research Part F: Traffic Psychology and Behaviour 14 (6), 555-566.

Neale, V.L., Dingus, T.A., Klauer, S.G., Sudweeks, J., Goodman, M., 2005. An overview of the 100-car naturalistic study and findings. National Highway Traffic Safety Administration, Paper no 05-0400.

Nelder, J.A., Baker, R., 1972. Generalized linear models John Wiley & Sons.

NHTSA, 2014. Driver electronic device use in 2012. Traffic Safety Facts. Paper No. DOT HS 811884. National Highway Traffic Safety Administration, Washington, DC.

Pan, W., 2001. Akaike's information criterion in generalized estimating equations. Biometrics 57 (1), 120-125.

Redelmeier, M.D., Tibshirani, R.J., 1997. Association between cellular-telephone callsand motor vehicle collisions. New England Journal of Medicine 336 (7), 453-458.

Ranney, T., Watson, G., Mazzae, E.N., Papelis, Y.E., Ahmad, O., & Wightman, J.R., 2004. Examination of the distraction effects of wireless phone interfaces using the National Advanced Driving Simulator-Preliminary report on freeway pilot study. Paper No. DOT 809 737. National Highway Transportation Safety Administration: East Liberty, OH.

Saifuzzaman, M., Zheng, Z., 2014. Incorporating human-factors in car-following models: A review of recent developments and research needs. Transportation Research Part C: Emerging Technologies 48, 379-403.

Schömig, N., Metz, B., Krüger, H.-P., 2011. Anticipatory and control processes in the interaction with secondary tasks while driving. Transportation Research Part F: Traffic Psychology and Behaviour 14 (6), 525-538.

Stavrinos, D., Jones, J.L., Garner, A.A., Griffin, R., Franklin, C.A., Ball, D., Welburn, S.C., Ball, K.K., Sisiopiku, V.P., Fine, P.R., 2013. Impact of distracted driving on safety and traffic flow. Accident Analysis & Prevention 61, 63-70.

Strayer, D.L., Cooper, J., Drews, F.A., 2011. Profiles in cell phone-induced driver distraction.

Strayer, D.L., Drews, F.A., Johnston, W.A., 2003. Cell phone-induced failures of visual attention during simulated driving. Journal of experimental psychology: Applied 9 (1), 23.

Taylor, M.A.P., Woolley, J.E., Zito, R., 2000. Integration of the global positioning system and geographical information systems for traffic congestion studies. Transportation Research Part C: Emerging Technologies 8 (1), 257-285.

Törnros, J., Bolling, A., 2006. Mobile phone use–effects of conversation on mental workload and driving speed in rural and urban environments. Transportation Research Part F: Traffic Psychology and Behaviour 9 (4), 298-306.

Wedderburn, R. W. M. (1974). Quasi-likelihood functions, generalized liner models, and the Gauss-newton method. Biometrika 61, 439–447.

White, K.M., Hyde, M.K., Walsh, S.P., Watson, B., 2010. Mobile phone use while driving: An investigation of the beliefs influencing drivers' hands-free and hand-held mobile phone use. Transportation Research Part F: Traffic Psychology and Behaviour 13 (1), 9-20.

Zheng, B., 2000. Summarizing the goodness of fit of generalized linear models for longitudinal data. Statistics in medicine 19 (10), 1265-1275.

Zheng, Z., 2014. Recent developments and research needs in modeling lane changing. Transportation Research Part B: Methodological 60, 16-32.

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Chapter 4

Revisiting the Task-Capability Interface model for incorporating human factors into Car-following models

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Revisiting the Task-Capability Interface model for incorporating human factors into Car-following models

Mohammad Saifuzzaman[1], Zuduo Zheng[1], Md. Mazharul Haque[1, 2], Simon Washington[1, 2]

[1] School of Civil Engineering & Built Environment, Science and Engineering Faculty, Queensland University of Technology (QUT), Brisbane, Australia

[2] Centre for Accident Research and Road Safety (CARRS-Q), Faculty of Health, Queensland University of Technology (QUT), Brisbane, Australia

Publication status: This article is published in *Transportation Research Part B: Methodological.* Volume: 82, pages: 1-19, published: December, 2015. doi:10.1016/j.trb.2015.09.011

Journal quality: The journal in which this paper appears is a peer-reviewed publication with an international readership. The journal's Impact Factor is 2.952, and ranks Q1, 3/69 (Transportation) according to the SCImago Journal Rank.

Foreword: This article addresses the third research objective of this thesis, stated in Section 1.2 of chapter 1. Experiencing from the driving simulator experiment presented in the previous chapter (Chapter 3) this chapter (article) proposes a framework to incorporate human factors' influences in car-following models. An established driver behavior theory is used to depict risk-taking behaviors. Two conventional CF models have been improved based on the proposed method and their superiority over the original models is confirmed.

Statement of contribution of co-authors for thesis by published paper

Publication title: Revisiting the Task-Capability Interface model for incorporating human factors into Car-following models

The authors listed below have certified that:

- They meet the criteria for authorship in that they have participated in the conception, execution, or interpretation, of at least that part of the publication in their field of expertise;
- They take public responsibility for their part of the publication, except for the responsible author who accepts overall responsibility for the publication;
- There are no other authors of the publication according to these criteria;
- Potential conflicts of interest have been disclosed to (a) granting bodies, (b) the editor or publisher of journals or other publications, and (c) the head of the responsible academic unit, and
- They agree to the use of the publication in the student's thesis and its publication on the Australasian Digital Thesis database consistent with any limitations set by publisher requirements.

Each author's contributions are listed below:

Contributor	***Statement of contribution***
Mohammad Saifuzzaman Signature: Saifuzzaman Date: 15/06/2016	Developed the methodology, conducted data analysis, and wrote the manuscript. The candidate was also responsible for any revisions made at the suggestions of journal reviewers.
Zuduo Zheng	Supervised the research, helped developing the methodology, and reviewed the manuscript. Also played the role of the corresponding author.
Md. Mazharul Haque	Commented on the methodology and reviewed the manuscript.
Simon Washington	Commented on the methodology and reviewed the manuscript.

Principal Supervisor Confirmation:

I have sighted email or other correspondence from all co-authors confirming their certifying authorship.

Dr. Zuduo Zheng		15/06/2016
(Name)	(Signature)	(Date)

Revisiting the Task-Capability Interface model for incorporating human factors into Car-following models

Mohammad Saifuzzaman, Zuduo Zheng, Md. Mazharul Haque, Simon Washington

Abstract

Human factors such as distraction, fatigue, alcohol and drug use are generally ignored in car-following (CF) models. Such ignorance overestimates driver capability and leads to most CF models' inability in realistically explaining human driving behaviors. This paper proposes a novel car-following modeling framework by introducing the difficulty of driving task measured as the dynamic interaction between driving task demand and driver capability. Task difficulty is formulated based on the famous Task Capability Interface (TCI) model, which explains the motivations behind driver's decision making. The proposed method is applied to enhance two popular CF models: Gipps' model and IDM, and named as TDGipps and TDIDM respectively. The behavioral soundness of TDGipps and TDIDM are discussed and their stabilities are analyzed. Moreover, the enhanced models are calibrated with the vehicle trajectory data, and validated to explain both regular and human factor influenced CF behavior (which is distraction caused by hand-held mobile phone conversation in this paper). Both the models show better performance than their predecessors, especially in presence of human factors.

4.1. Introduction

Driver’s competence of driving a vehicle is determined by many factors, e.g., driver’s basic physiological characteristics, education, training and experience, which together define a driver’s optimal capability. However, what a driver actually delivers (also referred as driving performance) often falls short of the optimal capability because of various factors that can impair driving performance, including (but not limited to) distraction, fatigue, drowsiness, and alcohol and drug use. These factors are collectively named as human factors (Fuller, 2002a).

Increase in reaction time/delay is reported as a common impairment in human behavior as an influence of human factors (Burns et al., 2002; Haque and Washington, 2014; Leung et al., 2012; Young et al., 2009). Drivers who are distracted by secondary tasks (e.g. mobile phone use, eating and talking to passengers) are most likely to increase spacing (distance from the preceding vehicle) and reduce speed (for a detail review on distracted driving see Young et al., 2009). In prolonged driving activities, drivers often become tired due to fatigue and thus increase time headway to reduce collision risk (Fuller, 1984). Alcohol and drug use are also found to have serious impact on driving performance. Moskowitz and Fiorentino (2000) in their literature review reported significant impairment of perceptual abilities (such as anticipation time, signal detection, visual search, pattern recognition, and hazard perception) even with blood alcohol content (BAC) below the legal limit (0.08gm/100ml). Intoxicated drivers also make poor decisions, dangerously follow the preceding vehicle, drive faster, and apply more force while braking (Fuller, 2002a; Harrison and Fillmore, 2011; Strayer et al., 2006).

Despite the negative effect of human factors on driving performances, road collisions are still regarded as relatively rare events. In most cases drivers are aware of the potential risk and take necessary actions to be safe, a behavior commonly known as risk-compensation. For example, a tired driver might opt to select a less congested route, or drive more slowly. Risk of collision increases only when driving capability impairment has not been fully and timely recognized, and subsequently accounted for (e.g. after heavy drinking; when the driver is under pressure to reach the destination within a limited time period). Under these conditions, driving task demand may well exceed driver's momentary driving capability, and consequently any sudden change in the driving environment likely leads to a collision.

Along with lane changing (Zheng, 2014), car-following (CF) is one of the two primary driving tasks that drivers routinely perform. Rules governing CF are typically simplified as a set of mathematical models that aim for reproducing the longitudinal interactions in the driver-vehicle system when one follows another. As one of the oldest topic in traffic engineering, numerous CF models have been proposed in the literature (see Saifuzzaman and Zheng, 2014 for the latest review). The large number of CF models proposed in the literature is mainly caused by the fact that our understanding on CF is still incomplete, and that particularly researchers are still facing a challenge to incorporate human factors. Without adequately accommodating human factors, fitting models over collected vehicular data cannot fully explain the complex dynamics behind the actions of the driver. This limitation first came to debate after the historical review of CF models by Brackstone and McDonald (1999).

Since then CF models have been heavily criticized for their inability in realistically explaining human driving behaviors (see for example, Boer, 1999; Hamdar, 2012; Hancock, 1999; Saifuzzaman and Zheng, 2014; Treiber and Kesting, 2013). Despite the well-acknowledged impact of human factors on driving, only few attempts are found to enhance CF models to incorporate these factors. Methodological limitations and data availability have often hindered this development. Reaction time is among the few human factors that have been used in CF models (Bando et al., 1998; Gazis et al., 1961; Gipps, 1981; Hamdar et al., 2008). Several models have also considered drivers' perceptual limitations by imposing thresholds on spacing and speed difference between the subject and the preceding vehicle (e.g. CF models proposed by Fritzsche, 1994 and by Wiedemann, 1974). For a detail discussion, see Saifuzzaman and Zheng (2014).

As a consequence of ignoring human factors, the existing CF models are not capable of reproducing human factor induced collisions. To overcome this issue, Yang and Peng (2010) proposed an errorable CF model which allows human errors caused by distraction, reaction delay and perceptual limitations. The model assumes that a distracted driver does not update their driving status and adopts the same speed/acceleration prior to being distracted. It makes the driver oblivious of any changes in the driving environment during the distracted period. Similar assumption is also applied in Przybyla et al. (2012) and Bevrani and Chung (2012) to explain distracted driving. Although the underlying logic of the errorable CF model is interesting, the assumption about distracted behavior is too simple and might be unrealistic because research suggests that distracted drivers can react to the changes in the driving environment, although the reaction time may increase (Haque and Washington, 2013, 2014, 2015; Strayer et al., 2006).

This study aims to incorporate human factors into the CF models. Inspired by the Task-Capability Interface model (TCI; Fuller, 2000, 2005), a new approach of modeling CF behavior is proposed. With this approach the difficulty of a driving task dictates human motivations behind driving decisions. A formulation of task difficulty is proposed, and a framework is introduced for integrating TCI with two existing CF models. To avoid the so-called “narrative fallacy”, which is the practice of offering a plausible explanation after the occurrence of an event (Taleb, 2010), a driving simulator experiment is carefully designed and implemented in a controlled environment. The new models are calibrated and validated with the vehicle trajectory data obtained from the driving simulator experiment.

The reminder of this paper is organized as follows. Section 2 presents an introduction of the TCI model. Section 3 describes the proposed formulation of task difficulty based on the TCI model and a framework for integrating TCI with the existing CF models. Section 4 provides results of integrating TCI with Gipps’ CF model and IDM. Section 5 discusses in detail the calibration and validation of the original and reformulated Gipps’ model and IDM. Finally, Section 6 summarizes main conclusions and discusses future research.

4.2. Background: Task-Capability Interface (TCI) MODEL

From human factors perspective, Fuller (2000, 2005) presents the Task-Capability Interface (TCI) model where the difficulty of driving task dominates driver behavior. In this model, task difficulty (*TD*) arises out of the dynamic interaction between driver capability and driving task demand. Driver capability is assumed to be limited by constitutional characteristics (such as knowledge and skills developed through education and training) and biological capabilities (such as perceptual acuity, reaction time and visual acuity), and shaped by momentary variations in human factors. Task demand arises out of a combination of environmental conditions (e.g. surface condition, visibility, time of the day), vehicle characteristics (e.g. engine power, braking, and driver assistance system), speed, and position of the vehicle with respect to other road users. The model projects the interaction between driver capability and task demand through control and collision as illustrated in Figure 4.1. When capability exceeds demand, the task is easy and within control of the driver. However, loss of control occurs when, for a multitude of possible reasons, task demand exceeds driver capability (Fuller, 2011).

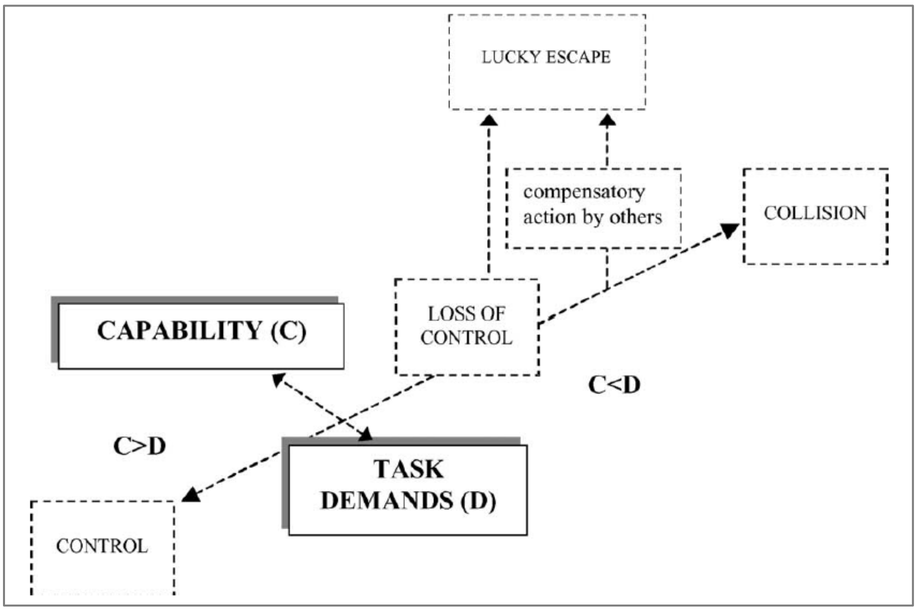

Figure 4.1 Task-Capacity Interface model
(Source: Fuller, 2005)

6.1 Task difficulty homeostasis

The key hypothesis behind TCI model is the “task difficulty homeostasis” theory. According to this theory a driver continuously makes real-time decisions to maintain perceived difficulty of driving task within their acceptable limit by adjusting control variables like speed and headway (Fuller, 2002b, 2011). Thus, if the perceived task difficulty is higher than the acceptable limit, for example driving in adverse weather condition (e.g. fog, snow or rain), driver is likely to slow down to decrease the level of task difficulty within the acceptable limit. On the other hand when the driving task is boringly easy, for example driving in a straight highway with no nearby road users, driver speeds up to make the task more challenging. The range of task difficulty targeted by the driver is determined by their perceived capability and motivation for engaging in a particular level of task difficulty. During the steady-state following the task difficulty reaches to the acceptable limit.

4.3. Formulation of Task Difficulty for Car-Following models

According to the TCI model, task difficulty (*TD*) can be expressed as an interaction between task demand and driver capability. This paper assumes this interaction as the ratio of task demand and driver capability. Fuller (2002) explained that the task demand at any instance could be explained by the speed of the driven vehicle and the spacing (distance) from the preceding vehicle. Other things being equal, the higher the speed or the smaller the spacing, the less time there is available for decision making and response which leads to increased task demands.

Driver capability is difficult to be measured due to the presence of a number of variables, which are unobservable in nature (such as the constitutional characteristics and biological capabilities). However, past studies have discovered a correlation between driver capability and time headway selection. For example, Johansson and Rumar (1971) stated that minor changes in human factors (for example motivation, aggression and alertness) might unknowingly influence driver's time headway selection. Saifuzzaman et al. (2015) found a negative correlation between driving experience and time headway selection where experienced drivers are more likely to keep shorter time headways than novice drivers. Furthermore, sensation seekers keep lower time headways than sensation avoiders (Henio et al., 1992). Time headway is also found to be affected by task related factors. For example, conversing over phone puts an additional mental demand, which reduces driver's concentration on car following, and to compensate the risk drivers are found to keep higher time headways (Saifuzzaman et al., 2015; Ranney et al., 2004).

Generally each driver has a desired time headway (also known as preferred time headway) that the driver wishes to maintain during the steady-state CF. Desired time headway can be defined as the time available to the driver to give an appropriate braking response in case the lead vehicle decelerates (Winsum and Heino, 1996). It is independent of speed. Henio et al. (1992) and Heino et al. (1996) summarized that a forced decrease of time headway from preferred level increases experienced risk at both the cognitive and physiological level; and the more a situation is perceived as being risky the more mental effort is invested to cope with it. Similar conclusion is also drawn in Lewis-Evans et al. (2010) who found that below the desired level drivers consider the task difficult, risky and uncomfortable, and apply more effort to follow the lead vehicle. Therefore, it is assumed in this paper that driver capability is inversely proportional to driver's desired time headway selection.

From the above discussion a formulation of task difficulty is proposed in Equation (4.1):

$$TD_n(t) = \left(\frac{V_n(t-\tau_n')\tilde{T}_n}{(1-\delta_n)S_n(t-\tau_n')}\right)^{\gamma} \tag{4.1}$$

where TD_n represents task difficulty as perceived by driver *n* at time *t*, S_n is spacing measured as the distance between the front of the subject (driven) vehicle to the back of the preceding vehicle; V_n is speed of the subject vehicle; $\tilde{T}_n$ is desired time headway, δ_n is a risk parameter, τ_n' is the modified reaction time (more discussion on δ_n and τ_n' is provided later) and γ is a sensitivity parameter which is used to capture driver's sensitivity towards the task difficulty level. In Equation (4.1) the task difficulty increases with an increase in speed or a decrease in spacing or both. The calculation of task difficulty is lagged by the reaction time, which means that it produces the perceived task difficulty at time *t* based on the observations at time $(t-\tau_n')$. In addition, the same task that is easy to one driver may be difficult to another, depending on their desired time headways, which is consistent with observations and reflects the soundness of the task difficulty definition in Equation (4.1).

The risk parameter ($\delta_n < 1$) captures the perceived risk that arises from human factors. A positive risk parameter indicates that the driver acknowledges the impairment caused by human factors and perceives the risk of driving with reduced capability. Consequently, the perceived level of task difficulty increases. A negative risk parameter indicates aggressive driving where the driver underestimated the risk. For example, driving under the influence of alcohol or other drugs may lead to lack of concern for safety and lead to aggressive behavior (e.g., dangerously flowing the preceding vehicle, or speeding). In regular driving (in absence of human factors) the driver can drive with the full capability, and thus the risk parameter will be zero. The risk parameter can also be zero in presence of human factors. In this case it simply explains that the human factor influence is not strong enough for that particular driver to consider any risk from it. The risk parameter will be one in situations when the driver perceives that crash would be unavoidable if driving continues, e.g., when the driver feels too tired to drive or when the vehicle suddenly starts malfunctioning. To avoid crash, the driver will immediately stop the vehicle. In this study, the risk parameter is kept smaller than one for continuous driving.

In Equation (4.1) a modified reaction time is used which is calculated as: $\tau_n' = \tau_n + \varphi_n$, where φ_n denotes the reaction time increase (in seconds). The reaction time increase φ_n can be either estimated from driving experiments or extracted from previous studies. A wide range of values for reaction time impairment due to human factors is reported in the literature. For example, a meta-analysis based on 33 studies (Caird et al., 2008) reported a 0.25-second increase in reaction time caused by phone-related distractions.

The task difficulty homeostasis theory is used to incorporate TD_n in a CF model. According to this theory every driver has a range of acceptable task difficulty which they try to achieve and maintain during steady-state following. It is situation dependent and varies among the drivers. It will be same as the task difficulty level at equilibrium (TD_e) expressed as $TD_e = \left(V_e\tilde{T}/(1-\delta)S_e\right)^{\gamma}$, where V_e and S_e are equilibrium speed and equilibrium spacing respectively. The equilibrium level of task difficulty depends on the desired time headway, driver's risk perception, the sensitivity parameter and the equilibrium speed-spacing relationship. $TD_n = 1$ explains that the perceived level of the task demand is equals to driver capability. At $TD_n = 1$, a driver is satisfied with following the speed generated by the original model. On the other hand, $TD_n \neq 1$ suggests that the driver is not satisfied with the proposed speed from the original model. For example, if $TD_n < 1$, the driver wishes to have a higher speed than the one proposed by the original model due to the fact that the task demand is lower than driver's capability. Therefore, the role of TD_n is to modify the speed/acceleration behavior of the original model based on the relation between task demand and driver capability. A task difficulty car-following (TDCF) framework is proposed in Figure 4.2 to incorporate TD_n in CF models.

It is assumed that each driver has a particular reaction time and desired time headway. To allow driver heterogeneity, distributions of these two parameters can be used. The two human-factor parameters (δ_n, φ_n) can be a time or space dependent matrix to let the model know when, where and how much the driver is influenced by human factors. In the TDCF framework, TD_n should be used to modify either spacing or speed (not both) of the CF model. This modification is critical and could be different for different CF models and should be consistent with the risk homeostasis theory.

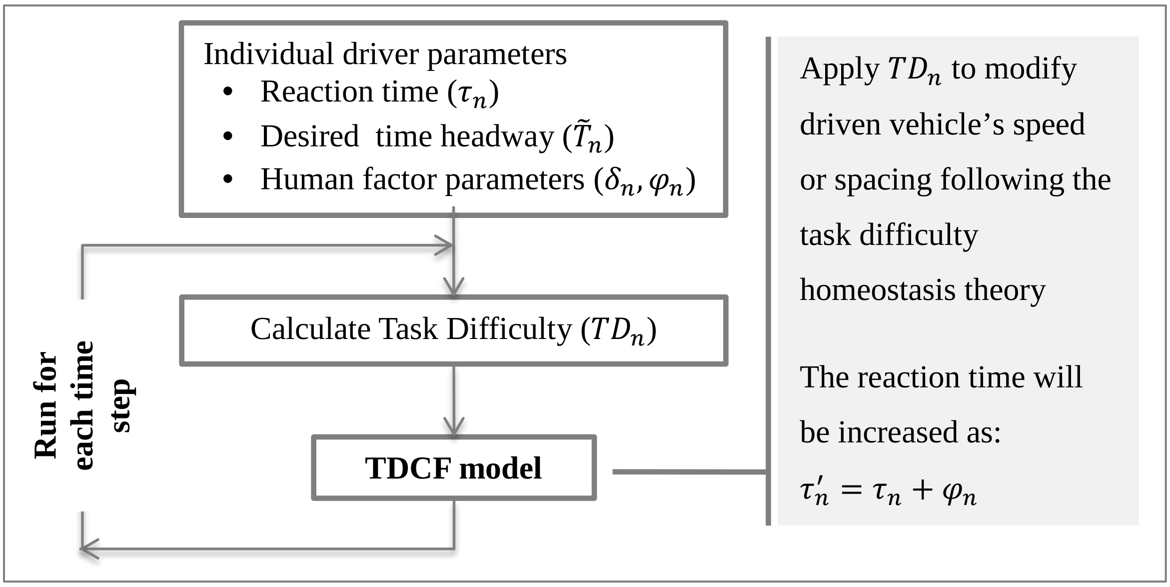

Figure 4.2 The Task difficulty car-following (TDCF) framework

4.4. Application of TDCF

To demonstrate the performance of the TDCF framework, it is applied to two popular CF models: Gipps' model (Gipps, 1981) and Intelligent Driver Model (IDM, Treiber et al., 2000). As an influential CF model in the literature, Gipps' model has been used in several traffic simulation packages including AIMSUN (Barceló and Casas, 2005). IDM is also a well-established CF model, and its good performance is reported in the literature (e.g., Brockfeld et al. 2003). Please note that the authors of this paper acknowledge that both Gipps' model and IDM perform well in describing traffic characteristics when they are properly calibrated and validated. However, both being engineering CF models they inherently lack mechanisms of capturing and explaining the influence of human factors on CF (for a detail discussion on this matter see Saifuzzaman and Zheng, 2014). In contrast, derived from a well-established risk taking theory, the TDCF framework proposed in this study offers more explanatory and predictive power. Particularly, with a single set of parameters the improved models are capable of capturing both regular and human factor influenced CF behavior, as confirmed by the analysis discussed later.

4.4.1. TDCF on Gipps' model

Gipps' model has separate formulas for free-flow regime (Equation 2) and for CF regime (Equation 4.3). The two regimes can switch between each other according to a simple switching rule (Equation 4.4).

$$V_{a,n}(t+\tau_n) = V_n(t) + 2.5\tilde{a}_n\tau_n\left(1 - \frac{V_n(t)}{\tilde{V}_n}\right)\left(0.025 + \frac{V_n(t)}{\tilde{V}_n}\right)^{\frac{1}{2}} \tag{4.2}$$

$$V_{b,n}(t+\tau_n) = \tilde{b}_n\tau_n + \sqrt{\tilde{b}_n^2\,\tau_n^2 - \tilde{b}_n\left[2(\Delta X_n(t) - L_n - s_n) - V_n(t)\tau_n - \frac{V_{n-1}(t)^2}{\hat{b}_n}\right]} \tag{4.3}$$

$$V_n(t+\tau_n) = \min\{V_{a,n}(t+\tau_n), V_{b,n}(t+\tau_n)\} \tag{4.4}$$

Where V_n denotes the speed of the subject vehicle n, $\tilde{a}_n$ is the desired acceleration, $\tilde{b}_n$ is the desired deceleration, ΔX_n is the space headway between the subject and preceding vehicles ($\Delta X_n = x_{n-1} - x_n$; where x_n is the position of the vehicle n), L_n is the vehicle length, s_n is the minimum spacing at a standstill situation, $\hat{b}_n$ is an estimate of the deceleration applied by the preceding vehicle (b_{n-1}), and $\tilde{V}_n$ is the desired speed of vehicle n, and τ_n is the reaction time.

The TDCF framework is applied to Gipps' model as shown in Equation (4.5) and (4.6). TD_n is applied in Equation (4.5) to modify the acceleration behavior as such that $TD_n < 1$ leads to an increase in desired acceleration; in contrast, a decrease in desired acceleration occurs for $TD_n > 1$. Likewise, TD_n modifies the deceleration behavior in Equation (4.6) so that when $TD_n > 1$ the desired deceleration increases and vice-versa. Modification in desired acceleration and deceleration subsequently modifies the speed behavior of the driver. More specifically, the TDCF framework generates a lower speed than Gipps' model does when $TD_n > 1$ and vice-versa. Furthermore, to prevent the model from producing unrealistic acceleration and deceleration behaviors, the maximum and the minimum limits of speed are imposed, as shown in Equation (4.7) and (4.8), respectively. Finally, Equation (4.9) controls the switching among the calculated speeds. The proposed model is called task difficulty Gipps' model (TDGipps) in the rest of this paper.

$$V_{a,n}(t+\tau'_n) = V_n(t) + 2.5\frac{\tilde{a}_n\tau'_n}{TD_n(t+\tau'_n)}\left(1-\frac{V_n(t)}{\tilde{V}_n}\right)\left(0.025+\frac{V_n(t)}{\tilde{V}_n}\right)^{\frac{1}{2}} \tag{4.5}$$

$$\begin{aligned} V_{b,n}(t+\tau'_n) \\ = \tilde{b}_n\tau'_n TD_n(t+\tau'_n) \\ + \sqrt{\left(\tilde{b}_n\tau'_n\right)^2 - \tilde{b}_n\left[2(\Delta X_n(t) - L_n - s_n) - V_n(t)\tau'_n - \frac{V_{n-1}(t)^2}{\hat{b}_n}\right]} \end{aligned} \tag{4.6}$$

$$V_{c,n}(t+\tau'_n) = V_n(t) + a_n^{max}\tau'_n \tag{4.7}$$

$$V_{d,n}(t+\tau'_n) = \max\{0, V_n(t) + b_n^{max}\tau'_n\} \tag{4.8}$$

$$V_n(t+\tau'_n) = \max\left\{V_{d,n}(t+\tau'_n), \min\{V_{a,n}(t+\tau'_n), V_{b,n}(t+\tau'_n), V_{c,n}(t+\tau'_n)\}\right\} \tag{4.9}$$

Where a_n^{max} and b_n^{max} are the maximum allowable acceleration and deceleration, respectively.

In the free flow regime the spacing is large which produces a low task difficulty level ($TD_n < 1$). Therefore, simulated speeds by TDGipps model in the free flow regime would be higher and simulated spacings would be smaller than those simulated by the original Gipps' model when other parameters are the same. On the other hand, in the car-following regime, the simulated speed and spacing varies according to the task difficulty level. TDGipps model will produce higher spacing than the original Gipps' model when $TD_n > 1$ and vice-versa. The two models will have similar performance at $TD_n = 1$.

The equilibrium solution of Gipps' model for uniform flow was first developed by Wilson (2001). In equilibrium all vehicles are travelling with an equilibrium speed of V_e and an equilibrium spacing of S_e. Assuming that all vehicles have the same parameter values and all drivers have the same characteristics, the equilibrium solution for Gipps' model is shown in Equation (4.10).

$$V_e = \begin{cases} \text{mid}\left[0,\ \frac{3\tau}{2\left(\frac{1}{\tilde{b}}-\frac{1}{\hat{b}}\right)}\left(-1+\sqrt{1+\frac{8(S_e-s)\left(\frac{1}{\tilde{b}}-\frac{1}{\hat{b}}\right)}{9\tau^2}}\right),\ \tilde{V}\right], & \tilde{b} \neq \hat{b} \\ \text{mid}\left[0,\ \frac{2(S_e-s)}{3\tau},\ \tilde{V}\right] & , \tilde{b} = \hat{b} \end{cases} \tag{4.10}$$

where $\text{mid}[0, V_e, \tilde{V}] = \min\{\tilde{V}, \max(0, V_{eq})\}$. A close examination of Equation (4.10) discloses that when $\tilde{b} > \hat{b}$ the equilibrium speed can be unstable. As explained in Punzo and Tripodi (2007), when the driver underestimates the leader's deceleration capability, i.e. when $\tilde{b} > \hat{b}$, the steady state flow is not always stable, thus Gipps' model should be used with an assumption of $\tilde{b} < \hat{b}$. However, adding this assumption makes Gipps' model only produce conservative driver behavior.

The steady state solution can also be derived for the proposed TDGipps model from Equation (4.6). In the equilibrium condition Equation (4.6) can be reorganized in terms of V_e and S_e as shown in Equation (4.11).

$$\tilde{b}\tau^2\left(\frac{\tilde{T}}{(1-\delta)S_e}\right)^{2\gamma} {V_e}^{2\gamma} + 2\tau\left(\frac{\tilde{T}}{(1-\delta)S_e}\right)^{\gamma} {V_e}^{\gamma+1} + \left(\frac{1}{\tilde{b}}-\frac{1}{\hat{b}}\right){V_e}^2 + \tau V_e \\ - \tilde{b}\tau^2 - 2(S_e - s) = 0 \tag{4.11}$$

When $\gamma = 1$, Equation (4.11) becomes a quadratic equation with only one positive root (as shown in Equation (4.12); see Appendix A for more detail). For other values of γ Equation (4.11) becomes higher order polynomial equation that does not have a simple solution.

$$V_e = \mathrm{mid}\left[0,\ \frac{\tilde{b}\tau}{2A}\left(-1+\sqrt{1+4A\left[1+\frac{2(S_e-s)}{\tilde{b}\tau^2}\right]}\right),\ \tilde{V}\right];\quad A = \left[\left(1+\frac{\tilde{b}\tau\tilde{T}}{(1-\delta)S_e}\right)^2-\frac{\tilde{b}}{\hat{b}}\right], \tag{4.12}$$

As speed cannot be negative, A cannot be negative. The only case in which this solution could be unstable is when $A = 0$, which is also prevented by setting an upper limit of $\tilde{V}$. Therefore, there is no stability issue for TDGipps model even when $\tilde{b} > \hat{b}$. This is a significant improvement over Gipps' model.

The equilibrium speed-spacing and flow-density relations of Gipps' and TDGipps model are presented in Figure 4.3. It shows a detail comparison of the two models based on their steady state behaviors. It shows how the equilibrium speed-spacing and flow-density relation differs in TDGipps model compared to the Gipps' model depending on the level of task difficulty.

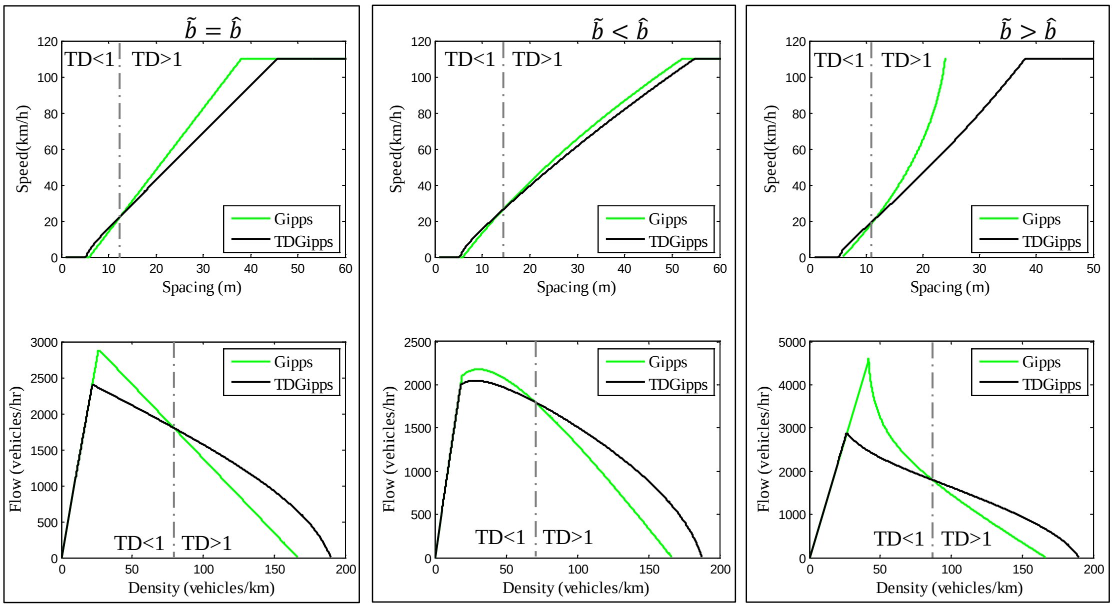

Figure 4.3 Equilibrium flow-density and speed-spacing plot of Gipps' and TDGipps models

(Model parameters are $\tilde{\boldsymbol{b}} = [\mathbf{3.0}, \mathbf{2.75}, \mathbf{3.0}]$m/s^2, $\hat{\boldsymbol{b}} = [\mathbf{3.0}, \mathbf{3.0}, \mathbf{2.75}]$m/s^2, s = 6m, $\tilde{\boldsymbol{V}} = \mathbf{110}\boldsymbol{m/s}$, $\boldsymbol{\tau}$=0.7s, $\tilde{\boldsymbol{T}} = \mathbf{2}\boldsymbol{s}, \boldsymbol{\delta} = \mathbf{0}$)

When *TD*<1 the speed in TDGipps model becomes higher than that in the Gipps' model, which also results in a higher flow for the same density. The situation is reversed for *TD*>1. At *TD*=1 the equilibrium relation for the two models becomes the same. Furthermore, *TD* level is not constant at equilibrium. This feature explains the fact that every driver has a range of acceptable task difficulty, which is situation dependent as postulated in the task difficulty homeostasis theory (Fuller, 2002b). Figure 4.3 also shows that the standstill spacing in TDGipps model is smaller than that of the Gipps' model. Hence, the jam density of TDGipps model is higher than that of the Gipps' model. Another noteworthy observation from Figure 4.3 is that TDGipps model produces realistic flow when $\tilde{b} > \hat{b}$ while the Gipps' model fails to do so even when $\tilde{b}$ is only slightly larger ($\tilde{b} = 3m/s^2, \hat{b} = 2.75m/s^2$).

To gain more insight on TD's impact on characteristics of the equilibrium traffic flow, in Figure 4.4 the parameters of TD (Equation 1) are varied, and their effects on the equilibrium are shown.

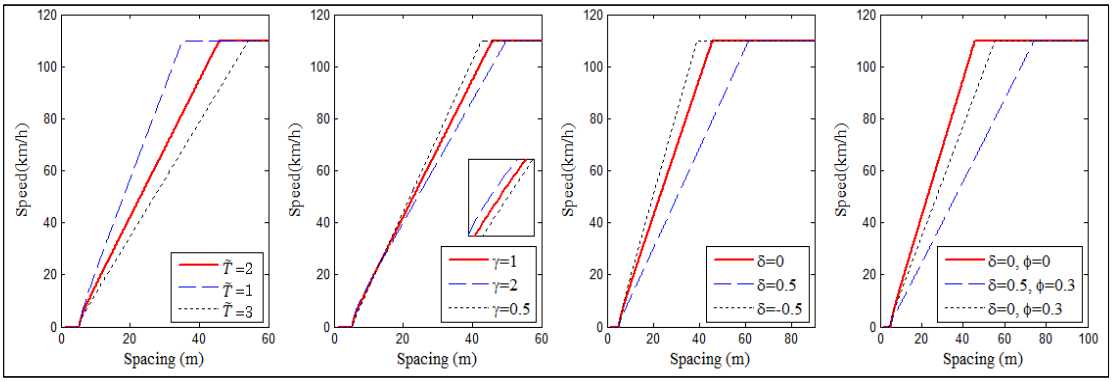

Figure 4.4 Effect of different parameters of TDGipps model on equilibrium

In Figure 4.4(a) the desired time headway is varied; and the figure shows that for the same speed a driver with a lower desired time headway keeps a smaller spacing compared to a driver with a higher desired time headway. As explained before, the desired time headway is a measure of driver's capability. Therefore, a capable driver tends to have a low desired time headway and thus a smaller spacing compared to a less capable driver. Figure 4.4(b) shows that the steady state behavior is not very sensitive towards γ, especially in low speeds. Figure 4.4(c) shows how the risk parameter affects the steady state behavior of the model. When the risk parameter is positive it shows risk compensatory behavior; and when it is negative the model shows aggressive behavior. Figure 4.4(d) explains how the model behaves in equilibrium when reaction time increases. In a regular driving without the influence of any human factor, a driver pays full attention on driving related tasks, which is represented by the case (the red solid line in the figure) where both the risk and reaction time parameters are zero. When human factor influence the driving and the driver perceives the risk, a risk-compensatory behavior is observed as shown by the blue big dashed line in Figure 4.4(d). When the driver does not perceive the risk appropriately, the line for describing the equilibrium behavior will lie in between the black small dashed and blue big dashed line. Obviously, in presence of human factor, any line above the blue big dashed line represents risky behavior.

4.4.2. TDCF on IDM

The Intelligent Driver Model (IDM, Treiber et al., 2000) is presented in Equation (4.13-4.14):

$$a_n(t) = a_n^{max}\left[1 - \left(\frac{V_n(t)}{\tilde{V}_n}\right)^{\beta} - \left(\frac{\tilde{S}_n(t)}{S_n(t)}\right)^2\right] \tag{4.13}$$

$$\tilde{S}_n(t) = s_n + V_n(t)\,\tilde{T}_n - \frac{V_n(t)\,\Delta V_n(t)}{2\sqrt{a_n^{max} a_n^{comf}}} \tag{4.14}$$

where $a_n^{max}$is maximum acceleration/deceleration of the subject vehicle *n*, $\tilde{S}_n$ is desired spacing, $\tilde{V}_n$ is desired speed, ΔV_n is speed difference, and a_n^{comf} is comfortable deceleration. The introduction of both a maximum acceleration and a comfortable deceleration rate prevents the model from producing unrealistically high accelerations/decelerations. TDCF framework is applied to modify the desired spacing in Equation (4.13), as shown in Equation (4.15). The new model is named as TDIDM.

$$a_n(t + \tau_n') = a_n^{max}\left[1 - \left(\frac{V_n(t)}{\tilde{V}_n}\right)^{\beta} - \left(\frac{\tilde{S}_n(t) * TD_n(t + \tau_n')}{S_n(t)}\right)^2\right] \tag{4.15}$$

Please note that reaction time is included in TDIDM which is not available in IDM model. The equilibrium spacing (S_e) for IDM model is derived in Treiber et al. (2000), and is shown in Equation (4.16).

$$S_e = \left(s + V_e\tilde{T}\right)\left[1 - \left(\frac{V_e}{\tilde{V}}\right)^{\beta}\right]^{-1/2} \tag{4.16}$$

Similarly, the equilibrium solution for TDIDM is derived in Appendix A and presented in Equation (4.17).

$$S_e = \left[\left(\frac{V_e\tilde{T}}{1-\delta}\right)^{\gamma} \frac{\left(s + V_e\tilde{T}\right)}{\sqrt{\left[1 - \left(V_e/\tilde{V}\right)^{\beta}\right]}}\right]^{\frac{1}{\gamma+1}} \tag{4.17}$$

The equilibrium speed-spacing and flow-density relations of IDM and TDIDM model are presented in Figure 4.5; and the effect of different parameters of *TD* on the equilibrium is shown in Figure 4.6.

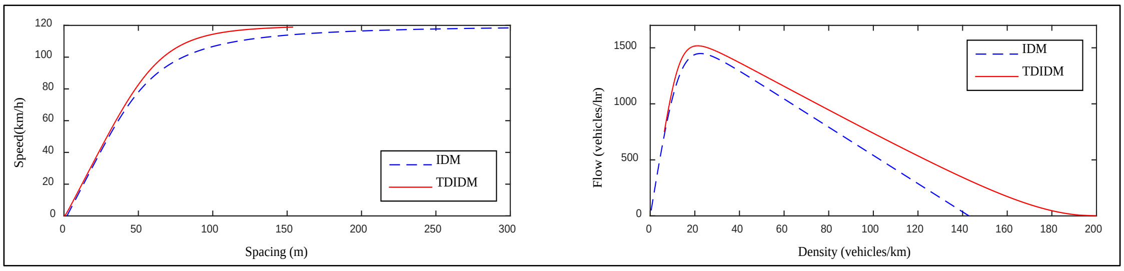

Figure 4.5 Equilibrium flow-density and speed-spacing plot of IDM and TDIDM models

(Model parameters are: $\boldsymbol{s = 2m, \beta = 4}$, $\boldsymbol{\tilde{V} = 120m/s}$, $\boldsymbol{\tau}$=0.7s, $\boldsymbol{\tilde{T} = 2s, \delta = 0}$)

In Figure 4.5 the task difficulty level for TDIDM model remains below one. As a result the speed in TDIDM model stays higher than that in IDM; similarly, the flow in TDIDM model is also larger.

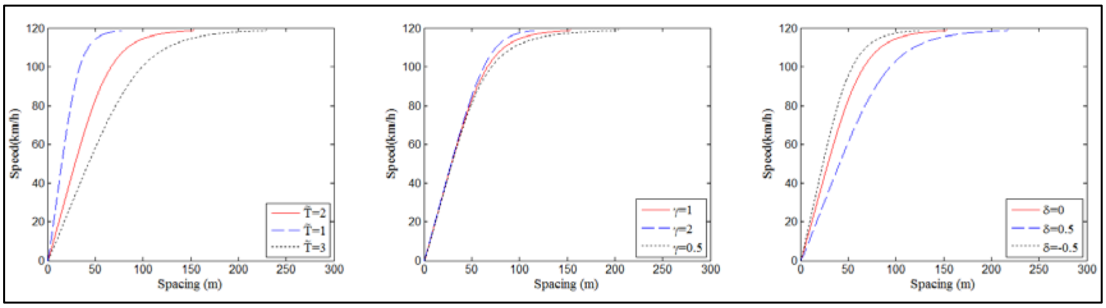

Figure 4.6 Effect of different parameters of TDIDM model on equilibrium

Figure 4.6 reveals similar observations as reported above for TDGipps model. For example, the equilibrium state of TDIDM is not sensitive to γ. To save space, no further discussion is provided. Note that, unlike TDGipps model the reaction time is incorporated as an external parameter. Thus, it does not influence the equilibrium behavior of TDIDM model.

4.4.3. A hypothetical example of collision occurrence

As indicated in the introduction the existing CF models are not capable of reproducing human factor induced collisions. Both Gipps' model and IDM have a built-in safety mechanism that prevents the model from collision. The upgraded models proposed in this paper are capable of reproducing human factor induced collisions. More specifically, an increase in reaction time can cause a collision when the risk compensatory action is not sufficient to cancel out the risk. It mostly occurs in a close following situation when the safety gap is very low. In this situation a sudden brake of the leader is likely to cause a collision, which can be captured by TDCF framework. An example is given below.

Assume that two vehicles travel at the same speed, 20km/h with a spacing of 10m. Suddenly the leader decelerates rapidly at -4.5m/s^2. The other parameters are as follows: $\tau_n = 2$s, $\tilde{V}_n = 80$km/h, $\tilde{a}_n = 2$m/s^2, $\tilde{b}_n = -2$m/s^2, $\hat{b}_n = -2$m/s^2, $s_n = 2$m, $a_n^{max} = 4$m/s^2, $b_n^{max} = -4.5$m/s^2, $L_n = 4$m, $\tilde{T}_n$=1s and $\gamma = 1$. To simulate the follower's response to the sudden deceleration of the leader, four models are used, and their outputs are summarized in the table below.

Table 4.1 Results of the hypothetical simulation

Gipps' model	TDGipps (not distracted) ($\delta = 0, \varphi = 0$)	TDGipps (distracted) ($\delta = 0.6, \varphi = 0.3$)	TDGipps (distracted) ($\delta = 0, \varphi = 0.3$)
$V_n = 12.6$ km/h	$V_n = 19.1$ km/h	$V_n = 4.7$ km/h	$V_n = 18.4$ km/h
S_n =3.0 m	$S_n = 1.3$ m	S_n =3.0 m	$S_n = -1.4$ m
	$TD_n = 0.6$	$TD_n = 1.4$	$TD_n = 0.6$

As seen from the table above, in Gipps' model the follower reduces speed and stays safe. The same conclusion is drawn in TDGipps model when the driver is not distracted, although the speed reduction is not so high as that in Gipps' model due to a low level of perceived task difficulty. Furthermore, if the driver is distracted and appropriately perceives the risk level of such distraction, a collision is still successfully avoided in TDGipps model (see the 3rd column of Table 1). However, when the risk of being distracted is underestimated by the follower, a collision occurs in TDGipps model, as indicated by the negative spacing (see the 4th column of Table 1). This simple example shows one instance of collision occurrence through the proposed TDGipps model.

4.5. Calibration and Validation

4.5.1. Data

Calibration and validation of the proposed model requires vehicle trajectory data along with information about human factors. In this paper vehicle trajectory data are collected from a carefully designed driving simulator experiment where participants were exposed to distractions caused by mobile phone conversations while driving. The experiment was conducted using the CARRS-Q Advanced Driving Simulator located at the Centre for Accident Research and Road Safety – Queensland (CARRS-Q), Queensland University of Technology. In this experiment 32 young drivers, aged between 18-26 years, drove the simulator vehicle in a number of traffic events including car following. Participants had to repeat the simulator driving in three scenarios: baseline (no phone conversation), hands-free (conversation through a hands-free device) and handheld (conversation through a handheld mobile phone) scenarios.

The car-following (CF) event occurred on urban roads where the speed limit was 40 km/h. A detail of the CF event is shown in Figure 4.7. To observe CF behaviors from all the participants, a roadway segment of 245m long was selected as marked with a thick border in Figure 4.7(c). The roadway has four lanes with unidirectional traffic flow. Lane 1 and lane 4 had parked vehicles, leaving only lane 2 and lane 3 available for driving. In this CF event, when the driven vehicle (shown as the black rectangle in Figure 4.7(c)) stopped at the signalized intersection I1, two leading vehicles (shown as rectangle with hatched lines) appeared on the two lanes of the road section R2. No other vehicles were present in between the driven vehicle and the leading vehicles. When the spacing between the driven vehicle and the leading vehicle reached 60m, the speed of both leading vehicles increased up to 20km/h. When the spacing was 30m or less, leading vehicles accelerated to 35km/h and maintained that speed till the end of the CF event. The signal at intersection I2 was kept green to ensure uninterrupted flow. Data like position and speed of vehicles were recorded at a 0.05 second interval.

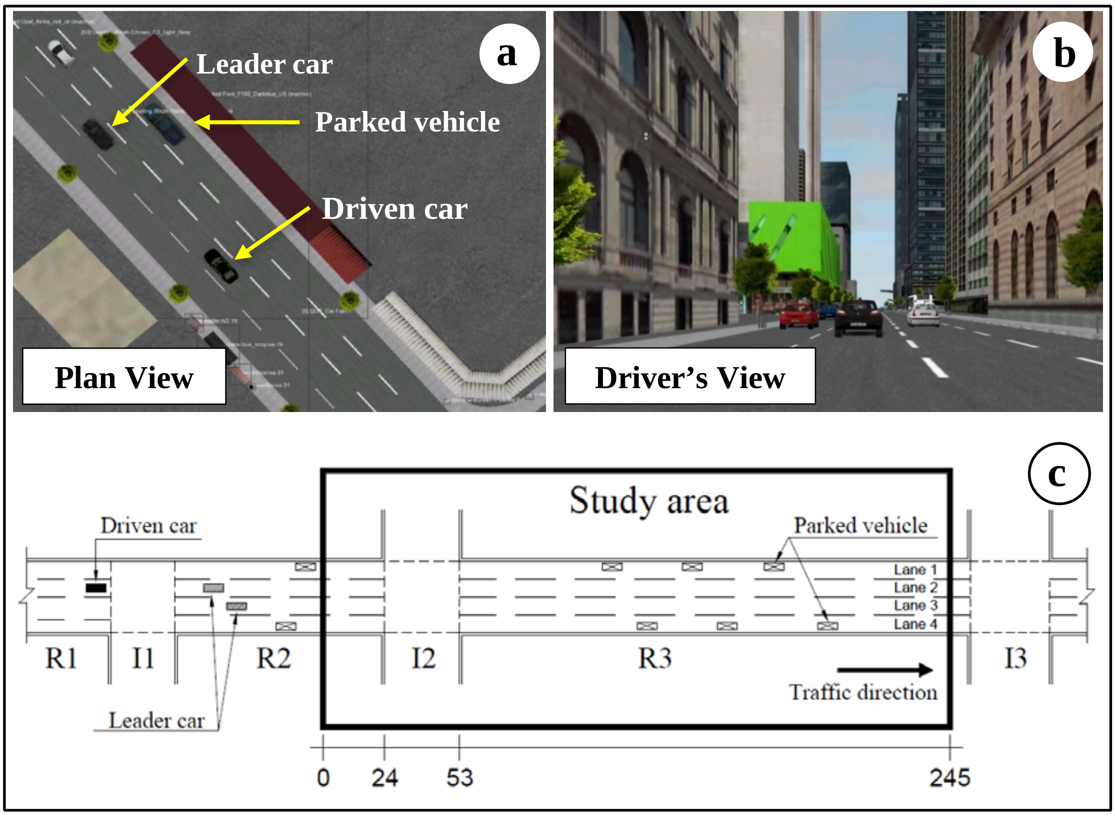

Figure 4.7 Detail of the CF event: (a) plan view showing driven and leader vehicles; (b) driver's view showing leader vehicles; (c) the study area

The CF duration within the study area is ranged between 22 to 39 seconds. The phone conversation was cognitive in nature, which required simultaneous storage and processing of information, and thus distracted the drivers by increasing their cognitive load. More detail of the experiment can be found in Haque and Washington (2013; 2014). Note that although the data were generated from the same driving simulator experiment, the data used in this study is totally different from the data used by Haque and Washington (2013; 2014; 2015): Haque and Washington (2014; 2015) analyzed the traffic event where a pedestrian entered a zebra crossing from the sidewalk; Haque and Washington (2013) used the data related to the traffic event where a leading vehicle braked suddenly. In contrast, the data used in this paper were collected from a different road segment, which was designed for the CF event only.

Among the 32 participants, 3 have changed lanes within the study area and thus are removed from the analysis to avoid any bias from lane changing. The data are randomly divided in two groups where trajectories from 20 participants are used for model calibration and the rest for model validation. To illustrate the performance of the TDGipps model, CF trajectories from two scenarios are used in this study: baseline (no phone use while driving) and handheld (handheld phone conversation while driving). In the rest of the paper these trajectories are respectively referred as 'baseline' and 'distracted'.

4.5.2. Calibration

Both Gipps' and TDGipps model will be calibrated using the baseline trajectories. However, because the reaction time parameter and the risk parameter of TDGipps model are only necessary in the presence of human factors, these two parameters are calibrated with the distracted trajectories while keeping the other parameters fixed to the ones obtained from calibration using the baseline trajectories.

4.5.2.1. Calibration Process

The calibration involves finding a set of model parameters, which minimize the difference between values of simulated and observed variables. This is often achieved using optimization algorithms. In this paper Genetic Algorithm (GA) has been implemented to find the optimum set of model parameters. Genetic Algorithms are widely used for calibrating microscopic traffic simulation models because they can often avoid local minima and thus reach the global optimum by using a stochastic global search method for solving both constrained and unconstrained optimization problems. GA was also deployed to estimate parameters in car-following models (e.g., Kesting and Treiber, 2008; Punzo et al. 2012).

A big difference between GAs and classical optimization algorithms is that they start with a population of potential solutions to the problem, and over iterations the probability of finding a global solution increases. Although it may cost longer computational time, with a large population size, the chance for GA algorithms to be trapped in a local minimum reduces considerably (Powell, 1973).

Literature on GA optimization is rich. Reviewing GA literature and introducing GA theories are beyond the scope of this paper. For interested readers, see Holland (1975) and Spall (2005) for a detail review.

Objective function

The objective function is defined by measuring the difference (i.e., the error) between the simulated and observed variable. Technically, any variable, which is not fixed during the simulation process, can be used in the objective function, such as the speed, speed difference and spacing. According to Kesting and Treiber (2008), spacing is preferred when vehicle trajectories are used in calibration, because when optimizing with respect to spacing, the average error in speed are often simultaneously reduced; however, the opposite may not be true.

In this study the root mean squared normalized error (RMSNE) or root mean squared percent error (RMSPE) is used as the objective function, as shown in Equation (4.18)

$$RMSNE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(\frac{S_i^{sim} - S_i^{obs}}{S_i^{obs}}\right)^2} \tag{4.18}$$

where *i* denotes observation id, S_i^{sim} is the i^{th} simulated spacing, S_i^{obs} is the i^{th} observed (real) spacing and *N* is the total number of observations.

Genetic Algorithm setup

The Genetic Algorithm Toolbox in MATLAB is used in this study, and the relevant parameters are specified as follows: population size is 200, maximum number of generations is 600 and number of stall generations is 100. Maximum number of generations controls the maximum number of iterations allowed. The algorithm calculates the weighted average relative change in the fitness function value over stall generations, and if the change is less than function tolerance (1e-6 in our study) the algorithm stops. Furthermore, upper and lower bounds of the parameters (see Table 4.2) are set to improve computational efficiency.

Table 4.2 Parameter settings for model calibration

Parameter name (unit)	Range	Parameter name (unit)	Range
Reaction time (τ_n, second)[a]	[0.1, 3.0]	Desired time headway ($\tilde{T}_n$, second)	[0.1, 4.0]
Desired speed ($\tilde{V}_n$, km/hr)[a]	[1.0, 150]	Risk compensatory parameter (δ)	[-10, 1]
Desired acceleration ($\tilde{a}_n$, m/s^2)[b]	[0.1, 4.0]	Reaction time increment (φ, second)	[0, 0.5]
Desired deceleration ($\tilde{b}_n$, m/s^2)[c]	[0.1, 4.5]	Maximum acceleration (a_n^{max}, m/s^2)	4
Leader's deceleration ($\hat{b}_n$, m/s^2)[c]	[0.1, 4.5]	Maximum deceleration (b_n^{max}, m/s^2)	4.5
Safety distance (s_n, meter)[a]	[1.0, 10]	Comfortable deceleration (a_n^{comf}, m/s^2)	[0.1, 4.5]
Sensitivity parameter (γ)	[0, 4]		

Source: [a]Ciuffo et al. (2012); [b]HCM (2000); [c]AASHTO (2004)

As GA is stochastic, and finds slightly different solutions in each optimization run, to find a solution closer to the global optimum, the optimization process is repeated 20 times for each driver. The set of parameters with the minimum error (i.e., RMSNE) is selected.

4.5.2.2. Calibration with synthetic data

Before formally calibrating the models, the performance of the proposed calibration process is tested with synthetic data that are generated by using a similar procedure proposed in Punzo et al. (2012). The trajectory of a leading vehicle is randomly selected from the baseline scenario. The model parameters to generate the synthetic follower are set as: $\tau_n = 0.8$, $\tilde{V}_n = 70$, $\tilde{a}_n = 2$, $\tilde{b}_n = -2.5$, $\hat{b}_n = -2.5$, $L_n = 4$ and $s_n = 4$. The calibration process in Section 5.2.1 was implemented, which produced 20 sets of parameters. The parameter set with the lowest RMSNE is selected as the optimum set of parameters. This calibration process is repeated three times (Trial 1-3 in Table 4.3) on the synthetic data and the selected parameters from each trial is presented in Table 4.3. This table clearly shows that the selected parameters from each trial are very close to their true values, and the calibration error (i.e., RMSNE) is very small (<0.001). Hence, it is reasonable to believe that the proposed calibration process is capable of finding optimum model parameters when used for a real data set.

Table 4.3 Calibration result for synthetic data

	τ_n	$\tilde{V}_n$	$\tilde{a}_n$	$\tilde{b}_n$	$\hat{b}_n$	s_n	RMSNE
Synthetic value	0.80	70.00	2.00	-2.50	-2.50	4.06	
Trial 1	0.83	63.11	2.11	-2.51	-2.50	4.06	0.03%
Trial 2	0.84	58.44	2.17	-2.53	-2.51	4.18	0.05%
Trial 3	0.79	77.53	2.02	-2.52	-2.48	4.34	0.06%

4.5.2.3. Calibration results

Both Gipps' model and IDM are calibrated for each of the 20 trajectories from both baseline and distracted scenarios. As discussed in Section 4 these models are proposed to capture both regular and human factor influenced driving with a single set of parameters for these different conditions by introducing two human factor (HF) parameters. Therefore, non-HF parameters of both models are calibrated using the baseline data without considering the HF parameters (because in the baseline human factor influence is absent), while the HF parameters are calibrated using the distracted trajectories by keeping non-HF parameters the same as the ones obtained from the baseline calibration. The summary of the calibration results are presented in Table 4.4-4.7. The calibration performances in terms of RMSNE of both TDGipps and TDIDM are better than their predecessors (Gipps Vs TDGipps: *t*-stat = 2.11, *p*-value <0.05; IDM vs TDIDM: *t*-stat =3.45, *p*-value < 0.01).

Examining the estimated human factor parameters reveals two interesting observations about distracted CF behavior. First, the risk parameter (δ) is expected to capture risk compensation behavior. This parameter is zero for three drivers in both models, which simply implies the absence of risk compensatory behavior, that is, the driver did not perceive any extra risk of collision caused by the distraction. Another explanation of this result could be that the human factor influence was not so strong for these drivers to consider any risk from it. Also the risk parameter is found negative for a couple of drivers in both models who drove more aggressively compared to their driving in the baseline. Second, the reaction parameter (φ) is zero for 7 drivers in the TDGipps calibration and for a couple of drivers in the IDM calibration, which implies no impairment in reaction time due to mobile phone conversations for these drivers. These two observations are consistent with the literature. A recent survey on distracted driving attitudes and behaviors reported that about half of the respondents believed that talking on the phone makes no difference on their driving performance (Tison et al., 2011). Moreover, using a different scenario from the same simulator experiment, Haque and Washington (2013) did not find any significant increase in reaction time of distracted drivers in the event of a sudden braking of the preceding vehicles.

Table 4.4 Calibration result of Gipps' model

Parameter	Baseline data					Distracted data				
	mean	**median**	std	min	max	**mean**	**median**	std	min	max
τ_n	**1.14**	**1.03**	0.62	0.11	2.58	**1.29**	**1.23**	0.70	0.13	2.96
$\tilde{V}_n$	**53.10**	**41.31**	28.85	31.92	142.70	**75.16**	**55.16**	42.49	26.33	146.86
$\tilde{a}_n$	**1.75**	**1.12**	1.26	0.30	4.00	**1.57**	**1.44**	1.24	0.10	3.96
$\tilde{b}_n$	**-2.40**	**-2.36**	1.41	-4.48	-0.45	**-2.08**	**-1.81**	1.23	-4.08	-0.11
$\hat{b}_n$	**-1.64**	**-1.22**	0.99	-3.88	-0.42	**-1.71**	**-1.25**	1.41	-4.50	-0.10
s_n	**4.24**	**3.58**	2.37	1.08	9.96	**5.59**	**4.98**	2.96	1.17	10.00

Table 4.5 Calibration result of TDGipps model

Parameter	Baseline data					Distracted data				
	mean	**median**	std	min	max	**mean**	**median**	std	min	max
τ_n	**1.30**	**1.34**	0.75	0.14	2.82	Baseline parameters used				
$\tilde{V}_n$	**50.24**	**39.23**	26.65	31.45	125.21					
$\tilde{a}_n$	**0.86**	**0.73**	0.48	0.26	2.15					
$\tilde{b}_n$	**-1.67**	**-1.57**	0.98	-4.10	-0.39					
$\hat{b}_n$	**-1.33**	**-0.94**	0.94	-3.82	-0.36					
s_n	**3.47**	**2.86**	1.86	1.01	6.83					
$\tilde{T}_n$	**1.86**	**1.80**	0.98	0.10	3.48					
γ	**1.26**	**1.12**	0.90	0.12	4.00					
δ						**0.45****	**0.39**	2.13	-8.05	0.93
φ						**0.19**	**0.17**	0.18	0.00	0.46

** Excluding negative values

Table 4.6 Calibration result of IDM

Parameter	Baseline data					Distracted data				
	mean	**median**	std	min	max	**mean**	**median**	std	min	max
a_n^{max}	**1.24**	**0.79**	1.182	0.11	4.00	**1.64**	**1.35**	1.24	0.10	4.00
a_n^{comf}	**1.69**	**1.10**	1.495	0.10	4.50	**2.07**	**0.80**	1.93	0.10	4.50
s_n	**5.81**	**6.03**	3.316	1.00	9.98	**7.39**	**8.80**	3.26	1.00	10.00
$\tilde{T}_n$	**0.62**	**0.55**	0.473	0.10	1.66	**1.15**	**1.14**	0.81	0.10	2.72
$\tilde{V}_n$	**78.75**	**70.83**	42.311	32.61	150.00	**87.77**	**92.68**	44.66	28.63	150.00

Table 4.7 Calibration result of TDIDM

Parameter	Baseline data					Distracted data				
	mean	**median**	std	min	max	**mean**	**median**	std	min	max
a_n^{max}	**0.80**	**0.73**	0.570	0.11	2.27					
a_n^{comf}	**1.18**	**0.92**	1.417	0.11	4.50					
s_n	**3.92**	**3.39**	2.781	1.00	9.94					
$\tilde{T}_n$	**1.39**	**1.40**	0.815	0.31	3.63	Baseline parameters used				
$\tilde{V}_n$	**72.67**	**55.60**	41.935	30.38	150.00					
τ_n	**1.67**	**1.83**	0.785	0.31	2.49					
γ	**0.83**	**0.57**	0.846	0.10	2.91					
δ						**0.42****	**0.42**	3.21	-10.00	0.99
φ						**0.27**	**0.27**	0.17	0.00	0.50

** Excluding negative values

By allowing the reaction parameter to be negative, TDGipps and TDIDM performance could be further improved from the data fitting/ error-minimization perspective. However, allowing a negative reaction parameter in the distracted case would violate the logic of TD concept, the cornerstone of the TDCF framework, because logically when a driver is not influenced by any human factors, her/his reaction time should be the optimum, and the reaction time should increase when the driver is distracted. If Gipps' model is implemented in the distracted case, such illogical phenomenon indeed could occur. This further demonstrates the soundness and contribution of the TDCF framework.

To gain more insight into the risk parameter, two drivers (Driver 6 and Driver 12) were selected for a comparison analysis because the human-factor parameters for

Driver 6 are zeros whereas those for Driver 12 are large. The spacing and speed profiles for the two drivers are presented in Figure 4.8. For simplicity of presentation only results from Gipps' and TDGipps models are shown here. Similar results are also observed from IDM and TDIDM models.

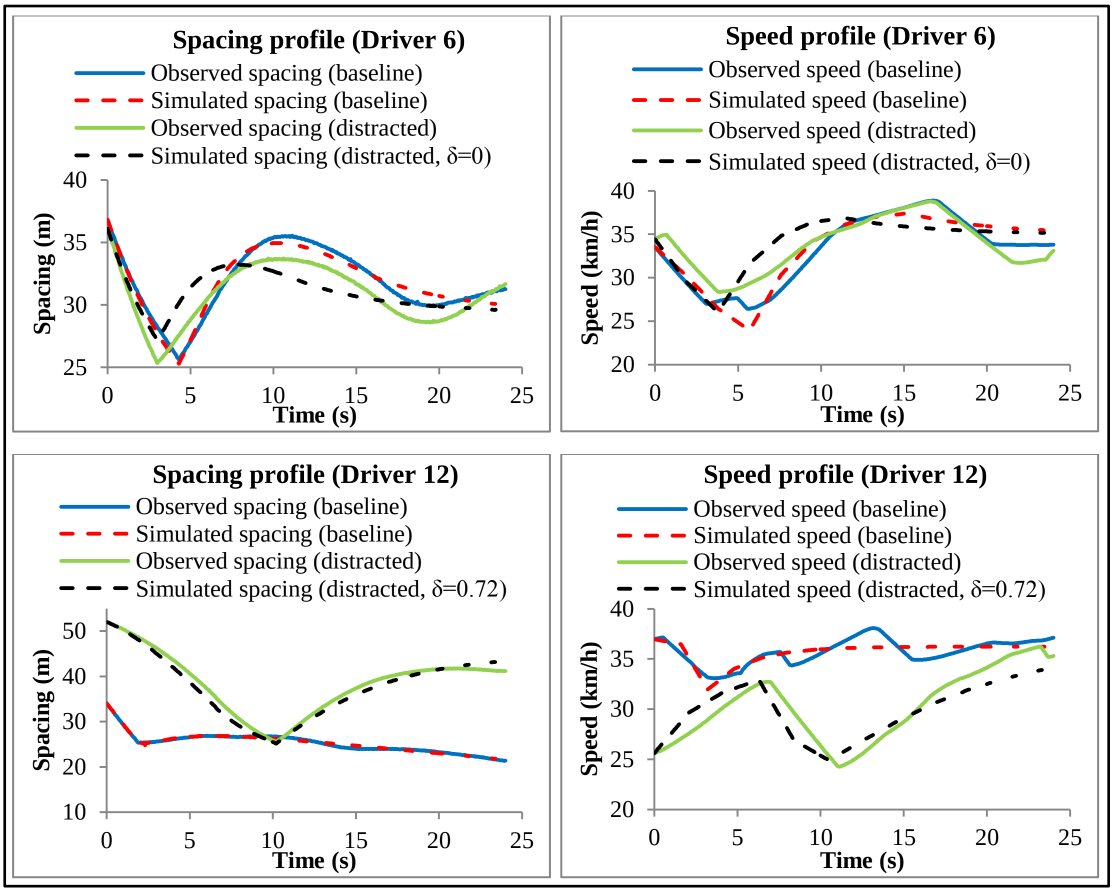

Figure 4.8 Comparison of CF behaviour for Driver 6 and 12

The simulated spacing and speed profiles in the baseline scenario show a good fit to the observed profiles for both drivers, which indicates a good calibration result. The observed spacing and speed profiles in the baseline and distracted scenarios display different behaviors of the two drivers. Driver 12 kept larger spacing and maintained lower speed when following the preceding vehicle in the distracted scenario, compared to how Driver 12 drove in the baseline scenario. More specifically, the average spacing was 25.1m and 38.8m and the average speed was 35.8 km/h and 31.0 km/h in the baseline and distracted scenarios, respectively. In contrast, Driver 6 maintained similar spacing and speed profiles in both scenarios, i.e., the average spacing was 31.7m and 30.9m and the average speed was 33.2 km/h and 31 km/h in the baseline and distracted scenarios, respectively. This implies that

Driver 6 did not perceive any additional risk that might arise from conversing over a handheld phone while driving. As a result the driver did not feel the urge to reduce speed or increase spacing while distracted and drove similarly as the driver did in the baseline scenario. The absence of risk compensatory behavior is reflected by the zero value of the risk parameter for this driver. In contrast, Driver 12 showed a typical risk compensatory behavior, which is also rightly captured by the risk parameter (δ) in TDGipps.

4.5.3. Validation

To validate the two models, both the models with the calibrated parameters are used to simulate the remaining 18 trajectories that have not been used in the model calibration. To thoroughly assess the models' performance, both the baseline and the distracted driving scenarios were considered; in addition, to test the models' robustness towards different calibrated parameters, validation was implemented for the average and the median of the calibrated parameter values. In total, six validation scenarios were considered as summarized in Table 4.8.

Table 4.8 Description of validation setting

	Data	Type of parameters	Parameters obtained from	
			Gipps / IDM	TDGipps / TDIDM
Validation 1	Baseline	Average	Baseline	Baseline
Validation 2	Baseline	Median	Baseline	Baseline
Validation 3	Distracted	Average	Baseline	Baseline
Validation 4	Distracted	Median	Baseline	Baseline
Validation 5	Distracted	Average	Distracted	Baseline
Validation 6	Distracted	Median	Distracted	Baseline

Validation 1 and 2 evaluate the performance of the models in the regular driving situation. All the other validations are designed to evaluate the models in the distracted situation. The validation results for individual drivers are summarized in Figure 4.9-4.10. In 49 out of 54 (91%) cases, the TDGipps model outperformed the Gipps' model as shown in Figure 4.9. In only five occasions, the performance of

Gipps' model was better than that of the TDGipps model. Similar results are obtained for TDIDM (see Figure 4.10).

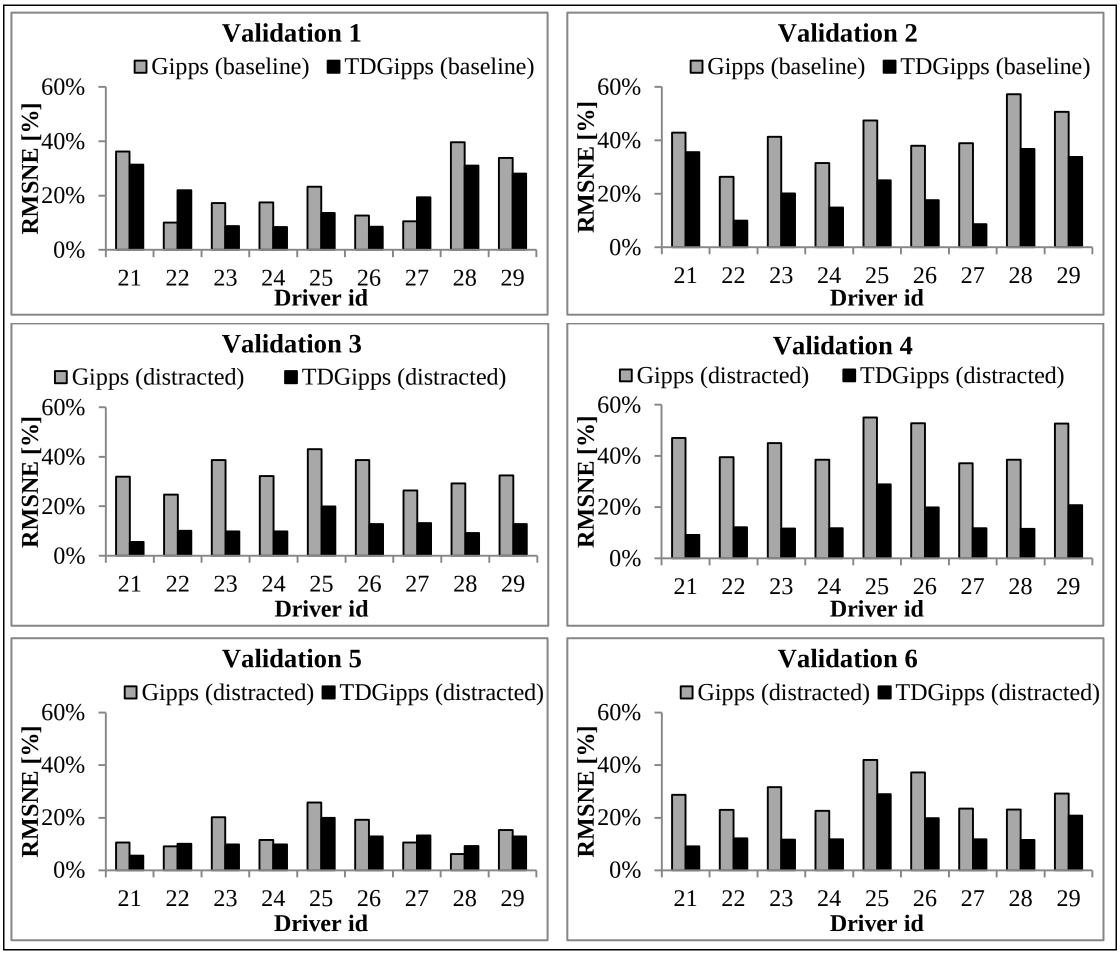

Figure 4.9 Comparison of validation errors in Gipps' and TDGipps model

Moreover, average validation errors across all the drivers are summarized in Table 4.9. Two noteworthy observations from this table are: i) in each validation case TDGipps model (TDIDM) outperforms Gipps' model (IDM); ii) compared to Gipps' model (IDM) with parameters from the distracted situation, even TDGipps model (TDIDM) with parameters from the baseline performs better in explaining distracted CF behavior. Statistical analysis also supports this conclusion as the difference in RMSNE between the original and improved models are significant in all cases as shown in Table 4.10.

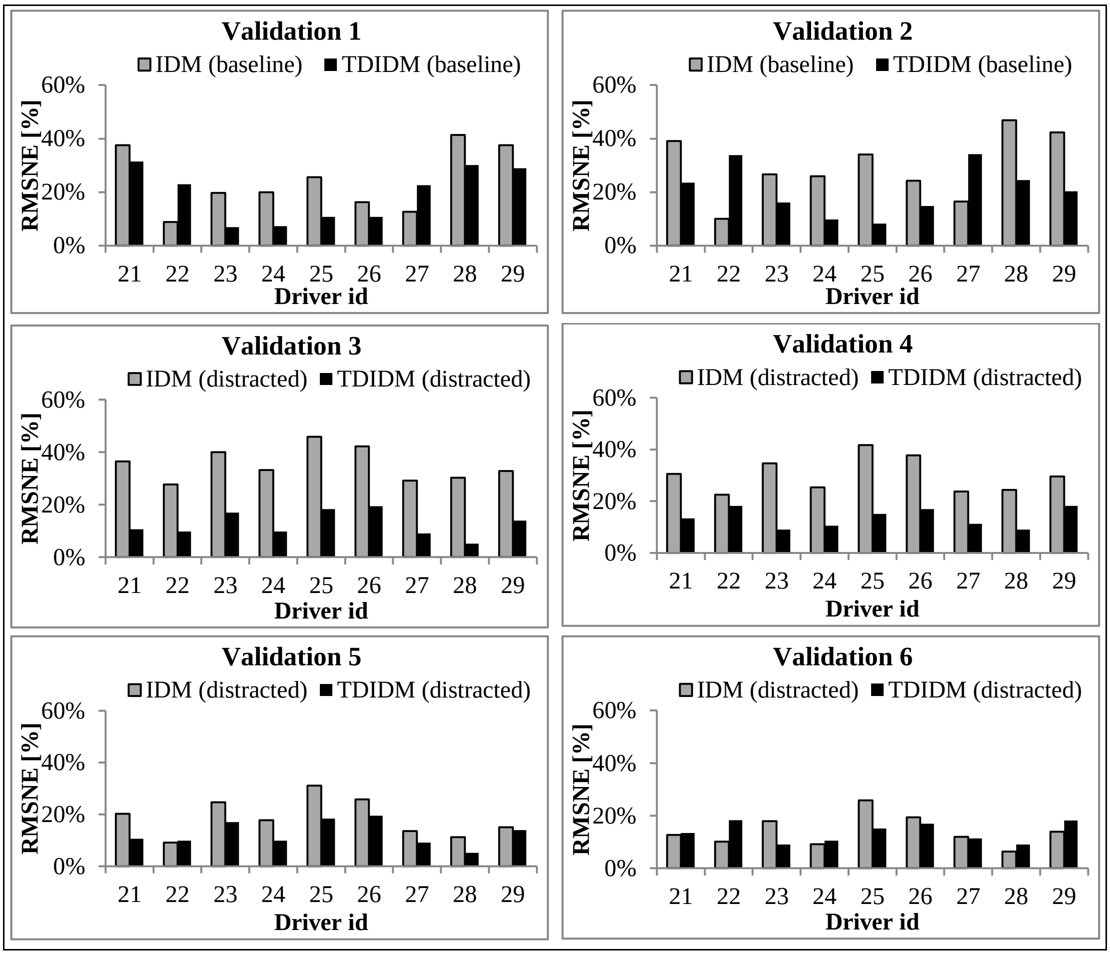

Figure 4.10 Comparison of validation errors in IDM and TDIDM model

Table 4.9 Comparison of average validation errors

	Results (Average RMSNE [%])					
	Gipps	TDGipps without HF	TDGipps	IDM	IDM without HF	TDIDM
Validation 1	22.31		19.01	24.41		19.06
Validation 2	41.61		22.49	29.51		20.59
Validation 3	33.08	27.61	11.48	35.34	24.53	12.56
Validation 4	45.17	31.80	15.30	30.05	18.18	13.55
Validation 5	14.27		11.48	18.73		12.56
Validation 6	29.00		15.30	14.18		13.55

Table 4.10 Statistical analysis of model performance

	Baseline (Validation 1&2)	Distracted (Validation 3&4)	Distracted (Validation 5&6)
Gipps Vs TDGipps	t-stat = 4.45, $p < 0.001$	t-stat = 17.22, $p < 0.001$	t-stat = 4.97, $p < 0.001$
IDM vs TDIDM	t-stat = 2.13, $p = 0.048$	t-stat = 13.40, $p < 0.001$	t-stat = 2.51, $p = 0.023$

This finding confirms that TDGipps model (TDIDM) does not require different sets of parameters to explain regular and distracted behavior. Rather, the two HF parameters can capture the distracted behavior well. Even more remarkably, the validation analysis above clearly indicates that even with a different set of parameters for distracted CF, Gipps' model and IDM do not perform as well as the TDGipps and TDIDM with parameters calibrated from the baseline.

Furthermore, to specifically test the contribution of the two human factor parameters in TDGipps and TDIDM in the distracted scenarios, performance of TDGipps and TDIDM without the two human factor parameters is compared with that of TDGipps and TDIDM with the two human factor parameters (i.e., risk parameter δ and reaction parameter φ). As shown in Table 4.9, Both TDGipps and IDM with the human factor parameters have generated smaller errors. Statistical tests further confirms that the improvement is induced by the inclusion of HF parameters as the analysis show that the model with HF parameters shows significantly lower RMSNE than the one without HF parameters (TDGipps without HF Vs TDGipps with HF: t-stat = 14.00, p-value < 0.001; TDIDM without HF vs TDIDM with HF: t-stat =5.19, p-value < 0.001). Thus, clearly the two human factor parameters are capable of capturing the distracted CF behavior.

As mentioned previously, to test the models' robustness towards different calibrated parameters, validation was implemented for the average and the median of the calibrated parameter values, and the results are summarized in Table 4.9. This table shows that Gipps' model's performance is highly sensitive to its parameter values, and that a small change of the parameter value can cause a dramatic change in its performance. For example, when using the average of calibrated parameters, the average RMSNE of Gipps' model in the baseline scenario (validation 1) is 22.3%; however, when using the median of calibrated parameters (validation 2), although the change in the parameter values is not big (see Table 4.3), the average RMSNE of Gipps' model is almost doubled (41.6%). Similar phenomenon is also observed for the distracted scenario. Meanwhile, IDM performance was not found as sensitive to a small change of its parameter values, which makes IDM more attractive. In contrast, both TDGipps and TDIDM model's performance were not significantly influenced by a small change in the calibrated parameter values because of the incorporation of task difficulty, which also enables the TDGipps and TDIDM models even in absence of HF parameters to outperform the original Gipps' model and IDM, respectively.

In order to investigate the validation performance at the microscopic level, the spacing and speed profiles of one driver (profiles of Driver 24 that are generated from Gipps' model and TDGipps model is selected for demonstration purpose) are plotted in Figure 4.11 for both the baseline and distracted scenarios.

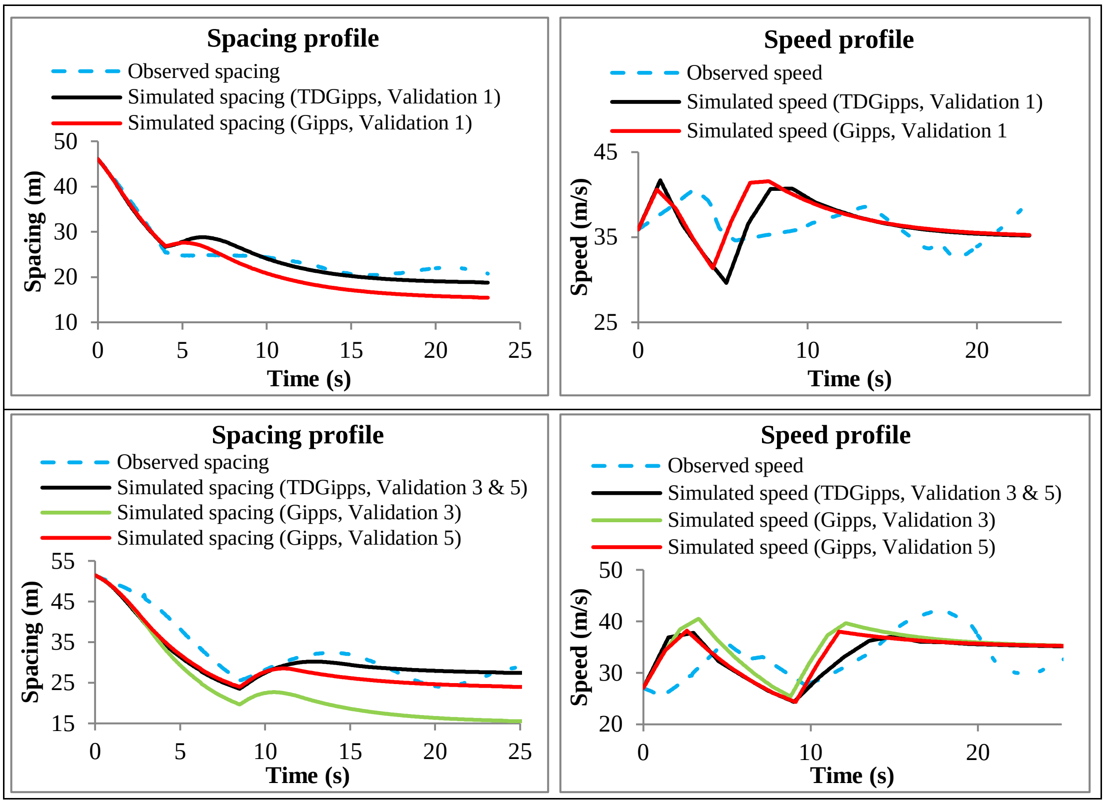

Figure 4.11 Validation performance of Driver 24

While the validation errors are higher than calibration errors (which is intuitive), Figure 4.11 clearly shows that TDGipps model consistently performed better than Gipps' model. Furthermore, although in Validation 1 Gipps' model performed reasonably, when the same model parameters were used to describe the distracted behavior in Validation 3, it did not perform well, which is caused by its failure to capture the risk-compensatory behavior of the driver in the distracted situation. On the contrary, the HF parameters of TDGipps model successfully captured this risk-compensatory behavior, and led to smaller validation errors. TDGipps model even performed better than Gipps' model in Validation 5 where Gipps' model was calibrated using the distracted scenario specifically for explaining the distracted behavior while TDGipps model was calibrated using the baseline scenario.

4.6. Conclusion

In an attempt to address a widely criticized shortcoming of most existing CF models, that is, inadequate accommodation of human factors, this paper has proposed a car following modeling framework inspired by the Task-Capability Interface model (TCI). More specifically, task difficulty, a key factor that influences driving decision and performance, is measured and incorporated into the existing CF models within the task difficulty car-following (TDCF) framework. Derived from a well-established risk taking theory and tested by carefully designed experiments, the TDCF framework offers more explanatory and predictive power. The proposed framework is applied to enhance two popular CF models in the literature: Gipps' model and IDM. The new models are named as TDGipps and TDIDM, respectively. The steady state conditions of the new models have been derived, and the stability analysis has confirmed the stability of both models. Furthermore, both models have been calibrated and validated with the vehicle trajectory data collected from a carefully-designed driving simulator experiment. Both TDGipps and TDIDM models have been found to consistently and notably outperform their predecessors in both normal and distracted CF scenarios. In addition, compared with Gipps' model, the TDGipps model is less sensitive towards changes in calibrated parameters. Such robustness of TDGipps model makes it even more attractive to practitioners.

The intended primary usage of TDCF is two-fold: Road safety-oriented applications and Traffic operations-oriented applications. To calibrate TDCF for these two types of applications, driving experiments should be conducted for a representative sample of the drivers from the target population either using driving simulator e.g., the experiment implemented in this study, or using instrumented vehicles. Experimental design should include at least two types of driving conditions for each driver: with and without distraction. Since TDCF is a general framework independent of distraction sources and not oriented to any specific type of human factors, distraction in these experiments can be created by many sources, e.g., talking over a mobile phone, texting, rubbernecking, etc. The collected trajectories can be used to calibrate and validate the model as demonstrated in this study. The calibrated and validated model can be directly used as a simulation tool just like other CF models to better reproduce traffic dynamics for the target population, or used a policy evaluation tool to assess levels of various human factors' implications on road safety and/or operations by changing δ and φ to different values.

The use of both average and median of the calibrated parameters sheds light on the sensitivity of the two models. The consistent results obtained in this study show the robustness of the TDCF framework's performance. However, more work is needed for a more comprehensive sensitivity analysis on these two models' parameters.

Another primary driver behavior – lane-changing maneuvers – can be also modelled by incorporating the task difficulty concept (Zheng et al. 2013; Zheng 2014). More specifically, the gap acceptance mechanism in a lane changing decision-making process could be more realistically described by utilizing the TD concept, although the formulation of task difficulty could be different.

Finally, by introducing task difficulty into CF models in the framework of TDCF, the method that is proposed in this paper can more realistically accommodate human factors' impact on driver behavior. Thus, this method can potentially better explain driver behavior triggered phenomena of traffic flow, such as capacity drop (Cassidy and Rudjanakanoknad, 2005; Chen et al., 2014), stop-and-go oscillation (Zheng et al., 2011) and traffic hysteresis (Chen et al., 2012; Laval, 2011). The difference in risk perception leads to aggressive and timid behavior, which is reported in the literature to be the underlying reason of traffic hysteresis. Also there is a potential linkage between the change of drivers' risk perception and the evolution (such as formation and/or growth) of stop-and-go traffic oscillations. It is possible to trace the change in driver's risk perception along the driving course from trajectory data. This may give valuable insight into the causality between driver behaviors and traffic dynamics. Such work is ongoing.

Appendix: Equilibrium solutions

Equilibrium solution for TDGipps model

For TDGipps model the speed of the follower at equilibrium can be obtained from Equation (4.6) as shown in Equation (A1).

$$V_e = -\tilde{b}\tau * \left(\frac{V_e\tilde{T}}{(1-\delta)S_e}\right)^{\gamma} + \sqrt{\tilde{b}^2\tau^2 + \tilde{b}\left[2(S_e - s) - V_e\tau + \frac{{V_e}^2}{\hat{b}}\right]} \tag{A1}$$

$$\left(V_e + \tilde{b}\tau * \left(\frac{V_e\tilde{T}}{(1-\delta)S_e}\right)^{\gamma}\right)^2 = \tilde{b}^2\tau^2 + \tilde{b}\left[2(S_e - s) - V_e\tau + \frac{{V_e}^2}{\hat{b}}\right]$$

$${V_e}^2 + 2 * {V_e}^{\gamma+1} * \tilde{b}\tau * \left(\frac{\tilde{T}}{(1-\delta)S_e}\right)^{\gamma} + \tilde{b}^2\tau^2 * \left(\frac{V_e\tilde{T}}{(1-\delta)S_e}\right)^{2\gamma} = \tilde{b}^2\tau^2 + \tilde{b}\left[2(S_e - s) - V_e\tau + \frac{{V_e}^2}{\hat{b}}\right]$$

By dividing both sides of the equation above by $\tilde{b}$ and reorganizing we get Equation (A2).

$$\tilde{b}\tau^2 * \left(\frac{\tilde{T}}{(1-\delta)S_e}\right)^{2\gamma} {V_e}^{2\gamma} + 2\tau\left(\frac{\tilde{T}}{(1-\delta)S_e}\right)^{\gamma} {V_e}^{\gamma+1} + \left(\frac{1}{\tilde{b}} - \frac{1}{\hat{b}}\right){V_e}^2 + \tau V_e - \tilde{b}\tau^2 - 2(S_e - s) = 0 \tag{A2}$$

When $\gamma = 1$, Equation (A2) becomes Equation (A3)

$$\left(\left(1 + \frac{\tilde{b}\tau\tilde{T}}{(1-\delta)S_e}\right)^2 - \frac{\tilde{b}}{\hat{b}}\right){V_e}^2 + \tilde{b}\tau V_e - \left(\tilde{b}^2\tau^2 + 2\tilde{b}(S_e - s)\right) = 0 \tag{A3}$$

The solutions of this quadratic equation are

$$V_e = \frac{-\tilde{b}\tau \pm \sqrt{\tilde{b}^2\tau^2 + 4A\left(\tilde{b}^2\tau^2 + 2\tilde{b}(S_e - s)\right)}}{2A};$$

$$V_e = \frac{\tilde{b}\tau}{2A}\left(-1 \pm \sqrt{1 + 4A\left(1 + \frac{2\tilde{b}(S_e - s)}{\tilde{b}\tau^2}\right)}\right); \quad \text{where } A = \left[\left(1 + \frac{\tilde{b}\tau\tilde{T}}{(1-\delta)S_e}\right)^2 - \frac{\tilde{b}}{\hat{b}}\right]$$

As speed cannot be negative, only the positive solution is possible, which is

$$V_e = \frac{\tilde{b}\tau}{2A}\left(-1 + \sqrt{1 + 4A\left(1 + \frac{2\tilde{b}(S_e - s)}{\tilde{b}\tau^2}\right)}\right)$$

Equilibrium solution for TDIDM model

At equilibrium $a_n = 0$; $\Delta V_n = 0$. Therefore, Equation (15) can be rewritten as

$$\left(\frac{s+V_e\tilde{T}}{S_e} * \left(\frac{V_e\tilde{T}}{(1-\delta)S_e}\right)^{\gamma}\right)^2 - \left[1-\left(\frac{V_e}{\tilde{V}}\right)^{\beta}\right] = 0 \qquad \text{(A4)}$$

Equation (A4) can be rewritten as Equation (A5)

$$\frac{s+V_e\tilde{T}}{S_e{}^{\gamma+1}} * \left(\frac{V_e\tilde{T}}{(1-\delta)}\right)^{\gamma} = \sqrt{\left[1-\left(\frac{V_e}{\tilde{V}}\right)^{\beta}\right]} \qquad \text{(A5)}$$

It is straightforward to derive the solution of Equation (A5):

$$S_e = \left[\left(\frac{V_e\tilde{T}}{1-\delta}\right)^{\gamma} \frac{(s+V_e\tilde{T})}{\sqrt{\left[1-(V_e/\tilde{V})^{\beta}\right]}}\right]^{\frac{1}{\gamma+1}}$$

References

Bando, M., Hasebe, K., Nakanishi, K., Nakayama, A., 1998. Analysis of optimal velocity model with explicit delay. Physical Review E 58 (5), 5429–5435.

Barceló, J., Casas, J., 2005. Dynamic network simulation with AIMSUN, in: Kitamura, R., Kuwahara, M. (Eds.), Simulation Approaches in Transportation Analysis. Springer, pp. 57-98.

Bevrani, K., Chung, E., 2012. A safety adapted car following model for traffic safety studies, in: Stanton, N.A. (Ed.), Advances in Human Aspects of Road and Rail Transportation. CRC Press, San Francisco, pp. 550-559.

Boer, E.R., 1999. Car following from the driver's perspective. Transportation Research Part F: Traffic Psychology and Behaviour 2, 201-206.

Brackstone, M., McDonald, M., 1999. Car-following: a historical review. Transportation Research Part F: Traffic Psychology and Behaviour 2, 181-196.

Brockfeld, E., Kühne, R.D., Wagner, P., 2004. Calibration and validation of microscopic traffic flow models. Transportation Research Record: Journal of the Transportation Research Board 1876, 62-70.

Burns, P., Parkes, A., Burton, S., Smith, R., Burch, D., 2002. How dangerous is driving with a mobile phone? Benchmarking the impairment to alcohol. TRL Report 547, 1-56.

Caird, J.K., Willness, C.R., Steel, P., Scialfa, C., 2008. A meta-analysis of the effects of cell phones on driver performance. Accident Analysis & Prevention 40, 1282-1293.

Cassidy, M. J., Rudjanakanoknad, J., 2005. Increasing the capacity of an isolated merge by metering its on-ramp. Transportation Research Part B: Methodological 39(10), 896-913.

Ciuffo, B., Punzo, V., Montanino, M., 2012. The calibration of traffic simulation models. Report on the assessment of different goodness of fit measures and optimization algorithms. MULTITUDE Project–COST Action TU0903. JRC Scientific Report.

Chen, D., Ahn, S., Laval, J., Zheng, Z., 2014. On the periodicity of traffic oscillations and capacity drop: the role of driver characteristics. Transportation Research Part B 59, 117-136.

Chen D., Laval J., Zheng Z., Ahn S., 2012. A behavioral car-following model that captures traffic oscillations. Transportation Research Part B: Methodological 46 (6), 744-761.

Drews, F.A., Strayer, D.L., 2009. Cellular Phones and Driver Distraction, in: Regan, M.A., Lee, J.D., Young, K.L. (Eds.), Driver Distraction: Theory, Effects, and Mitigation. CRC Press, pp. 169-190.

Fastenmeier, W., Gstalter, H., 2007. Driving task analysis as a tool in traffic safety research and practice. Safety Science 45, 952-979.

Fritzsche, H.-T., 1994. Amodel for traffic simulation. Traffic Engineering and Control 35, 317-321.

Fuller, R., 2000. The task-capability interface model of the driving process. Recherche - Transports - Sécurité 66, 47-57.

Fuller, R., 2002a. Human factors and driving. In: Fuller, R., Sanots, J.A. (Eds.), Human factors for highway engineers.

Fuller, R., 2002b. Psychology and the highway engineer. In: Fuller, R., Sanots, J.A. (Eds.), Human factors for highway engineers. Elsevier Science Ltd., Oxford, UK, pp. 1-10.

Fuller, R., 2005. Towards a general theory of driver behaviour. Accident Analysis & Prevention 37, 461-472.

Fuller, R., 2011. Driver control theory. In: Porter, B.E. (Ed.), Handbook of traffic psychology. Academic Press, USA, pp. 13-26.

Fuller, R.G., 1984. Prolonged driving in convoy: the truck driver's experience. Accident analysis & prevention 16, 371-382.

Gazis, D.C., Herman, R., Rothery, R.W., 1961. Nonlinear follow-the-leader models of traffic flow. Operations Research 9 (4), 545–567.

Gipps, P.G., 1981. A behavioural car-following model for computer simulation. Transportation Research Part B: Methodological 15, 105-111.

Hamdar, S.H., Mahmassani, H. S., 2008. From existing accident-free car-following models to colliding vehicles: exploration and assessment. Transportation Research Record: Journal of the Transportation Research Board 2088 (1), 45-56.

Hamdar, S., 2012. Driver Behavior Modeling. Handbook of Intelligent Vehicles. Springer, pp. 537-558.

Hancock, P., 1999. Is car following the real question–are equations the answer? Transportation Research Part F: Traffic Psychology and Behaviour 2, 197-199.

Haque, M. M., Washington, S., 2013. Effects of mobile phone distraction on drivers' reaction times. Journal of the Australasian College of Road Safety 24, 20-29.

Haque, M.M., Washington, S., 2014. A parametric duration model of the reaction times of drivers distracted by mobile phone conversations. Accident Analysis & Prevention 62, 42-53.

Haque, M. M., Washington, S., 2015. The impact of mobile phone distraction on the braking behaviour of young drivers: A hazard-based duration model. Transportation Research Part C: Emerging Technologies 50, 13-27.

Harrison, E.L., Fillmore, M.T., 2011. Alcohol and distraction interact to impair driving performance. Drug and alcohol dependence 117, 31-37.

HCM, 2000. Highway Capacity Manual. Transportation Research Board.

Heino, A., van der Molen, H.H., Wilde, G.J., 1996. Differences in risk experience between sensation avoiders and sensation seekers. Personality and Individual Differences 20, 71-79.

Heino, A., van der Molen, H.H., Wilde, G.J., 1992. Risk-homeostatic processes in car-following behaviour: Individual differences in car-following and perceived risk. Report VK92-02, Traffic Research Centre, University of Groningen, Haren ReportVK92-02.

Holland, J.H., 1975. Adaptation in natural and artificial systems: An introductory analysis with applications to biology, control, and artificial intelligence. University of Michigan Press, Oxford, England.

Johansson, G., Rumar, K., 1971. Drivers' brake reaction times. Human Factors: The Journal of the Human Factors and Ergonomics Society 13, 23-27.

Kesting, A., Treiber, M., 2008. Calibrating car-following models by using trajectory data: Methodological study. Transportation Research Record: Journal of the Transportation Research Board 2088, 148-156.

Laval, J. A., 2011. Hysteresis in traffic flow revisited: an improved measurement method. Transportation Research Part B: Methodological 45 (2), 385-391.

Leung, S., Croft, R.J., Jackson, M.L., Howard, M.E., Mckenzie, R.J., 2012. A comparison of the effect of mobile phone use and alcohol consumption on driving simulation performance. Traffic injury prevention 13, 566-574.

Lewis-Evans, B., De Waard, D., Brookhuis, K.A., 2010. That's close enough—A threshold effect of time headway on the experience of risk, task difficulty, effort, and comfort. Accident Analysis & Prevention 42, 1926-1933.

Moskowitz, H., Fiorentino, D., 2000. A review of the literature on the effects of low doses of alcohol on driving-related skills. NHTSA HS-809 028.

Powell, M.J., 1973. On search directions for minimization algorithms. Mathematical Programming 4, 193-201.

Przybyla, J., Taylor, J., Jupe, J., Zhou, X., 2012. Simplified, data-driven, errorable car-following model to predict the safety effects of distracted driving. In: 15th International IEEE Conference on Intelligent Transportation Systems (ITSC). IEEE, pp. 1149–1154.

Punzo, V., Ciuffo, B., Montanino, M., 2012. Can results of car-following model calibration based on trajectory data be trusted? Transportation Research Record: Journal of the Transportation Research Board 2315, 11-24.

Punzo, V., Tripodi, A., 2007. Steady-state solutions and multiclass calibration of Gipps microscopic traffic flow model. Transportation Research Record: Journal of the Transportation Research Board 1999, 104-114.

Ranney, T., Watson, G.S., Mazzae, E.N., Papelis, Y.E., Ahmad, O., Wightman, J.R., 2004. Examination of the distraction effects of wireless phone interfaces using the national advanced driving simulator-preliminary report on freeway pilot study. Paper No HS-809737, National Highway Traffic Safety Administration, Washington, D.C.

Roehrs, T., Beare, D., Zorick, F., Roth, T., 1994. Sleepiness and ethanol effects on simulated driving. Alcoholism: Clinical and Experimental Research 18, 154-158.

Saifuzzaman, M., Haque, M.M., Zheng, Z., Washington, S., 2015. Impact of mobile phone use on car-following behaviour of young drivers. Accident Analysis & Prevention 82, 10-19.

Saifuzzaman, M., Zheng, Z., 2014. Incorporating human factors in car-following models: A review of recent developments and research needs. Transportation Research Part C: Emerging Technologies 48, 379-403.

Spall, J.C., 2005. Introduction to stochastic search and optimization: estimation, simulation, and control. John Wiley & Sons.

Stavrinos, D., Jones, J.L., Garner, A.A., Griffin, R., Franklin, C.A., Ball, D., Welburn, S.C., Ball, K.K., Sisiopiku, V.P., Fine, P.R., 2013. Impact of distracted driving on safety and traffic flow. Accident Analysis & Prevention 61, 63-70.

Strayer, D.L., Drews, F.A., Crouch, D.J., 2006. A comparison of the cell phone driver and the drunk driver. Human factors: The journal of the human factors and ergonomics society 48, 381-391.

Taleb, N.N., 2010. The black swan: The impact of the highly improbable fragility. Random House.

Tison, J., Chaudhary, N., Cosgrove, L., 2011. National phone survey on distracted driving attitudes and behaviors. Paper No H S-811555, National Highway Traffic Safety Administration, Washington, D.C.

Törnros, J.E.B., Bolling, A.K., 2005. Mobile phone use—Effects of handheld and handsfree phones on driving performance. Accident Analysis & Prevention 37, 902-909.

Treiber, M., Kesting, A., 2013. Modeling human aspects of driving behavior, Traffic Flow Dynamics. Springer, pp. 205-224.

Wiedemann, R., 1974. Simulation des StraBenverkehrsflusses, Schriftenreihe des tnstituts fir Verkehrswesen der Universitiit Karlsruhe, Germany.

Wilson, R.E., 2001. An analysis of Gipps's car-following model of highway traffic. IMA journal of applied mathematics 66, 509-537.

Winsum, W.V., Heino, A., 1996. Choice of time-headway in car-following and the role of time-to-collision information in braking. Ergonomics 39, 579-592.

Yang, H.H., Peng, H., 2010. Development of an errorable car-following driver model. Vehicle System Dynamics 48, 751-773.

Young, K., Lee, J.D., Regan, M.A., 2009. Driver distraction: Theory, effects, and mitigation. CRC Press.

Zheng Z., Ahn S., Chen D., Laval J., 2011. Freeway traffic oscillations: Microscopic analysis of formations and propagations using Wavelet Transform. Transportation Research Part B: Methodological 45 (9), 1378-1388.

Zheng, Z., Ahn, S., Chen, D., Laval, J., 2013. The effects of lane-changing on the immediate follower: anticipation, relaxation, and change in driver characteristics. Transportation Research Part C 26, 367-379.

Zheng Z., 2014. Recent developments and research needs in modeling lane changing. Transportation Research Part B 60, 16-32.

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Chapter 5

Understanding the mechanism of traffic hysteresis and traffic oscillations through the change in task difficulty level

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Understanding the mechanism of traffic hysteresis and traffic oscillations through the change in task difficulty level

Mohammad Saifuzzaman[1], Zuduo Zheng[1], Md. Mazharul Haque[1, 2], Simon Washington[1, 2]

[1] School of Civil Engineering & Built Environment, Science and Engineering Faculty, Queensland University of Technology (QUT), Brisbane, Australia

[2] Centre for Accident Research and Road Safety (CARRS-Q), Faculty of Health, Queensland University of Technology (QUT), Brisbane, Australia

Publication status: This article is submitted to *Transportation Research Part B: Methodological.*

Journal quality: The journal in which this paper appears is a peer-reviewed publication with an international readership. The journal's Impact Factor is 2.952, and ranks Q1, 3/69 (Transportation) according to the SCImago Journal Rank.

Foreword: This chapter (article) covers the application of the task difficulty formula developed in the previous chapter (Chapter 4) to understand two most widely reported puzzling traffic flow phenomena: traffic oscillation and traffic hysteresis. This article addresses the fourth research objective of this thesis stated in Section 1.2 of chapter 1.

Statement of contribution of co-authors for thesis by published paper

Publication title: Understanding the mechanism of traffic hysteresis and traffic oscillations through the change in task difficulty level

The authors listed below have certified that:

- They meet the criteria for authorship in that they have participated in the conception, execution, or interpretation, of at least that part of the publication in their field of expertise;
- They take public responsibility for their part of the publication, except for the responsible author who accepts overall responsibility for the publication;
- There are no other authors of the publication according to these criteria;
- Potential conflicts of interest have been disclosed to (a) granting bodies, (b) the editor or publisher of journals or other publications, and (c) the head of the responsible academic unit, and
- They agree to the use of the publication in the student's thesis and its publication on the Australasian Digital Thesis database consistent with any limitations set by publisher requirements.

Each author's contributions are listed below:

Contributor	***Statement of contribution***
Mohammad Saifuzzaman Signature: Saifuzzaman Date: 15/06/2016	Developed the methodology, conducted data analysis, and wrote the manuscript. The candidate was also responsible for any revisions made at the suggestions of journal reviewers.
Zuduo Zheng	Supervised the research, helped developing the methodology, and reviewed the manuscript. Also played the role of corresponding author.
Md. Mazharul Haque	Provided guidance during data analysis, and reviewed the manuscript.
Simon Washington	Reviewed the manuscript

Principal Supervisor Confirmation:

I have sighted email or other correspondence from all co-authors confirming their certifying authorship.

Dr. Zuduo Zheng	[signature]	15/06/2016
(Name)	(Signature)	(Date)

Understanding the mechanism of traffic hysteresis and traffic oscillations through the change in task difficulty level

Mohammad Saifuzzaman, Zuduo Zheng, Md. Mazharul Haque, Simon Washington

Abstract

This chapter provides a detailed understanding of the mechanism of traffic hysteresis and traffic oscillations from driver behavior perspective. Microscopic evaluation of trajectories inside seven selected oscillations is performed to obtain a comprehensive picture of these puzzling phenomena. A new method is proposed, to capture changes in driver behavior in response to the disturbance caused by traffic oscillations, by using driver's task difficulty (TD) profile. A close connection between the TD profile and evolution (such as formation and growth) of the stop-and-go traffic oscillations is found. Furthermore, different driver behaviors inside the oscillations are identified based on driver's TD profile, and their connection with hysteresis magnitudes is established. Finally, a generalized linear model of the hysteresis magnitude is formulated with important variables from both traffic flow and driver characteristics.

5.1. Introduction

Stop-and-go traffic oscillation is commonly observed for congested traffic and can have various adverse impacts including increased safety risk (Zheng et al., 2010) and reduced fuel efficiency (Bilbao-Ubillos, 2008). Caused by the retarded recovery of speed in the deceleration-acceleration process (Ahn et al., 2013; Chen, 2012), traffic hysteresis is an inseparable part of traffic oscillation. As both the phenomena are intertwined with each other, they are discussed side by side in this paper.

Several theories and models have been proposed to explain traffic hysteresis and oscillation. However, most studies analyzed the phenomena out of physical or mathematical curiosity (Gayah and Daganzo, 2011; Newell, 1965; Zhang, 1999; Zhang and Kim, 2005) while the triggering driving behavior underlying these phenomena received little attention. There are a few exceptions. Among them, Yeo and Skabardonis (2009) conjecture that human errors (e.g., maneuvering errors) and anticipative behaviors might be associated with the origin and propagation of stop-and-go oscillation. However, the relationship between human errors and traffic oscillation was not investigated. After observing the fact that follower's trajectory in congested region deviates from the perfect follower created by Newell's (1962) model, Laval and Leclercq (2010) proposed that traffic oscillations, with which traffic hysteresis is usually associated, may have a strong connection with aggressive and timid driver behavior. Their findings were confirmed by Zheng et al. (2011) and Chen et al. (2012, 2014) with empirical evidence.

Overall, our understanding of these puzzling phenomena remains elusive. Moreover, we believe that the use of the term 'aggressive-timid' can be misleading in explaining hysteresis because it is quite unlikely for the same driver to change from an aggressive to a timid behavior and vice versa within a short time interval (e.g., less than one second). This sudden behavior shift is inconsistent with the literature from the behavioral research where aggressive/timid driving is found to be closely related to driver's personal traits, which are relatively stable. For example, a bulk of the evidence indicates that men drive more aggressively than women (Rhodes and Pivik, 2011); high anger drivers have a tendency to be engaged in risky behavior, even when they are not angry (Deffenbacher et al. 2003). We have also observed similar results for car-following (CF) behavior in our driving simulator experiment where the aggressive drivers not only drove differently than the timid drivers; they also responded in a different way when they experienced distractions (mobile phone use distraction in this case). However, for a particular driver, his/her aggressiveness or timidness largely remains stable throughout the entire experiment, which makes it hard to explain traffic hysteresis or oscillation. The detail on this matter is presented in Section 5.2. Moreover, aggressiveness/timidness is difficult to be quantified by using traffic data commonly available to researchers (e.g., loop detector data, or vehicle trajectories). In this study, a different approach is proposed to analyze hysteresis and oscillation phenomena by linking the difficulty of the driving task to the hysteresis and oscillation properties.

To date, most of the conjectures about the relationship between driver behavior and the formulation of hysteresis and oscillation are proposed after an extensive analysis of the vehicle trajectory data. In other words, the conjectures are post hoc and data driven. The problem of a data-driven model in describing driver behavior is that they are not backed up by an established psychological/behavioral theory. As a result, a model that works fine with one data set might not function properly with another dataset. Moreover, engineering CF models (models that use Newtonian laws of motion to describe CF behavior) are found to be used in most cases to understand and reproduce hysteresis and oscillation, which is not adequate as they do not explicitly consider human factors (see Saifuzzaman and Zheng, 2014 for a detail discussion on this issue). As a result reproducing hysteresis and oscillatory behavior with Engineering CF models is not easy. Fine tuning model parameters might give a closer representation of the reality; however, the underlying reason behind these puzzling phenomena remains elusive.

In the previous chapter, we have introduced “Task difficulty” as a new CF variable which captures the dynamic interaction between driving task demand and driver capability (Saifuzzaman et al., 2005). Task difficulty is formulated based on the famous Task Capability Interface (TCI; Fuller, 2005) model, which explains the motivations behind driver’s decision making. According to the task difficulty homeostasis theory, driver continuously makes real-time decisions to maintain perceived difficulty of driving task within certain boundaries (Fuller, 2002, 2011). We believe that the underlying reason behind traffic hysteresis and the formation and propagation of traffic oscillation can be better explained by the change in driver’s risk-perception which is reflected on the level of task difficulty. The perceived risk of the driving situation may change in different circumstances causing the driver to modify their behavior so that the perceived level of task difficulty remains within their acceptable limit. For example, after experiencing sudden deceleration the driver may proceeds cautiously (assuming a higher risk and maintaining a higher time headway than their normal driving), maintaining a lower level of task difficulty in the acceleration phase to avoid/minimize future decelerations. Thus, the acceleration behavior becomes different than the deceleration behavior, and this asymmetric behavior is likely to create hysteresis loop. More discussion on this issue will be presented later.

The objective of this article is to understand the mechanism of traffic hysteresis and traffic oscillations through the change in task difficulty level over the driving course. A microscopic evaluation of each trajectory inside an oscillation is performed to get more insight on these puzzling phenomena. However, before moving to the main research objectives, we have presented a brief analysis of the CF behavior of aggressive and timid drivers in both regular and demanding situations to demonstrate the implausibility of using aggressiveness/timidness to explain traffic hysteresis or oscillation because for a particular driver, his/her aggressiveness or timidness largely remains stable throughout the entire experiment. This observation has partially motivated this study.

The rest of this chapter is organized as follows: Section 5.2 presents a brief analysis of the car-following behavior of aggressive and timid drivers; Section 5.3 provides a description of the data and methodologies; Section 5.4 gives a detailed analysis of both traffic oscillation and hysteresis properties; and finally, Section 5.5 discusses main findings and limitations of the study.

5.2. Stability of a driver's aggressiveness or timidness

In this section, we have investigated the effect of driver aggression and distraction on car-following (CF) behavior. Both of these factors are associated with risky behaviors. The car-following data is taken from the CARRS-Q Advanced Driving Simulator experiment on distracted driving. In this study, 32 young Australian drivers aged 18 to 26 years has participated in the driving simulator study along with a questionnaire survey about different aspects of their driving including their responses when they get angry on the road. The simulator driving experiment was conducted in three randomized phone conditions: baseline (no phone conversation), hands-free (conversation through a hands-free device) and handheld (conversation through a handheld mobile phone). The phone conversation was cognitive in nature, which required simultaneous storage and processing of information, and thus distracted the drivers by increasing their cognitive load. Participants' CF behavior in normal and distracted situations is one of the objectives of this simulator driving experiment. In order not to deviate the readers from the main focus of this study detail of the driving simulator experiment is not provided here. However, it can be found in Section 3.2 and Haque et al. (2014).

The level of driver anger is measured by the Driving Anger Expression Inventory (DAX; Deffenbacher et al. 2001, 2002). The DAX is widely used to measure the way drivers express their anger in the driving context (e.g., Herrero-Fernandez, 2011; Sarbescu, 2012), and contains 49 questions in 4 categories:

1) Verbally Aggressive Expression (VAE, 12 items) assesses verbal means of anger expression. The questionnaire includes for example, 'I make negative comments about the other driver'.
2) Physically Aggressive Expression (PAE, 11 items) includes physical forms of expressing anger for example, 'I try to force the other driver to the side of the road'.
3) Using the Vehicle for Aggressive Expression (UVAE, 11 items) assesses the way drivers use their vehicles to express anger. The questionnaire includes for example, 'I drive right up on the other driver's bumper'.
4) Adaptive/Constructive Expression (ACE, 15 items) includes adaptive or constructive statements for example, 'I tell myself it's not worth getting all mad about'.

All these questions are rated on a 4-point Likert scale (1 = almost never, 4 = almost always). The questions in VAE, PAE, and UVAE categories are designed to find aggressive responses when drivers are angry or frustrated. The ACE category focuses on constructive and adaptive expression and thus is excluded from the analysis. The average responses for VAE, PAE, and UVAE categories are 2.34, 1.14, and 1.51, respectively, indicating that the participants in this study mostly use VAE to express their anger. Hence, the participants are divided into two groups based on the median score of VAE: Aggressive (mean of the VAE score ≥ 2.125) and Non-aggressive (mean of the VAE score <2.125). Car-following (CF) behavior is measured by various variables including driving speed, spacing, time headway, and fluctuations of speed and spacing. A comparison of CF performance between the two groups (i.e., aggressive and non-aggressive) is presented in Table 5.1.

Table 5.1 Comparison of car-following performance of aggressive and non-aggressive drivers

	Baseline condition			
	Aggressive	Non-Aggressive	*t*-value	*p*-value
Mean speed (km/hr)	34.69	34.66	0.03	0.97
Mean spacing (m)	27.15	27.83	-0.29	0.78
Mean time headway (s)	2.92	2.99	-0.19	0.85
	Hands-free condition			
	Aggressive	Non-Aggressive	*t*-value	*p*-value
Mean speed (km/hr)	34.78	32.12	2.19	0.04
Mean spacing (m)	27.46	31.98	-2.21	0.04
Mean time headway (s)	2.96	3.74	-2.27	0.03
	Handheld condition			
	Aggressive	Non-Aggressive	*t*-value	*p*-value
Mean speed (km/hr)	34.26	31.30	2.77	0.01
Mean spacing (m)	29.96	34.60	-2.29	0.03
Mean time headway (s)	3.25	4.31	-2.90	<0.01

At the baseline condition both the groups have shown similar CF behavior regarding maintaining driving speeds, vehicle spacings, and time headways. The similarity might have partially caused by the experimental settings which refrain the driver from increasing their speed due to a speed limit of 40 km/hr and maximum leader speed of 35 km/hr. Therefore, in the baseline situation both the groups are found to drive comfortably with average speed of 34.7 km/hr and time headway of 3 seconds. However, a significant difference in CF behavior is observed between the two groups in both hands-free and handheld conditions where the aggressive drivers keep higher speeds, and lower spacings and time headways compared to the non-aggressive drivers. The impact of distraction can be better understood from Table 5.2

which presents the CF behavior of the two groups in the three driving conditions (i.e., baseline, hands-free and handheld). As the same driver performed the simulator driving in the three driving conditions, one-way repeated measures ANOVA is applied to observe the effect of distraction on their CF behavior. Interestingly, the CF behavior of aggressive drivers remains similar to the baseline when distracted by either hands-free or handheld phone conversation. The non-aggressive drivers, on the other hand, have shown risk compensatory behavior in both the distracted situations by decreasing driving speeds, and increasing vehicle spacings and time headways. Overall, the distraction caused by the concurrent mobile phone conversation while driving has a greater influence on the non-aggressive drivers which made their CF behavior more risk averse than the aggressive drivers.

Table 5.2 Effect of distraction on the CF behavior of Aggressive and Non-Aggressive drivers

	Aggressive drivers (count = 16)				
	Baseline	Hands-free	Handheld	$F_{2,30}$	*p*-value
Mean speed (km/hr)	34.69	34.78	34.26	0.304	0.74
Mean spacing (m)	27.15	27.46	29.96	2.793	0.08
Mean time headway (sec)	2.92	2.96	3.25	2.209	0.13
	Non-aggressive drivers (count = 16)				
	Baseline	Hands-free	Handheld	$F_{2,30}$	*p*-value
Mean speed (km/hr)	34.66	32.12	31.30	14.22	<0.01
Mean spacing (m)	27.83	31.98	34.60	13.07	<0.01
Mean time headway (sec)	2.99	3.74	4.31	13.95	<0.01

The results in Table 5.1 and 5.2 show the aggregate behavior of the two driver groups. To understand the effect of distraction on CF behavior at the individual level, Figure 5.1 presents the difference in average time headways between normal and distracted situations for each driver. For a fair comparison between the two groups, the differences in time headways between baseline and distracted situations are sorted from low to high and plotted alongside. Only time headway is chosen for representing the CF behavior at the individual level in these plots for two reasons. Firstly, time headway presents a better picture about CF than spacing or speed alone could do, because it is calculated as the ratio of spacing over speed. And secondly, previous studies have found it very effective in explaining CF behavior (Saifuzzaman et al., 2015a; Ranney et al., 2004). Furthermore, Figure 5.2 displays the average time headway profiles in baseline and distracted situations for both the driver groups which are plotted along the length of the road section.

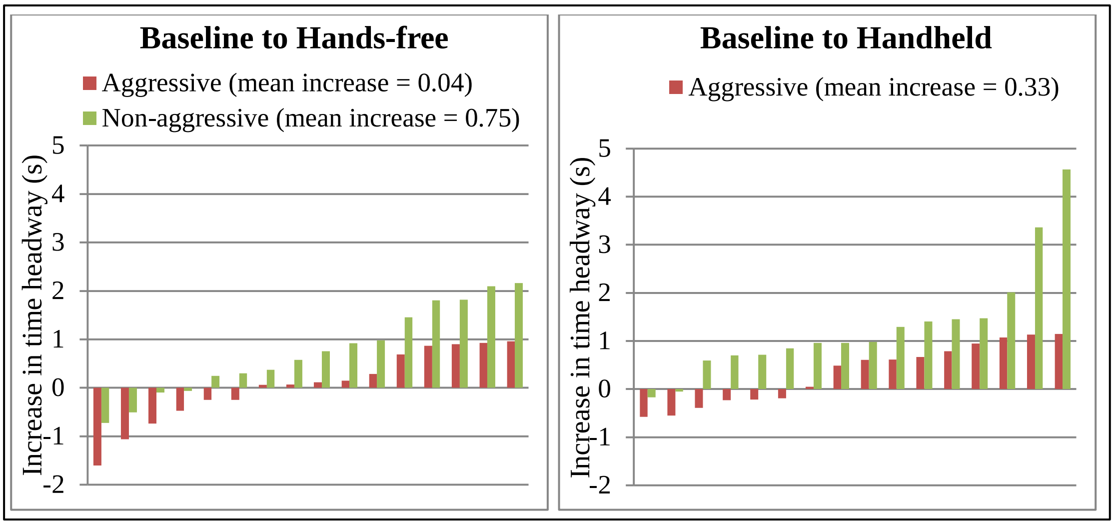


Figure 5.1 Increase in time headway from baseline to distracted situations

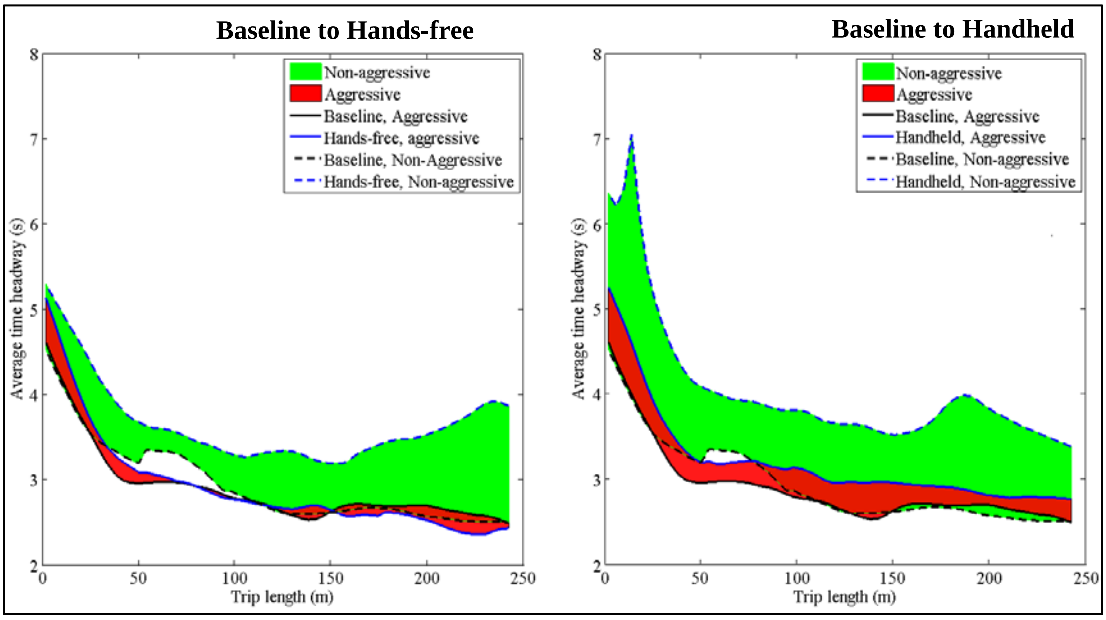


Figure 5.2 Average time headway profile of baseline and distracted CF

[The bottom and top lines of the shaded region represents the baseline and the distracted (hands-free on the left plot and handheld on the right plot) average time headway profiles respectively. The shaded portion shows the increase in average time headway from baseline to distracted situations]

The two plots in Figure 5.1 clearly show that the increase in time headways for non-aggressive drivers in both the distracted situations (i.e. hands-free and handheld) is much higher than aggressive drivers. Figure 5.2 further suggests that the increase in average time headways is stable over the driving period for non-aggressive drivers. Interestingly, the increase in average time headway is higher at the latter part of driving where CF was intense than approaching to CF part at the beginning, which indicates an added risk compensatory behavior when close following. On the other hand, the change in average time headway for the aggressive drivers in hands-free condition is barely noticeable. Although a slight increase in average time headway is observed during handheld situation, it was not statistically significant (p-value = 0.13). This is probably caused by the added workload of driving with one hand at the handheld situation. In either of the distracted cases, the increase in time headway for aggressive drivers is very low compared to the non-aggressive drivers. Furthermore, the risk compensatory behavior during close following is absent.

It is clearly evident from the above analysis that the driving pattern of these two groups of drivers is entirely different. Even if we accept that the two groups have some similarity in the normal situation, we cannot overlook the fact that, the aggressive drivers have completely ignored the risk of being distracted. The stable behavior of the aggressive drivers in all three driving phases might have resulted from their confidence or familiarity with the concurrent phone use while driving. However, there is insufficient evidence to assess their capability to overcome the increased crash risk arising from distraction. While previous studies have suggested a fourfold increase in accident risk for both hands-free and handheld phone uses while driving (McEvoy et al., 2005; Redelmeier and Tibshirani, 1997), the absence of risk-compensatory behavior has certainly made the aggressive drivers more risk-prone than the non-aggressive drivers. On the other hand the non-aggressive drivers have modified their actions to be safe from the possible negative consequences of distractions.

These findings should be sufficient enough to conclude that aggressive drivers are not likely to behave like timid (non-aggressive) drivers just because the driving complexity has increased. In fact, aggressiveness or timidness is closely related to a driver’s personal trait and way of responding to driving anger. Hence, it is difficult to justify the shift from aggressive into timid behavior especially within a very short period of time as the underlying reason behind hysteresis. A better approach could be to study driver behavior through their perceived level of task difficulty as Fuller (2002) explains that task difficulty dictates human motivations behind driving decisions. In this study, we have used the task difficulty profile to explain hysteresis and obtained some insightful findings which will be discussed in the rest of this paper.

5.2.1. Data and methodology

The vehicle trajectory data from the US-101 site provided by the Next Generation Simulation project (FHWA, 2008) is used in this study. The data were collected on a 6-lane 2100-foot road segment southbound of US-101 in Log Angles, California (see Figure 5.3-a) from 7:50 to 8:35 a.m. on June 15, 2005. The resolution of the collected data is 0.1 seconds which is sufficient for the investigation of oscillation and hysteresis behavior. We have selected seven traffic oscillations (shown in Figure 5.3-b and 5.3-c) that arise spontaneously and are well developed as they propagate upstream. Other oscillations contained in the dataset are excluded from our analysis because they are either intertwined with another nearby oscillation or do not have the developed stage.

5.2.2. Development of an oscillation

A complete oscillation can be divided into three stages: ‘precursor’, ‘developed’, and ‘decay’ stage (Zheng et al., 2011b, Chen et al., 2014), which are characterized as follows:

a) **Precursor:** It occurs at the beginning of oscillation. The speeds of the deceleration and acceleration waves are close to zero. The oscillation in the precursor period propagates from vehicle to vehicle, but not in space (oscillation wave propagation speed is near zero).
b) **Developed:** The oscillation wave propagates backward through space with a speed of 10-15 mph. The oscillation amplitude which is the difference in speed between the deceleration and acceleration start points remains stable among the vehicles.

c) **Decay:** The amplitude diminishes as the wave propagates and finally the oscillation comes to an end. No decay stage is found in our analysis.

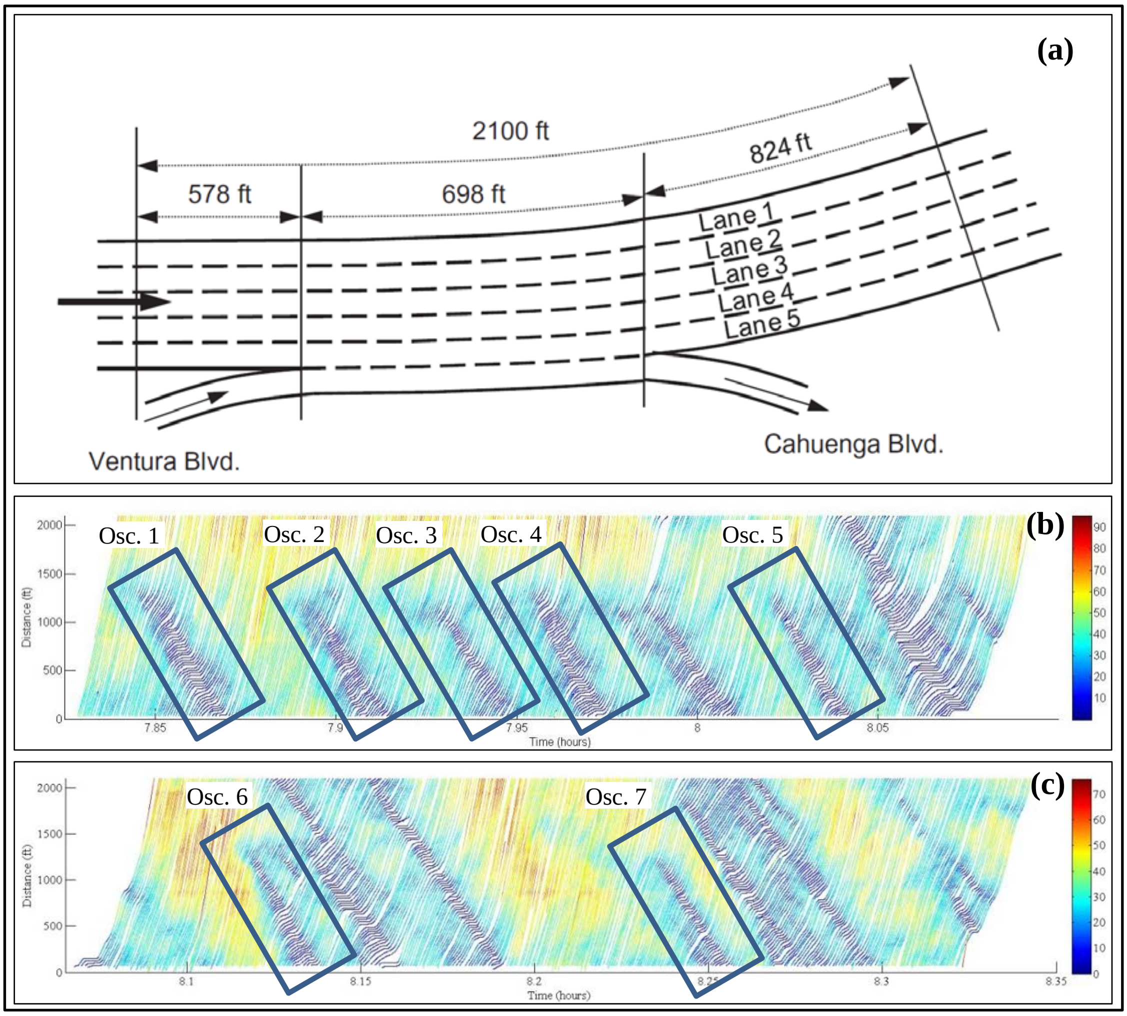


Figure 5.3 (a) Southbound US-101 in Los Angeles, California (Source: Zheng et al. 2011); (b) Selected oscillations from dataset 1 (Lane 1, 7:50 to 8:05 am); (c) Selected oscillations from dataset 2 (Lane 1, 8:05 to 8:20 am).

[Osc. stands for oscillation; the color bar represents speed in ft/sec]

In this study, the origin and propagation of each stop-and-go traffic oscillation are identified by using a method based on wavelet transformation (Zheng et al., 2011a, b). An example of identifying the origin of oscillation is presented in Figure 5.4. In this figure the wavelet energy distributions for the first 14 trajectories from the beginning (assumed) of oscillation are shown (on the right side). It is evident from the figure on the right side that the oscillation is originated by vehicle id 39 and not by the lane changer (vehicle id =2). The disturbance caused by vehicle 39 propagated to the following vehicles and finally created a fully developed oscillation. The origins of other six oscillations are identified similarly. Moreover, peaks of the wavelet energy can be used to approximate oscillation's propagation path, as shown in the left sub-figure of Figure 5.4. The same method can be applied to determine the end of an oscillation. Unfortunately, within the dataset, no complete oscillations are found to enable such analysis.

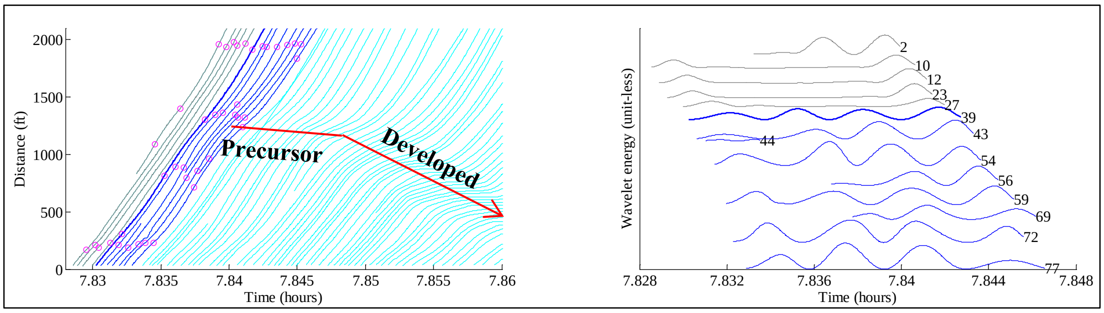


Figure 5.4 Identification of the origin of an oscillation

5.2.3. Traffic hysteresis

Traffic hysteresis was first observed by Newell (1962). He conjectured the existence of two different congested branches in the fundamental diagram as shown in Figure 5.5. When the acceleration branch stays above the deceleration branch in a flow-density diagram, it is known as a positive hysteresis, and the opposite is termed as a negative hysteresis (Laval, 2011). Negative hysteresis is also occasionally called as reverse hysteresis (Ahn et al., 2013).

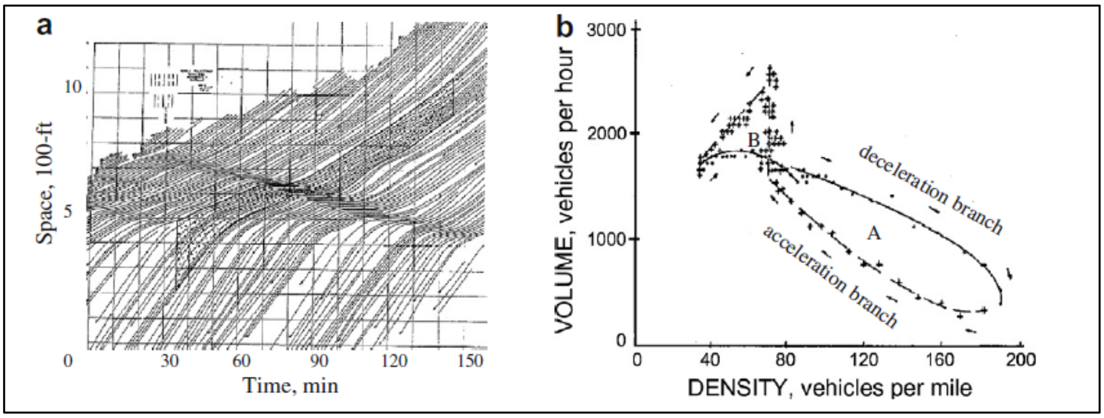


Figure 5.5 Hysteresis loop observed by Newell (1962)

Two different methods of measuring the hysteresis magnitude are proposed in the literature. Traditionally, hysteresis magnitude is measured as the flow difference between the deceleration and acceleration branches at a given density in the flow-density plane (Laval, 2011). This method is mostly used for a platoon of vehicles, and suitable for investigating hysteresis at a macroscopic level. By focusing on the speed-spacing relationship of a pair of vehicle trajectories, the other method measures the hysteresis magnitude as the average difference in spacing between acceleration and deceleration phases over the speed span of the hysteresis loop (Ahn et al., 2013; Chen et al., 2014). The speed span is the range of speed that is available at both the deceleration and acceleration phases. The average difference in spacing can be calculated by taking the area of the loop (the difference between the area under acceleration and deceleration branch) divided by the speed span. For positive (negative) hysteresis the acceleration branch stays over (under) the deceleration branch in the spacing vs. speed plot. Therefore the hysteresis magnitude will correspondingly be positive (negative). Obviously, this method is suitable for understanding hysteresis behavior at a microscopic level, thus, adopted in this study.

Different phases of the vehicle trajectory

In analyzing hysteresis, previous studies have considered two distinct phases in a vehicle’s trajectory: a deceleration phase followed by an acceleration phase. Besides these two phases, another phase is included in our analysis: a baseline phase which is right before the deceleration event. Car-following behavior at the baseline phase is assumed to represent driver’s regular CF behavior which is not influenced by any disturbance. Thus, the introduction of the regular phase allows us to observe the change in driver behavior caused by the oscillation. Hence, each vehicle trajectory inside the oscillatory region is divided into three phases: regular, deceleration, and acceleration. The baseline phase represents the regular driving behavior of a driver; the deceleration phase shows the deceleration behavior in response to the preceding vehicle’s braking, and the acceleration phase represents the recovery of speed. They are identified through the wavelet energy distribution (Zheng et al. 2011a).

Zheng et al. (2011a) first proposed to take the two consecutive peaks in a wavelet energy distribution near the oscillatory region as the start of the deceleration and acceleration phases respectively. Later this approach was adopted by other researchers (e.g. Chen et al., 2014; Ahn et al. 2013). We have extended this method to identify the start of the baseline phase by taking the nearest peak in the energy distribution before the deceleration phase. In the absence of such peak, the start of the trajectory is considered to be the beginning of the baseline phase. Similarly, the end of the acceleration phase is identified as the next nearest peak in the energy distribution after the onset of the acceleration phase or the end of the trajectory whichever is closer. An example of this identification process is presented in Figure 5.6.

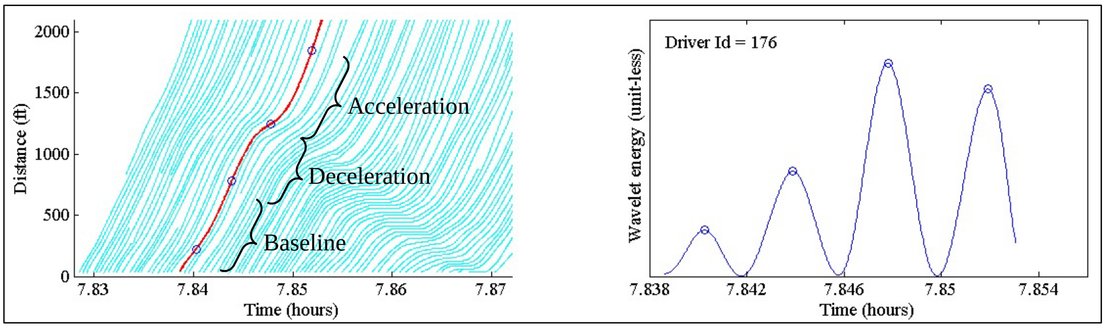


Figure 5.6 Identification of hysteresis phases

In this figure, the peaks of the wavelet energy are shown on the trajectory. Based on the position of these peaks the three phases are shown in the left of Figure 6. The analysis region of an individual trajectory is bounded by the start of the baseline and the end of the acceleration phases. For example, the analysis region for this particular trajectory (shown in Figure 6) is bounded by the positions corresponding to energy peaks 1 to 4. To ensure a complete loop of traffic hysteresis, in our analysis the acceleration phase should have at least the same speed span of the deceleration phase (without any influence of neighboring oscillations). In other words, we have only considered the trajectories that have fully recovered the speed that was lost in the deceleration phase. Trajectories that have failed to satisfy this condition are either influenced by a neighboring oscillation which prevented them from a full speed recovery or have an acceleration phase that lasted longer than the time window in which the dataset was collected. Also, the trajectories in the vicinity of lane-changing maneuvers were excluded to avoid confounding effects.

5.2.4. *Task difficulty and risk perception*

Saifuzzaman et al. (2015b) proposed a new approach to model CF behavior inspired by the Task-Capability Interface model (TCI; Fuller, 2005) where the difficulty of a driving task dictates human motivations behind driving decisions. Task difficulty is expressed as an interaction between task demand and driver capability, and the formulation is shown in Equation (5.1):

$$TD_n(t) = \left(\frac{V_n(t-\tau_n)\tilde{T}_n}{(1-\delta_n)S_n(t-\tau_n)}\right)^{\gamma} \tag{5.1}$$

where TD_n represents task difficulty as perceived by driver n at time t, S_n is spacing measured as the distance between the front of the subject (driven) vehicle to the back of the preceding vehicle; V_n is speed of the subject vehicle; $\tilde{T}_n$ is desired time headway, δ_n is a risk parameter (more discussion on this parameter is provided in the next paragraph), τ_n is the reaction time and γ is a sensitivity parameter which is used to capture driver's sensitivity towards the task difficulty level. In Equation (5.1) the task difficulty increases with an increase in speed or a decrease in spacing or both. In addition, the same task that is easy to one driver may be difficult to another, depending on their desired time headways. Please note here that, the calculation of TD is lagged by the reaction time to observe the perceived level of task difficulty. Hence, the task difficulty mentioned throughout this paper refers to the perceived task difficulty.

The risk parameter ($\delta_n < 1$) captures the risk perception of a driver for a specific driving task. A positive risk perception indicates that the driver acknowledges some risk in the driving environment which leads to a risk compensatory behavior such as increasing the time headway from the preceding vehicle. On the contrary, a negative risk perception point toward an underestimation of risk (caused by the negative influence of human factors such as intoxicated driving or motivation to drive faster) which results in aggressive behaviors such as tailgating, or speeding.

The aim of this study is to observe how the risk perception of the driver changes over the driving period, whether the disturbance caused by the oscillation has any impact on the risk perception, whether and how changes of a driver's risk perception trigger traffic hysteresis. It is assumed that the driver should perceive some additional risk when experiencing the disturbance posed by the oscillation. Therefore, the risk perception within the oscillatory region (bounded by the deceleration and acceleration phases of each trajectory) should be higher than that of outside the region. The best way to observe the change in driver's risk perception is to calibrate the model for the three driving phases (baseline, deceleration, and acceleration) and get an estimate of the risk parameter in each phase. However, the number of observation in each phase is too small to get a reliable estimation of the risk parameter. Furthermore, NGSIM data does not contain any human behavior information to help us estimate this parameter. Therefore, an alternative approach is considered: rather than directly estimating the risk parameter, we have calculated the Task Difficulty (TD) for each phase using Equation (1). According to the task difficulty homeostasis theory (Fuller, 2002) an increase in TD above the desired limit would raise the risk perception and the driver is likely to slow down to decrease the TD level. Therefore, any change in TD value gives an approximation of the change in risk perception.

To get an estimate of the TD parameters (reaction time τ, desired time headway $\tilde{T}$, and risk parameter δ) we have randomly selected ten pairs (leader-follower) of trajectories: five from inside and five from outside the oscillations. All the trajectories are selected from the same lane (lane-1) where the oscillations are observed. We have applied TDGipps model (Saifuzzaman et al., 2015b) on each follower's trajectory and calibrated the model parameters using Genetic Algorithm following the same procedure used in Saifuzzaman et al. (2015b). A comparison of the calibrated model parameters is presented in Table 5.3.

As shown in this table, although no notable difference between these two groups in either reaction time or desired time headway is found, the risk perception of the drivers inside the oscillations is found to be significantly larger compared with the counterparts outside of oscillations. More specifically, the average risk parameter for the drivers outside of the oscillations is close to zero, however, it increases to 0.20 for the drivers inside the oscillations. The result clearly indicates that traffic oscillations increase drivers' perceived risk, which is consistent with our daily driving experience. To the best of our knowledge, no previous studies have quantitatively investigated traffic oscillations' impact on driver's reaction time or risk perception.

Table 5.3 Comparison of calibrated parameters from inside and outside of oscillations *

Trajectories outside oscillations					Trajectories inside oscillations				
Id	τ	$\tilde{T}$	δ	RMSNE**	Id	τ	$\tilde{T}$	δ	RMSNE
23	0.74	0.48	0.02	0.026	239	0.87	0.92	0.24	0.041
240	0.63	1.02	0.02	0.040	913	1.24	0.89	0.23	0.047
719	1.02	1.23	0.00	0.029	1172	0.59	0.57	0.11	0.067
730	1.33	1.05	0.00	0.030	1284	1.03	1.18	0.28	0.051
2273	1.04	0.85	0.01	0.031	1533	1.19	1.10	0.15	0.057
Average	0.95	0.93	0.01	0.031	Average	0.98	0.93	0.20	0.052

* Parameters that are required to calculate TD are reported only

** RMSNE stands for Root Mean Squared Normalized Error. It gives an indication of the calibration performance. RMSNE is calculated based on the following formula: $RMSNE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(\frac{S_i^{sim}-S_i^{obs}}{S_i^{obs}}\right)^2}$; where N denotes number of observations, S_i^{sim} is the simulated spacing and S_i^{obs} is the observed spacing.

The calibrated parameters are used to calculate the task difficulty level at each phase. Among the parameters, reaction time and desired time headway are fixed for all drivers and for all three phases ($\tau = 1.0$sec, $\tilde{T} = 0.9$sec). This is done because the average of the estimated value for these two parameters is almost identical for both inside and outside of the oscillation. The only parameter that is changed among the three phases is the risk parameter. For the baseline phase of a trajectory, which stays outside the oscillatory region, the risk parameter is kept as $\delta = 0.01$, and for both deceleration and acceleration phases it is $\delta = 0.2$. Therefore, TD value will change in response to any change in speed, spacing and risk parameter only.

5.3. Properties of Oscillation and Hysteresis

This section describes different properties of oscillation and hysteresis that are observed in this study. Emphasis is given to find a relation between hysteresis and oscillation properties with task difficulty level. The change in driver behavior in the three phases (baseline, deceleration, and acceleration) is observed through the change in task difficulty values. The identification of the three phases is described in Section 5.2.2. For the trajectories inside the selected seven oscillations, those that meet the two conditions specified in Section 5.2.2 (i.e., having all three phases, and the full recovery of speed) are analyzed. In total, 225 trajectories is selected for the analysis.

5.3.1. Oscillation properties

A descriptive analysis of all the observed oscillations is presented in Table 5.4. Oscillation 5 and 6 consist fewer observations compared to the other five because many observations in these two oscillations do not have the full recovery of speed due to the influence from neighboring oscillations. The analysis is done separately for the ‘precursor’ and ‘developed’ stages of oscillation because drivers’ behavior in these two stages can be different. Main properties of these oscillations are summarized in Table 5.4, which clearly shows how the driver behavior changes between these two stages, as elaborated below.

The *p*-values from two-sample *t*-test suggest that all the variables in Table 5.4 except TD in the baseline are significantly different at 95% confidence level between the precursor and developed stages of oscillation. Both the amplitude and duration of oscillation are significantly higher at the developed stage compared to the precursor stage which implies a higher speed reduction and longer disturbance period in the developed stage of oscillation. Similarly, the oscillation intensity is also higher at the developed stage. Interestingly, the average magnitude of hysteresis at the precursor stage is larger than that at the developed stage, which may be because the drivers at the developed stage of oscillation have adequately adjusted to the situation, and thus they are unlikely to make any abrupt changes in their behavior. This becomes more evident when TD is brought into the picture, as discussed below.

The average TD value in the baseline is almost the same for both the precursor and developed stages of an oscillation (no significant difference is found from the two-sample *t*-test; *p*-value = 0.453), indicating that the task difficulty level prior to the arrival of oscillation is within the allowable range of the drivers i.e. they are satisfied with this driving condition in the baseline. The behavior changes at the deceleration phase where a sudden increase of TD level is observed for the trajectories that are at the precursor stage of oscillation. The increase in TD is caused by the delayed or inadequate reaction of the driver to the sudden deceleration of the preceding vehicle. According to the task difficulty homeostasis theory (Fuller, 2005), drivers generally take actions to keep the TD level within their acceptable limit. Consequently, a decrease in TD is observed at the acceleration phase. Hence, the acceleration behavior becomes different than the deceleration behavior. A different situation is found for the developed stage of oscillation, where the average TD level decreases in both the deceleration and acceleration phases compared with TD in the baseline. This is not surprising because for the developed stage of oscillation, drivers can better perceive the situation, and then better react to the leader’s behavior.

Another noteworthy observation is that the difference of TD level between the acceleration and deceleration phases is much lower at the developed stage than at the precursor stage of oscillation. This simply implies that driver behavior (and hence traffic dynamics) at the precursor stage is more versatile and instable. More specifically, the higher reduction of TD level at the precursor stage indicates more pronounced behaviour of risk compensation (i.e. increase in time headway) as an influence of the increased TD during deceleration. As a result, the hysteresis magnitude becomes larger at the precursor stage than that at the developed stage of oscillation. More insight on the magnitude of hysteresis and its relation to the change in TD level is presented in the next section.

As explained before driver behavior in this study is distinguished as three different phases: baseline, deceleration, and acceleration. For all three phases, the average speed and spacing at the precursor stage are higher than those at the developed stage of oscillation.

Table 5.4 Descriptive statistics of each oscillation[1]

		Osc.1	Osc.2	Osc.3	Osc.4	Osc.5	Osc.6	Osc.7	All Osc.	*p*-value[2]
Count[3]	Total	43	32	47	32	19	15	37	225	-
	Precursor	12	18	28	7	9	10	7	91	-
	Developed	31	14	19	25	10	5	30	134	-
Precursor stage of oscillation	Osc. Amplitude[4]	31.41	19.19	18.12	24.35	27.83	25.67	16.93	22.26	<0.001
	Osc. Duration[5]	13.38	10.36	11.69	17.00	11.78	10.72	15.77	12.27	0.002
	Osc. Intensity[6]	2.31	1.83	1.59	1.49	2.39	2.41	1.06	1.85	<0.001
	Hys. Magnitude	53.39	30.81	23.17	50.09	33.50	35.56	30.13	33.66	<0.001
	Baseline TD	0.48	0.58	0.44	0.48	0.55	0.50	0.52	0.50	0.453
	Dec. TD	0.65	0.71	0.65	0.60	0.64	0.67	0.60	0.66	<0.001
	Acc. TD	0.39	0.52	0.55	0.37	0.45	0.42	0.44	0.47	<0.001
	Baseline speed	44.52	46.31	36.83	31.15	42.68	44.36	36.52	40.66	<0.001
	Dec. speed	38.27	39.37	36.75	24.60	33.57	42.17	30.70	36.35	<0.001
	Acc. speed	41.25	47.75	44.30	37.69	40.96	37.48	32.99	42.12	<0.001
	Baseline spacing	92.17	76.69	80.03	62.49	85.47	91.30	68.19	80.49	0.001
	Dec. spacing	73.15	67.46	70.02	50.98	66.42	80.35	63.93	68.77	<0.001
	Acc. spacing	127.69	113.13	102.00	121.03	110.83	104.74	90.57	109.35	<0.001
Developed stage of oscillation	Osc. Amplitude[4]	35.70	31.54	31.03	28.67	38.60	37.67	24.48	31.07	-
	Osc. Duration[5]	17.23	13.67	12.44	13.49	11.02	11.76	13.19	13.91	-
	Osc. Intensity[6]	2.09	2.40	2.53	2.41	3.68	3.37	2.07	2.41	-
	Hys. Magnitude	21.43	25.93	25.40	18.69	28.14	35.66	18.04	22.23	-
	Baseline TD	0.50	0.53	0.47	0.52	0.59	0.81	0.48	0.52	-
	Dec. TD	0.43	0.53	0.52	0.45	0.59	0.75	0.48	0.49	-
	Acc. TD	0.35	0.38	0.37	0.35	0.41	0.41	0.39	0.37	-
	Baseline speed	35.75	39.50	37.39	32.24	41.89	42.65	29.91	35.13	-
	Dec. speed	16.95	22.30	24.50	16.19	24.70	28.66	17.47	19.57	-
	Acc. speed	25.61	27.35	29.08	21.53	29.24	24.14	26.93	26.03	-
	Baseline spacing	70.27	75.89	81.39	62.96	72.21	53.97	60.06	68.32	-
	Dec. spacing	43.47	48.81	57.35	42.56	50.56	46.29	42.71	46.29	-
	Acc. spacing	74.16	79.61	90.26	65.16	83.32	69.36	71.11	75.15	-

Osc., Hys., Dec., & Acc. stands for Oscillation, Hysteresis, Deceleration & Acceleration respectively

[1] Except 'Count' all the values presented in this table are the average of that specific variable

[2] *p*-value of a two-sample *t*-test between precursor and developed stages

[3] Count is the number of trajectories included in the analysis

[4] Oscillation amplitude is the speed difference between the starting point of the acceleration phase and that of the deceleration phase (Zheng et al., 2011b)

[5] Oscillation duration is calculated as the length of the deceleration phase (Zheng et al., 2011b)

[6] Oscillation intensity = amplitude / length (Zheng et al., 2011b)

Driver behavior in baseline, deceleration and acceleration phases

The deceleration and acceleration phases fall within the oscillatory region and, therefore are affected by the disturbance caused by the oscillation. Whereas, the baseline phase is free from any disturbance. A comparison of the driver behavior among the three phases is presented in Table 5. As the same driver is driving through these three consecutive driving phases, the dataset represents a panel data with a panel size of 3. To check whether the driving behavior is significantly different across the three phases one-way repeated measures ANOVA test is performed, and the test statistics are also included in Table 5.5.

Table 5.5 Comparison of driver behavior among baseline, deceleration and acceleration phases

Variable	Baseline	Deceleration	Acceleration	$F_{2,448}$	p-value
Average TD	0.51 (0.16)	0.56 (0.19)	0.41 (0.15)	111	<0.001
Average speed (ft/s)	37.37 (6.59)	26.36 (10.28)	32.54 (10.10)	256.9	<0.001
Average spacing (ft)	73.24 (25.34)	55.38 (20.14)	88.98 (36.85)	216.7	<0.001

[Value in the parenthesis displays the standard deviation.]

It is evident from Table 5.5 that the driver behavior is significantly different across the three phases. A pairwise t-test between each pair of phases (e.g. baseline vs. deceleration, baseline vs. acceleration, and deceleration vs. acceleration) for all the variables shows that the differences are significant at 95% confidence level (p-value <0.001). Overall, the task difficulty increases during deceleration but drops below the baseline during acceleration. The opposite trend is observed for speed and spacing as both the speed and spacing decreases from baseline during the deceleration and increases during acceleration. Such behavioral change suggests that the drivers act to resume their normal behavior during the acceleration phase. However, compared with the driving behavior in the baseline, the increased task difficulty at the deceleration phase made them to adopt a more risk-averse driving behavior. A detail discussion on this issue is presented in Section 5.4.2.2 where behavioral change of each driver is analyzed.

5.4. Hysteresis properties

5.4.1. Positive and negative hysteresis

Hysteresis behavior of individual drivers can be identified in a vehicle pair through the evolution of the follower's speed-spacing relationship during a deceleration-acceleration cycle. When the acceleration branch stays above the deceleration branch in a speed-spacing diagram, it is known as positive hysteresis, and the opposite is negative hysteresis (Ahn et al., 2013; Chen et al., 2014). Two typical examples of hysteresis are presented in Figure 5.7. A detailed comparison between the positive and negative hysteresis is presented in Table 5.6 for all the observed hysteresis.

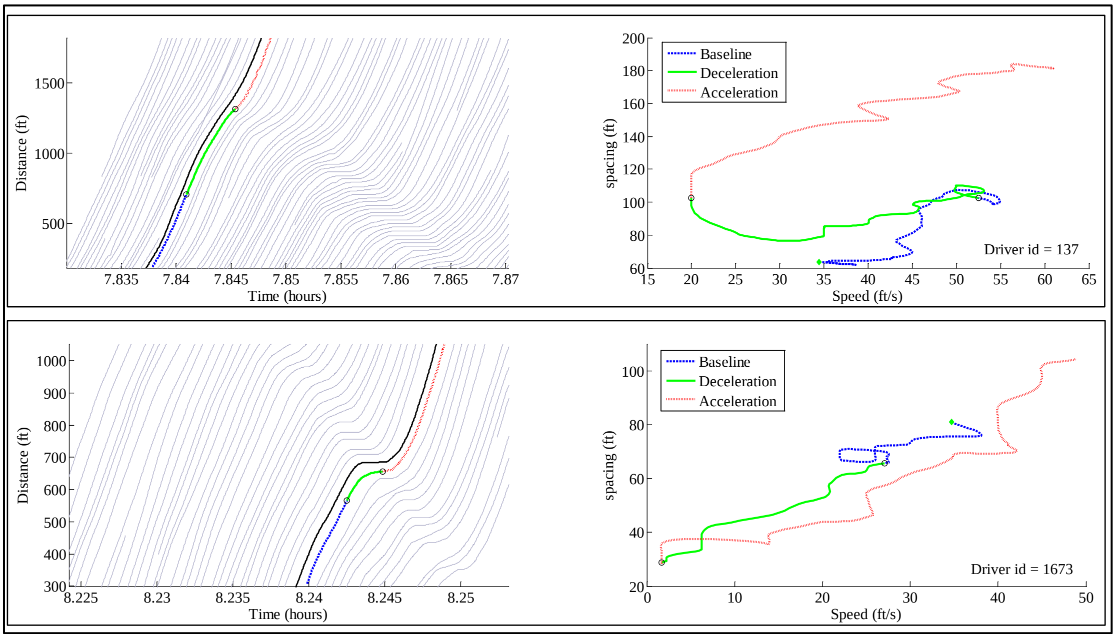


Figure 5.7 Top: Positive hysteresis; Bottom: Negative hysteresis

Table 5.6 presents some important properties of both positive and negative hysteresis. For positive (negative) hysteresis the acceleration phase comes above (under) the deceleration phase in a speed-spacing diagram, indicating that the driver at the acceleration phase keeps higher (lower) spacing than at the deceleration phase. Therefore, the hysteresis magnitude which is the average difference in spacing between the acceleration and deceleration phases becomes positive (negative) for a positive (negative) hysteresis. This behavior is consistently reflected through the change in average TD level. A positive hysteresis is associated with a substantial decrease in average TD level from deceleration to acceleration phase, and the opposite is observed for negative hysteresis. No such behavioral change is observed for average speed or spacing. This further demonstrates the advantage of using TD to explain hysteresis behavior.

Table 5.6 Descriptive analysis of positive and negative hysteresis

Variable	Positive hysteresis (count = 213)				Negative hysteresis (count = 12)			
	Mean	SD	Min	Max	Mean	SD	Min	Max
Hysteresis magnitude	28.66	20.92	0.33	111.97	-5.27	4.60	-18.03	-1.32
Oscillation amplitude	27.65	9.39	4.95	51.17	25.07	8.02	9.47	33.22
Oscillation duration	13.30	4.10	6.40	25.60	12.40	2.77	8.50	18.10
Oscillation intensity	2.19	0.86	0.39	5.81	2.07	0.68	0.70	2.98
Baseline TD	0.52	0.17	0.22	1.05	0.42	0.08	0.31	0.58
Deceleration TD	0.57	0.19	0.19	1.13	0.40	0.10	0.23	0.57
Acceleration TD	0.41	0.15	0.13	0.90	0.51	0.14	0.32	0.76
Baseline speed	37.48	6.51	20.82	53.24	35.28	7.91	22.58	48.38
Deceleration speed	26.57	10.20	7.09	47.99	22.53	11.33	11.02	41.27
Acceleration speed	32.62	10.07	10.23	55.08	31.13	11.09	18.51	50.27
Baseline spacing	72.81	25.37	28.52	174.00	80.87	24.47	47.71	116.20
Deceleration spacing	55.13	20.21	23.56	152.15	59.93	19.00	38.12	96.22
Acceleration spacing	90.45	37.13	27.21	209.97	62.89	17.47	42.16	96.39

5.4.2. Hysteresis types

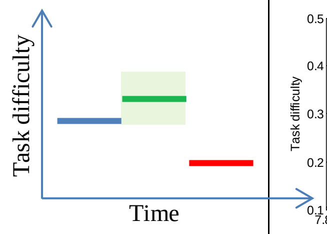
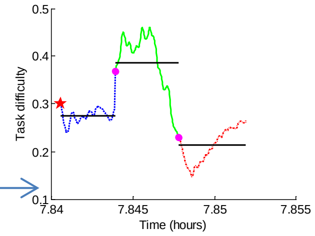
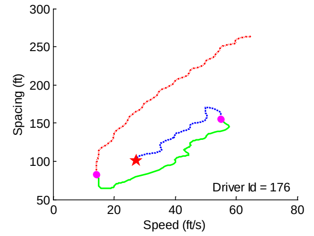
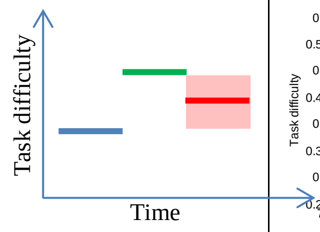
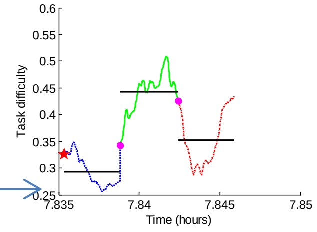
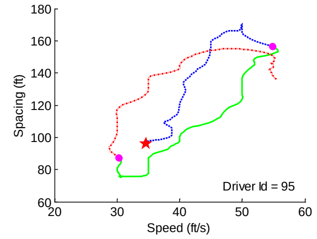
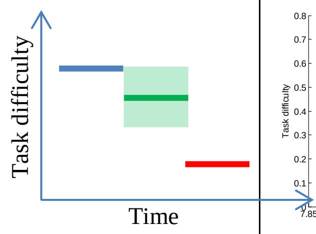
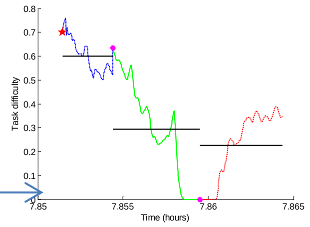
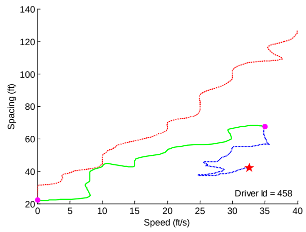
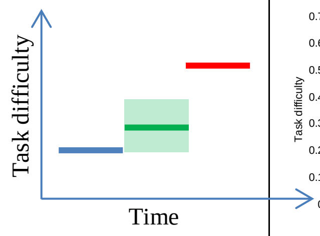
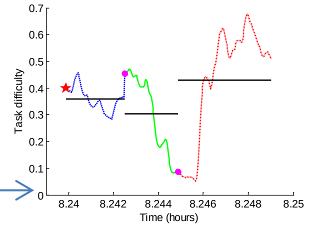
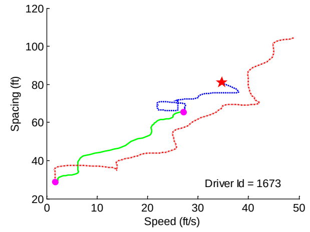
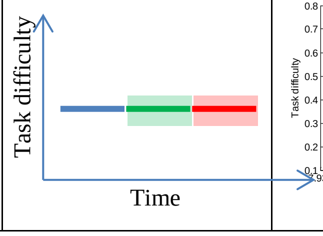
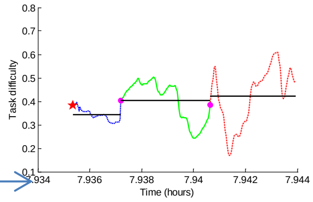
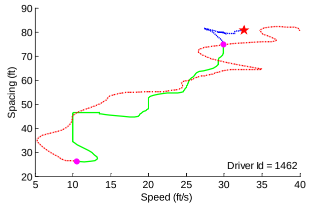
Every driver's driving behavior is different, and no two speed-spacing diagrams are the same. Hence, a categorization is necessary to simplify the analysis and to find some common trends. Hysteresis is mostly categorized as positive and negative hysteresis loops. Apart from this traditional classification, Laval (2011) characterized hysteresis into four types based on the magnitude of hysteresis measured as the flow at any given density: Strong (flow > 300veh/hr), weak (300 > flow > 50veh/hr), negligible (flow < 50veh/hr) and negative (reverse hysteresis loop). The thresholds for this categorization were selected without strong justification. Neither the driver behavior under each category nor their impact on oscillation was analyzed.

Both of these categorizations are based on hysteresis magnitude. We have categorized the hysteresis behavior from the task difficulty perspective. We have observed the task difficulty profile for each vehicle trajectory and noticed five consistent patterns of change in the average TD level across baseline, deceleration and acceleration phases. Thus, the trajectories are divided into five broad groups by keeping trajectories with similar behavior in the task difficulty in the same group, and their relation with hysteresis behavior is analyzed in detail. The categories are described in Table 5.7 with representative TD profiles and one selected example of real TD profile for each category. The pattern of change in the average TD values across the three phases remains consistent for a particular group. However, some variations are observed in the baseline part of the spacing vs. speed diagram where apart from maintaining a consistent time headway a few drivers are also found in either acceleration or deceleration state. Table 5.8 and Table 5.9 summarize descriptive properties of these hysteresis types and their frequency at each stage of the oscillations, respectively.

Detailed discussion on each hysteresis type is below. Note that to check whether the average TD values are significantly different between the three phases for all the observed trajectories in a specific hysteresis group, we performed one-way repeated measures ANOVA test, and the test statistics are presented in the discussion of each category.

Type 1: In this type, the average TD increases at the deceleration phase but drops at the acceleration phase. The relation of the average task difficulty (ATD) across the three phases satisfies $ATD_{deceleration} > ATD_{baseline} > ATD_{acceleration}$. This type is most frequently observed (39%), and it generates positive hysteresis. When a driver in this type faces disturbance (at the deceleration phase) s/he fails to react properly and becomes too close to the preceding vehicle, which leads to an increase of the TD level. To avoid collision the driver overreacts (i.e., risk compensation), which results in a significant drop of the TD level. The decrease in TD from deceleration to acceleration phase creates positive hysteresis. Among the five types, this behavior in Type 1 creates the largest TD difference between the deceleration and acceleration phases. Consequently, the hysteresis magnitudes in Type 1 are also the largest.

Table 5.7 Categorization of the observed hysteresis

Hysteresis type	Typical profile of average task difficulty (ATD)	Task difficulty profile	Spacing Vs speed
Type 1			
Tape 2			
Type 3			
Type 4			
Type 5			

Baseline

Deceleration

Acceleration

Transition points

Start point

Table 5.8 Descriptive statistics of hysteresis types

	Type 1 (Count = 87)				Type 2 (Count = 38)			
	Mean	SD	Min	Max	Mean	SD	Min	Max
Hysteresis magnitude	39.39	23.01	9.93	111.97	21.72	14.28	5.52	73.79
Baseline TD	0.52	0.15	0.24	0.87	0.41	0.13	0.22	0.79
Deceleration TD	0.63	0.19	0.29	1.09	0.61	0.20	0.34	1.13
Acceleration TD	0.39	0.13	0.17	0.73	0.51	0.18	0.25	0.90
Baseline speed	40.22	5.87	26.92	53.24	38.21	6.27	25.14	46.24
Deceleration speed	31.00	8.46	13.51	47.99	34.16	7.68	12.54	45.34
Acceleration speed	35.79	9.11	10.23	55.08	40.75	7.03	25.88	52.61
Baseline spacing	75.58	21.97	37.55	148.64	90.93	31.97	50.44	174.00
Deceleration spacing	59.63	20.00	31.33	152.15	67.74	21.71	38.77	116.36
Acceleration spacing	106.20	39.90	43.05	209.97	95.67	33.32	51.84	170.71
	Type 3 (Count = 71)				Type 4 (Count = 4)			
	Mean	SD	Min	Max	Mean	SD	Min	Max
Hysteresis magnitude	25.32	15.10	5.30	79.75	-9.99	5.37	-18.03	-6.92
Baseline TD	0.55	0.16	0.26	0.94	0.40	0.05	0.36	0.47
Deceleration TD	0.48	0.15	0.19	0.84	0.39	0.08	0.30	0.46
Acceleration TD	0.34	0.11	0.13	0.65	0.51	0.08	0.43	0.63
Baseline speed	34.50	5.93	20.82	47.63	35.55	12.29	22.58	48.38
Deceleration speed	18.40	7.07	7.09	38.60	20.86	9.79	11.68	30.74
Acceleration speed	25.43	7.36	11.87	42.76	31.23	6.15	25.43	37.34
Baseline spacing	62.73	18.64	34.90	122.02	84.98	31.51	47.71	116.20
Deceleration spacing	45.04	14.20	23.56	91.50	58.96	16.09	44.09	76.63
Acceleration spacing	76.94	27.18	32.02	167.45	63.21	13.00	50.57	81.34
	Type 5 (Count = 25)							
	Mean	SD	Min	Max				
Hysteresis magnitude	1.24	3.12	-4.85	4.78				
Baseline TD	0.56	0.21	0.30	1.05				
Deceleration TD	0.49	0.15	0.23	0.82				
Acceleration TD	0.53	0.15	0.24	0.81				
Baseline speed	34.58	6.05	23.47	45.18				
Deceleration speed	21.82	9.60	11.02	41.27				
Acceleration speed	29.18	10.46	15.56	50.27				
Baseline spacing	66.18	25.14	28.52	114.72				
Deceleration spacing	50.61	18.80	28.94	96.22				
Acceleration spacing	57.23	18.68	27.21	96.39				

Furthermore, the one-way repeated measure ANOVA test shows a significant difference in the average TD level between the three phases ($F_{2,172} = 258.6$, *p*-value

<0.001). Pairwise *t*-tests with adjusted *p*-value further suggest that the difference is also significant between each pairs (baseline vs. deceleration: *p*-value <0.001; baseline vs. acceleration: *p*-value <0.001; deceleration vs. acceleration: *p*-value <0.001).

Type 2: Driver behavior in Type 2 is similar to that in Type 1except that the average TD at the acceleration phase in Type 2 stays between the average TD at the baseline and at the deceleration. The relation of the average TDs in the three phases is $ATD_{deceleration} > ATD_{acceleration} \geq ATD_{baseline}$. Similar to Type 1, a driver in this category fails to react properly to the sudden deceleration of the preceding vehicle which results in an increase of the TD level at the deceleration phase. However, unlike in Type 1, the driver in Type 2 acts more sensibly to bring the TD level close to that in the baseline that represents normal driving. As a result, the difference in TD level between the deceleration and acceleration phases becomes much lower than Type 1. This also reduces the hysteresis magnitude. In fact, the average hysteresis magnitude in Type 2 is about half of that in Type 1. Type 2 is mostly observed in the precursor stage of oscillation.

The one way repeated measures ANOVA test shows a significant difference in the average TD level between the three phases ($F_{2,74} = 68.42$, *p*-value <0.001). Pairwise *t*-tests suggest that the difference is also significant between each pairs (baseline vs. deceleration: *p*-value <0.001; baseline vs. acceleration: *p*-value <0.001; deceleration vs. acceleration: *p*-value <0.001).

Type 3: Driver behavior in Type 3 shows a decreasing trend on the TD profile. The relation of average TDs across the three phases can be described as $ATD_{baseline} \geq ATD_{deceleration} > ATD_{acceleration}$. Type 3 is the second most frequently observed and mostly found in the developed stage of oscillation. The decrease in TD from the baseline to the deceleration phase indicates a milder response to the preceding vehicle's deceleration compared to Type 1. The hysteresis magnitude is lower than Type 1 but similar to Type 2.

The one way repeated measures ANOVA test shows significant difference in the average TD level across the three phases ($F_{2,140} = 164.3$, *p*-value <0.001). Pairwise *t*-tests further suggest that the difference is equally significant between each pairs (baseline vs. deceleration: p-value <0.001; baseline vs. acceleration: p-value <0.001; deceleration vs. acceleration: p-value <0.001).

Type 4: This type is characterized by the increase in TD from deceleration to acceleration phase (i.e. $ATD_{acceleration} > ATD_{deceleration}$). Driver behavior in Type 4 is completely opposite of the previous three types, and so as the hysteresis magnitude which is negative. This type is rarely observed (2%).

Type 5: Driver behavior in Type 5 does not show any significant change in TD between the three phases. No profound pattern is observed in either spacing vs. speed or Task difficulty vs. time plot. The hysteresis magnitude is very small (average hysteresis magnitude is 1.24 ft).

The one way repeated measures ANOVA test shows that no significant difference exists (at 95% confidence level) in the average TD level across the three phases ($F_{2,48} = 2.56$, p-value = 0.088). Pairwise t-tests also suggest that none of the differences between the pairs of observations are significant at 95% confidence level (baseline vs. deceleration: p-value = 0.108; baseline vs. acceleration: p-value = 0.443; deceleration vs. acceleration: p-value = 0.077).

As shown in Table 5.9, five out of the seven oscillations are originated from Type 1, and the rest are from Type 2. Both the types have the common feature of the increase of the TD level at the deceleration phase caused by inadequate car following behavior due to various reasons. For example, Chen et al. (2014) have attributed the aggressiveness of drivers to the formation of oscillations. This is only partially supported by our study because 3 out of 7 drivers who originated these oscillations in this study are found not aggressive as their average baseline speed is less than 35 ft/s and baseline average time headways are within the range of 1.73 to 2.14 seconds. Another issue could be presence of some external distraction on the road because all the seven oscillations started approximately at the same location. The study site includes an uphill segment and video footage of the study site shows some maintenance activity in the median during the data collection period. Hence, Zheng et al. (2011b) stated that the distraction along with the road gradient likely instigated the oscillations spontaneously. In either case the inappropriate car-following behavior brings the driver too close to the preceding vehicle and caused a big increase of the TD level. As a consequence, a notable risk compensatory behavior is observed at the acceleration phase to reduce the TD level.

Table 5.9 Hysteresis types at the two stages of oscillation

		Osc.1	Osc.2	Osc.3	Osc.4	Osc.5	Osc.6	Osc.7	Total
Originated by		Type 1	Type 1	Type 2	Type 2	Type 1	Type 1	Type 1	
Precursor stage	Type 1	6	12	8	4	5	8	6	49
	Type 2	4	4	15	1	2	2	1	29
	Type 3	2	1	0	2	1	0	0	6
	Type 4	0	0	0	0	0	0	0	0
	Type 5	0	1	5	0	1	0	0	7
	Total	12	18	28	7	9	10	7	91
Developed stage	Type 1	5	5	6	6	4	2	10	38
	Type 2	0	1	4	0	0	0	4	9
	Type 3	19	6	6	14	5	2	13	65
	Type 4	1	0	1	0	0	0	2	4
	Type 5	6	2	2	5	1	1	1	18
	Total	31	14	19	25	10	5	30	134
Total count		43	32	47	33	19	15	37	225

In the NGSIM US101 dataset, no oscillation is found to have experienced the complete cycle of a precursor, developed and decay stages. The precursor and part of the developed stage are observed for all the oscillations. In general, we can conclude here that Type 1 and Type 2 behavior are predominant at the precursor stage, and Type 3 is mostly observed at the developed stage. Furthermore, the negative hysteresis (Type 4) is found to occur only at the developed stage.

It is unlikely that all the five types will be present in every oscillation. Especially the negative hysteresis (Type 4) is rare. In our data only 12 (5.3%) trajectories exhibits negative hysteresis, and only 4 of them have a notable magnitude (reported in Type 4). In addition, we have also observed 11% trajectories (Type 5) that did not show any distinct hysteresis loops. These findings are consistent with the literature. For example, Ahn et al. (2013) also reported approximately 5% negative hysteresis loops and 10-13% trajectories that exhibit indistinct hysteresis loops in their analysis.

The magnitude of the positive hysteresis shows approximately a logarithmic distribution as illustrated in Figure 5.8, which indicates that majority of the hysteresis magnitudes are moderate. More specifically, this figure shows that only 25% have a magnitude higher than 36.9ft.

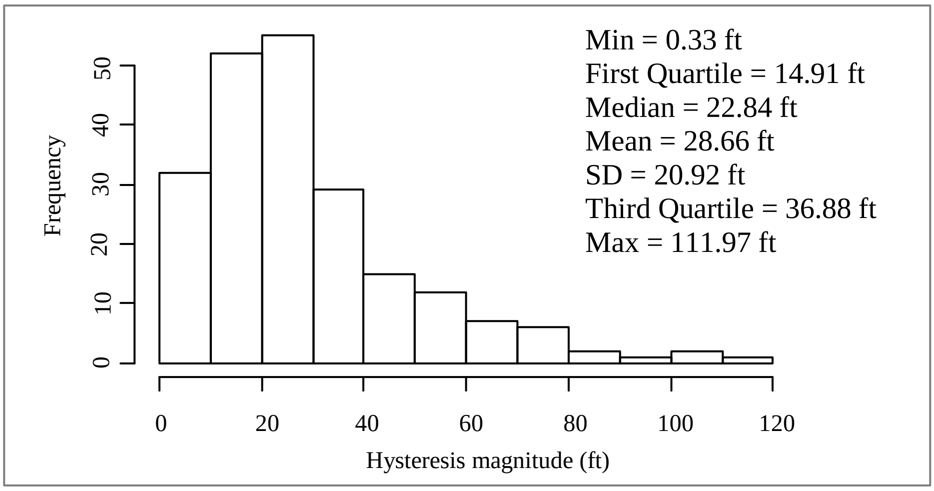


Figure 5.8 Distribution of the hysteresis magnitude

5.4.3. Statistical modeling of the hysteresis magnitude

A regression model has been developed to understand the effect of different driver and traffic characteristics on the magnitude of hysteresis. Only the positive hysteresis is considered in the regression analysis mainly for two reasons: i) the earlier analysis has revealed that the properties of the positive hysteresis are almost the opposite of the negative hysteresis, which indicates two distinctively different mechanisms; and ii) the number (i.e., the sample size) of negative hysteresis is too small to build a separate statistical model.

As discussed above, the distribution of hysteresis magnitude is logarithmic (see Figure 6). Thus, the Generalized Linear Model (GLM, McCullagh and Nelder, 1989) is adopted, assuming that the error component of the model is normally distributed (belongs to the Gaussian family) and the link function is “log”. Descriptive statistics of the variables considered in the model are presented in Table 5.10. The final model with six independent variables has succeeded to decrease the deviance by about 87% from the null deviance, and the model output is summarized in Table 5.11.

Table 5.10 Summary statistics of prospective variables for the model

Variable name	Description of the variable	Mean	SD	Min	Max	Count
Hysteresis magnitude	Continuous variable	28.66	20.92	0.33	111.97	213
Oscillation amplitude	Continuous variable	27.65	9.39	4.95	51.17	213
Oscillation duration	Continuous variable	13.30	4.10	6.40	25.60	213
Oscillation intensity	Continuous variable	2.19	0.86	0.39	5.81	213
Oscillation stage						
Precursor	If trajectory is in precursor stage = 1, else = 0	-		0	1	91
Developed	If trajectory is in developed stage = 1, else = 0	-	-	0	1	134
Baseline TD	Continuous variable	0.52	0.17	0.22	1.05	213
Deceleration TD	Continuous variable	0.57	0.19	0.19	1.13	213
Acceleration TD	Continuous variable	0.41	0.15	0.13	0.90	213
Average speed[1]	Continuous variable	31.96	8.31	15.94	52.64	213
Fluctuation in speed[2]	Continuous variable	11.72	2.70	4.32	20.64	213
Average spacing[1]	Continuous variable	74.14	25.64	28.07	152.16	213
Fluctuation in spacing[2]	Continuous variable	26.23	14.53	4.10	79.63	213
Hysteresis type						
Type 1	If hysteresis belongs to Type 1 = 1, else = 0	-	-	0	1	87
Type 2	If hysteresis belongs to Type 2 = 1, else = 0	-	-	0	1	38
Type 3	If hysteresis belongs to Type 3 = 1, else = 0	-	-	0	1	71
Type 5	If hysteresis belongs to Type 5 = 1, else = 0	-	-	0	1	25

[1] Average speed or spacing is measured for the whole trajectory that includes baseline, deceleration and acceleration phases.

[2] Fluctuation in speed (spacing) is measured as the standard deviation of speed (spacing) for the trajectory.

Table 5.11 Generalized Linear Model (GLM) of hysteresis magnitude

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	2.966	0.108	27.556	<0.001
Oscillation stage = “precursor’	0.140	0.042	3.316	0.001
Average speed	0.023	0.004	6.344	<0.001
Fluctuation in spacing	0.012	0.001	9.095	<0.001
Type 5 hysteresis	-1.567	0.651	-2.407	0.017
Deceleration TD	1.538	0.115	13.342	<0.001
Acceleration TD	-4.271	0.311	-13.717	<0.001

Dispersion parameter for gaussian family is taken to be 59.41

Null deviance: 92772 on 212 degrees of freedom

Residual deviance: 12241 on 206 degrees of freedom

AIC: 1483.3

All the variables of this model are significant. The model shows that hysteresis magnitude would be larger for a trajectory that belongs to the precursor stage than that to the developed stage of oscillation. If all the other parameters remain constant, the hysteresis magnitude of a trajectory that belongs to the precursor stage would be 15.0% $[(e^{0.14} - 1) * 100]$ higher than that of a trajectory that belongs to the developed stage. Both the average speed and fluctuation in spacing have positive impact on hysteresis magnitude. More specifically, one foot increase of the fluctuation in spacing would lead to 1.2% increase of hysteresis magnitude. This is reasonable because fluctuation in spacing is highly correlated with the hysteresis magnitude due to the fact that hysteresis magnitude is calculated as the difference in spacing between deceleration and acceleration phase. Meanwhile, one ft/sec increase of the average speed would lead to 2.3% increase of the hysteresis magnitude. The reason behind this positive relation is that compared to drivers with a lower speed, drivers with a higher speed are more likely to over-react (e.g., less time to perceive and react to the situation) to a disturbance, which would cause a larger hysteresis magnitude.

Trajectories that belong to Type 5 do not exhibit a distinctive hysteresis loop with a small magnitude. This phenomenon is captured by the model. According to the model, the hysteresis magnitude for a trajectory that belongs to Type 5 will be 79.1% lower than that for a trajectory from other types, provided that all other variables remain constant. The average TD at the deceleration phase has a positive impact on the hysteresis magnitude. A 0.1 unit increase of the TD level at the deceleration phase is likely to increase the hysteresis magnitude by 36.5%. In contrast, a 0.1 unit increase of the TD level at the acceleration phase is likely to decrease the hysteresis magnitude by 9.9%.

According to the estimated model, the hysteresis magnitude is mostly influenced by the TD level, particularly by the TD level at the deceleration phase. A possible explanation is that the increase of the TD level at the deceleration phase indicates an underestimation of the risk in the current driving situation, and consequently the subject vehicle comes too close to the preceding vehicle. To avoid collision, the driver reduces the TD level at the acceleration phase. The bigger the difference between the TD levels at these two phases, the larger the hysteresis magnitude becomes.

5.5. Discussion and conclusion

This paper attempts to provide a deeper understanding of the mechanism of traffic hysteresis and traffic oscillations from the change in driver behavior which is captured through the change in driver's TD level over the driving period. A close connection with the change in average TD level between the deceleration and acceleration phase and hysteresis magnitude is observed. A positive (negative) hysteresis is associated with a decrease (increase) in average TD level from deceleration to acceleration phase. No such behavioral change is observed for average driving speed or vehicle spacing to identify positive or negative hysteresis which confirms the appropriateness of using the TD as a representative of driver behavior in understanding hysteresis and oscillation.

The relation between the TD and hysteresis magnitude is also evident from the statistical model which shows that the two most influential variables on hysteresis magnitude are the TD at the deceleration and acceleration phases respectively. The bigger the difference between the TD levels at these two phases, the larger the hysteresis magnitude becomes.

Driver behaviors inside an oscillation are broadly categorized in five groups based on the TD profile. The first three types (Type 1,2 and 3) creates positive hysteresis as the TD at the acceleration phase decreases from the TD at the deceleration phase; Type 4 shows the opposite behavior which results negative hysteresis; and Type 5 does not show any profound hysteresis loops. All these five types of driver behavior may not be available in all oscillations. Especially, the negative hysteresis is rare.

The introduction of the baseline phase has helped us to observe the change in driver behavior due to oscillation. Driver behavior inside the oscillation (i.e., at the deceleration and acceleration phases) significantly differs from outside the oscillatory region (i.e., at baseline phase). Driver behavior also differs between the precursor and the developed stages of oscillation. Based on the estimation from the GLM, the hysteresis magnitude would be 15% higher in the precursor stage than the developed stage of oscillation. Furthermore, among the five Types of driver behavior, Type 2 is mostly occurred at the precursor stage and Type 4 is only found at the developed stage of oscillation.

In most cases, the behavior in the acceleration phase deviates from the baseline phase explaining that the drivers have not yet returned to their regular behavior after the disturbance. Zheng et al. (2011b) also reported a deviation from regular behavior after experiencing a disturbance. Including another traffic phase after the acceleration could explain how long it takes to return to the normal situation. However, the spatial extent of the trajectory was not big enough to allow us having another traffic phase after the acceleration.

Due to data limitation, this study has analyzed a part of the oscillations including the precursor and the developed stage. Understanding driver behavior in the decay stage of oscillation could provide valuable insight about how an oscillation comes to an end. It would also be helpful in developing countermeasures to stop the oscillation within short distance in order to reduce its impact on traffic flow. Future data collection attempts should increase the spatial extent of the study area so that complete oscillations can be observed. Furthermore, the short-lived oscillations should also be analyzed for a complete understanding about the different oscillation types.

References

Ahn, S., Vadlamani, S., Laval, J., 2013. A method to account for non-steady state conditions in measuring traffic hysteresis. Transportation Research Part C: Emerging Technologies 34, 138-147.

Bilbao-Ubillos, J., 2008. The costs of urban congestion: estimation of welfare losses arising from congestion on cross-town link roads. Transportation Research Part A: Policy and Practice 42 (8), 1098–1108.

Chen, D., 2012. Studies of traffic oscillations: a behavioral perspective. Georgia Institute of Technology, USA.

Chen, D., Laval, J.A., Zheng, Z., Ahn, S., 2012. Traffic oscillations: a behavioral car-following model. Transportation Research Part B: Methodological 46 (6), 744–761.

Chen, D., Ahn, S., Laval, J., Zheng, Z., 2014. On the periodicity of traffic oscillations and capacity drop: the role of driver characteristics. Transportation research part B: methodological 59, 117-136.

Deffenbacher, J. L., Lynch, R. S., Deffenbacher, D. M., & Oetting, E. R., 2001. Further evidence of reliability and validity for the Driving Anger Expression Inventory. Psychological Reports 89, 535-540.

Deffenbacher, J. L., Lynch, R. S., Oetting, E. R., & Swaim, R. C., 2002. The Driving Anger Expression Inventory: A measure of how people express their anger on the road. Behaviour Research and Therapy 40, 717-737.

Deffenbacher, J.L., Deffenbacher, D.M., Lynch, R.S., Richards, T.L., 2003. Anger, aggression, and risky behavior: a comparison of high and low anger drivers. Behaviour Research and Therapy 41, 701-718.

FHWA, 2008. The Next Generation Simulation (NGSIM). http://ops.fhwa.dot.gov/trafficanalysistools/ngsim.htm.

Fuller, R., 2002. Psychology and the highway engineer. In: Fuller, R., Sanots, J.A. (Eds.), Human factors for highway engineers. Elsevier Science Ltd., Oxford, UK, pp. 1-10.

Fuller, R., 2005. Towards a general theory of driver behaviour. Accident Analysis & Prevention 37, 461-472.

Fuller, R., 2011. Driver control theory. In: Porter, B.E. (Ed.), Handbook of traffic psychology. Academic Press, USA, pp. 13-26.

Gayah, V.V., Daganzo, C.F., 2011. Clockwise hysteresis loops in the Macroscopic Fundamental Diagram: An effect of network instability. Transportation Research Part B: Methodological 45, 643-655.

Haque, M.M., Washington, S., 2014. A parametric duration model of the reaction times of drivers distracted by mobile phone conversations. Accident Analysis & Prevention 62, 42-53.

Herrero-Fernandez, D., 2011. Psychometric adaptation of the Driving Anger Expression Inventory in a Spanish sample: Differences by age and gender. Transportation Research Part F: Traffic Psychology and Behaviour 14, 324 – 329.

Laval, J.A., 2011. Hysteresis in traffic flow revisited: An improved measurement method. Transportation Research Part B: Methodological 45, 385-391.

Laval, J.A., Leclercq, L., 2010. A mechanism to describe the formation and propagation of stop-and-go waves in congested freeway traffic. Phil. Trans. R. Soc. A 368, 4519-4541.

McCullagh, P., Nelder, J.A., 1989. Generalized linear models. CRC press.

Newell, G.F., 1965. Instability in dense highway traffic, a review. In: Almond, J. (Ed.), The 2nd International Symposium on Transportation and Traffic flow Theory, pp. 73-83.

Newell, G.F., 1962. Theories of instability in dense highway traffic. Journal of the Operations Research Society of Japan 1, 9-54.

Rhodes, N., Pivik, K., 2011. Age and gender differences in risky driving: The roles of positive affect and risk perception. Accident Analysis & Prevention 43, 923-931.

Saifuzzaman, M., Zheng, Z., 2014. Incorporating human-factors in car-following models: A review of recent developments and research needs. Transportation Research Part C: Emerging Technologies 48, 379-403.

Saifuzzaman, M., Haque, M.M., Zheng, Z., Washington, S., 2015a. Impact of mobile phone use on car-following behaviour of young drivers. Accident Analysis & Prevention 82, 10-19.

Saifuzzaman, M., Zheng, Z., Mazharul Haque, M., Washington, S., 2015b. Revisiting the Task–Capability Interface model for incorporating human factors into car-following models. Transportation Research Part B: Methodological 82, 1-19.

Sarbescu, P., 2012. Aggressive driving in Romania: Psychometric properties of the Driving Anger Expression Inventory. Transportation Research Part F: Traffic Psychology and Behaviour 15, 556 - 564.

Yeo, H., Skabardonis, A., 2009. Understanding stop-and-go traffic in view of asymmetric traffic theory, Transportation and Traffic Theory 2009: Golden Jubilee. Springer, pp. 99-115.

Zhang, H.M., 1999. A mathematical theory of traffic hysteresis. Transportation Research Part B: Methodological 33, 1-23.

Zhang, H.M., Kim, T., 2005. A car-following theory for multiphase vehicular traffic flow. Transportation Research Part B: Methodological 39, 385-399.

Zheng, Z., Ahn, S., Monsere, C.M., 2010. Impact of traffic oscillations on freeway crash occurrences. Accident Analysis and Prevention 42 (2), 626–636.

Zheng, Z., Ahn, S., Chen, D., Laval, J., 2011a. Applications of wavelet transform for analysis of freeway traffic: Bottlenecks, transient traffic, and traffic oscillations. Transportation Research Part B: Methodological 45, 372-384.

Zheng, Z., Ahn, S., Chen, D., Laval, J., 2011b. Freeway traffic oscillations: Microscopic analysis of formations and propagations using Wavelet Transform. Transportation Research Part B: Methodological 45, 1378-1388.

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Chapter 6

Conclusion

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6.1 Conclusion

This thesis has investigated the effect of human factors on car-following (CF) behavior. Inspired by the Task-Capability Interface (TCI) model and experienced from a carefully designed driving simulator experiment, a novel CF modeling framework is introduced. Two regular CF models have been updated with the proposed framework and their superiority to the original models in explaining both normal and human factor induced driving have been confirmed. Finally, this research has shed light on the understanding of traffic hysteresis and traffic oscillations.

6.1.1 Synthesis of research findings

This research is performed chronologically, following the specific objectives stated in Section 1.2. This section provides a synthesis of the research findings, structured according to each of the research objectives.

Objective 1: understanding the need to integrate human factors in CF modelling

To accomplish the first objective, a detailed literature review on the state-of-art on CF modelling was performed, focusing on the need to integrate human factors in CF models. The literature review has revealed the lack of human factors (such as risk-taking behavior, error, and distraction) interaction in most of the available CF models. As a result, the CF behavior in these models is unrealistically oversimplified and free from driver errors. For example, they do not capture the effect of the surrounding environment (such as visibility), driver capability to manage complex situations, inattentions and distractions. The review has emphasized the need to have an improved and comprehensive representation of human factors in CF models. It also provides some guidelines in data collection, model development, and model calibration and validation in modeling car-following behavior.

Objective 2: identifying the impact of distraction on car-following behavior

The driving simulator study has revealed some important characteristics of CF behavior in both normal and distracted situations. Most importantly, it shows how drivers adapt their behavior in demanding situations, for example, when controlling the vehicle with one hand and concurrently talking over a handheld phone. The time headway from the preceding vehicle is found to be the most crucial variable that reflects a driver's action in both normal and demanding situations. For example, an increase in time headway is observed with the increase in distraction level. Moreover, driver's gender and license type is found to play an important role in the selection of time headway. The increase in time headway could reflect drivers' attempts to compensate for the increased risk associated with mobile phone conversations, or could be an artefact of the distraction itself. On the other hand, increases in fluctuation in speed and spacing and acceleration noise suggest that distracted driving results in less consistent control in maintaining speed and vehicle spacing in car-following situations. Therefore, even if the increase in time headway reflects risk compensation, there could be circumstances when it may not be sufficient enough to offset the increased crash risk arising from distraction.

Objective 3: developing a novel methodology to incorporate human factors into conventional car-following models

The observed driver behavior in the simulator driving experiment follows the established TCI model, which simply states that a driver should slow down whenever the task difficulty exceeds their acceptable limit. However, the TCI model was lacking any established mathematical formulation. In this regard, a major contribution of this research is the formulation of task difficulty (TD) by incorporating human factors. The TD variable expresses the perceived task difficulty level of a driver through the interaction of task demand, driver capability and human factors. This formulation not only helps us to improve the CF models but also explains the underlying reason behind driver's action in different circumstances. Two human factor parameters are introduced to capture driver's risk perception (risk parameters) and reaction time increment. If a specific human factor has some positive influence on the driver, for example, the driver perceives the risk of being distracted, the risk parameter would be positive and consequently the perceived task difficulty increases. On the other hand, if the human factor has some negative influence on the driver, for example, intoxication motivates risk taking, the risk parameter would be negative, resulting a decrease in the perceived task difficulty level.

Another contribution of this thesis is the Task Difficulty Car-following (TDCF) framework, which describes a set of guidelines that should be followed in order to incorporate human factors in an existing Engineering CF model. The soundness of the TDCF framework has been demonstrated by extending two well-known CF models (Gipps and IDM) following those guidelines. The extended models (named TDGipps and TDIDM) were stable, and better explained both normal and distracted CF behavior than their predecessors. The validation result suggests that combining both normal and distracted situations in 91% of cases, the TDGipps model outperformed the Gipps model and in 82% of cases, the TDIDM model outperformed the IDM model. Moreover, the TDGipps model is free from the instability issue for which the Gipps model is criticized (i.e. when a driver underestimates the leader's deceleration capability). Another interesting feature of these extended models is that they are not accident free like their parent models. To demonstrate this feature, a hypothetical example of how a collision can occur in a distracted situation is presented. It shows that an increase in reaction time can cause a collision when the risk compensatory action is not sufficient enough i.e. when the driver has failed to perceive the appropriate risk.

The presence of driver heterogeneity is clearly observed through the estimated model parameters for different drivers. More importantly, the estimation result suggests that not all drivers perceive the extra risk of collision when distracted by a handheld phone conversation. It implies that the human factor influence on CF behavior varies, depending on driver confidence, and familiarity with the situation. For example, research showed that due to overuse of mobile phones, the majority of the surveyed respondents reported that talking on the phone makes no difference to their driving performance (Nurullah et al., 2013; Hallet et al., 2011; Tison et al., 2011).

Objective 4: understanding traffic oscillations and traffic hysteresis

This objective is about the application of the task difficulty (TD) formula developed in Chapter 4 to provide a better understanding of the two most widely reported puzzling traffic flow phenomena: traffic oscillation and traffic hysteresis. A detailed analysis of seven selected oscillations has revealed many important properties of the oscillations. All the trajectories inside the oscillations are analyzed to understand the relation between driver behavior and hysteresis. For ease of understanding, each trajectory has been divided into three distinct phases: baseline (before deceleration starts), deceleration (during deceleration) and acceleration (after deceleration).

This study criticizes the widely used ‘aggressive-timid’ term in explaining hysteresis due to its inappropriateness in describing the change in driver behavior when experiencing a disturbance. The sudden behavior shift from aggressive to timid or vice-versa is inconsistent with the literature from the behavioral research, where aggressive/timid driving is found to be closely related to a driver’s personal traits, which are relatively stable. Evidence from the driving simulator experiment data used in this thesis also supports this stable behavior. The experimental findings suggest that the behavior of aggressive and timid driver groups is entirely different from each other. The aggressive drivers have completely ignored the risk of being distracted, which has made them more risk-prone than the timid drivers. Therefore, a different approach has been used in this study, where driver behavior in CF is captured through their TD profile.

A total of five types of driver behavior have been identified inside an oscillation based on drivers’ TD profile. Only Type 1 and 2 are found responsible for the formation of oscillations. Both of these types showed inappropriate CF maneuvers during deceleration that brought them too close to the preceding vehicle and caused a big increase of the TD level during the deceleration. To avoid collision, the driver reduces the TD level at the acceleration phase, which creates a big difference between the TD levels of these two consecutive phases. A noteworthy finding is that the bigger the difference between the TD levels at these two phases, the larger the hysteresis magnitude becomes.

All the five driver types may not be available in all oscillations. Especially Type 4, the negative hysteresis, is rarely observed. Furthermore, driver behavior differs between the two stages of oscillations (e.g. precursor and developed). For example, Type 2 behavior is only found in the precursor stage. Also the hysteresis magnitude in the precursor stage is higher than the developed stage.

6.1.2 *Implications of the research findings*

The simulator driving experiment results can foster a better understanding of the consequence of distracted driving on road crashes, and shed light on the complexity involved with modelling driving behavior.

The intended primary usage of a TDCF model (i.e. CF model under the TDCF framework) is two-fold: road safety-oriented applications and traffic operations-oriented applications. To calibrate a TDCF model for these two types of applications, driving experiments should be conducted for a representative sample of the drivers from the target population, either using a driving simulator e.g., the experiment implemented in this study, or using instrumented vehicles. Experimental design should include at least two types of driving conditions for each driver: with and without distraction. Since TDCF is a general framework independent of distraction sources and not oriented to any specific type of human factors, distraction in these experiments can be created by many sources, e.g., talking over a mobile phone, texting, rubbernecking, etc. The collected trajectories can be used to calibrate and validate the model as demonstrated in this study. The calibrated and validated model can be directly used as a simulation tool, just like other CF models, to better reproduce traffic dynamics for the target population, or used as a policy evaluation tool to assess levels of various human factors' implications on road safety and/or operations by changing the two specific human factor parameters inside the model.

The TD formula can be used to understand driver behavior in various driving conditions. It would be useful to explain accident causation. TD can also be applied to identify near-crash events. At present the identification process of near-crash events is vehicle dependent (Klauer et al., 2006), which makes it difficult to generalize, due to large variations in vehicle characteristics. By setting a proper threshold, TD could be an effective alternative for identifying near-crash events.

The oscillation and hysteresis properties discussed in this thesis would be helpful to develop countermeasures to reduce their impact on traffic flow. This would also be beneficial for connected vehicle technologies, to ensure smooth traffic flow.

Simulator driving experiments are often questioned regarding their driving realism. Most studies support the use of simulators, finding that driving behavior in simulators approximates (relative validity), but does not exactly replicate (absolute validity), on-road driving behavior (Mullen et al., 2011). Hence, researchers should remain aware that simulators do not always provide an accurate picture of on-road driving behavior. Mullen et al. (2011) provided a comprehensive overview of driving simulator validation studies and concluded that, there is sufficient evidence to support the validity of driving simulator as a powerful tool for assessing a variety of driving performance measures such as speed, lateral position, and risky traffic behaviors. In particular, driving simulator is a valid tool for assessing the effects of divided attention on driving performance.

Similarly, a recent study by Risto and Martens (2014) also supported the use of driving simulator in studies on headway choice, as they did not find any significant difference between headway choice in the simulator and on real roads. A high quality motion-based driving simulator is used in this thesis, representing realistic driving scenarios. Hence, the findings of this study should be applicable to real road driving, especially in terms of relative differences observed among drivers.

6.2 Future works

The driving simulator experiment was focused on the car-following behavior of young drivers only; further study is required to investigate the effect of mobile phone distraction in a wider range of samples, to compare the CF behavior across different age groups. Future studies are also required to investigate distracted CF behavior in other scenarios, e.g. on longer road sections, with different speed limits, and on curve segments. The influence of other types of human factors (e.g. fatigue, drowsiness, alcohol and drug use, emotion and stress) on CF behavior should also be investigated in the future to obtain a better picture of human car-following behavior in different circumstances.

A traffic simulation model comprises two main components: CF model and Lane Changing (LC) model. TDCF framework has successfully incorporated human factors into the CF models. For a realistic traffic simulation, the LC models should also be improved by incorporating human factors. Hence, a proper simulation with the TDCF model is left for future. The simulation should be able to reproduce crashes or near-crash events. More importantly, when properly calibrated, the simulation model can be able to replicate realistic driving behavior with realistic crash frequency. Such simulation model would be highly beneficial for researchers in all areas of transportation.

The TDCF framework has successfully enhanced the Gipps and IDM models. Future work should focus on improving other well-known CF models by applying the TDCF framework. Even for TDGipps and TDIDM, a different formulation could provide a better result. The behavioral parameters in CF models are expected to be correlated (Kim and Mahmassani, 2011). Therefore, a correlation analysis among the calibrated model parameters should be performed. If any correlation exists, it should be properly accounted for during the simulation. Furthermore, a sensitivity analysis is also needed to be carried out in future to understand the impact of individual model parameters on the dependent variable (i.e. speed or acceleration).

An important issue regarding model development is to maintain the balance between model complexity and over-fitting. Zheng (2014) suggested that the performance gain from adding new variables should outweigh the disadvantage associated with the model's extra complexity. He recommended following a two-step approach where a series of prospective models should be compared statistically followed by empirical evidence (e.g. field observations and surveys) to justify the improvement. Furthermore, any improvement to an existing model should be grounded on valid assumption and/or established theory. The introduction of additional parameters is likely to improve the calibration performance at the cost of increased model complexity. However, it does not ensure better validation outcomes. Hence, any performance improvement should be confirmed through both calibration and validation results. In this thesis the impact of human factors are confirmed over empirical data analysis and the human factor parameters are incorporated in the CF models based on the established driver behavior theory (TCI model). This systematic approach rendered a significant improvement over the original CF models as observed in both the calibration and validation outcomes.

Present study has considered the interaction of only two vehicles in simple car-following scenario. Future works should also consider implementing the developed model in widely used simulation packages such as VISSIM, AIMSUN or other open source programs to see the consequences of the new model in complete driving environment. Effect of mix traffic should also be considered for realistic simulation. Such analyses should provide greater insight for microscopic traffic modelling.

In this thesis, TD profile has been used to understand driver behavior within some selected traffic oscillations. Due to data limitation, only a part of the oscillations were analyzed which consists the precursor and the developed stage. Future data collection attempts should increase the spatial extent of the study area so that complete oscillations can be observed. Some other applications of TD would be investigating driver errors, understanding driver behavior in adverse driving conditions, and real-time detection of erroneous behaviors to improve road safety.

The TD variable explains the motivations behind driving decisions. Hence, it can be applied to better understand driver behavior in various complex driving situations. In future studies, TD variable should be considered as a potential CF variable besides other well-known CF variables, such as speed, spacing and time headway. While the time headway is not convenient for trajectory data analysis due to its discontinuous nature at zero speed, the TD can be a better alternative with more explanatory power and no issue of discontinuity.

Future research should also focus on understanding the TD profile and their possible applications. Considering the potential of the TD profile in explaining driver and/or traffic behaviors (this thesis demonstrated one example of using the TD profile for identifying traffic hysteresis types) it could have various applications, including but not limited to, investigating traffic crash and near-crash events, identifying driving errors and thus training the drivers to maintain a reasonable task demand, and improving connected and autonomous vehicle technologies. When the consequences of certain TD profiles will be known, it would make notable changes in solving traffic problems, improving onboard safety devices, and developing connected and autonomous vehicle technologies. For example, assuming that the vehicle can easily trace the TD profile of the driver, whenever the program identifies a TD pattern in driver’s trajectory that could lead to a known consequence, it could warn the driver and recommend possible actions. In emergency cases it could also take control (partially/completely) of the vehicle to avoid any deadly consequences.

This advance warning system should improve the safety of future vehicles. In the connected and automated environment, it can also be applied to ensure smooth traffic flow without compromising with capacity.

References

Hallett, C., Lambert, A., Regan, M.A., 2011. Cell phone conversing while driving in New Zealand: Prevalence, risk perception and legislation. Accident Analysis & Prevention 43, 862-869.

Kim, J., Mahmassani, H., 2011. Correlated parameters in driving behavior models: car-following example and implications for traffic microsimulation. Transportation Research Record: Journal of the Transportation Research Board, 62-77.

Klauer, S.G., Dingus, T.A., Neale, V.L., Sudweeks, J.D., Ramsey, D.J., 2006. The impact of driver inattention on near-crash/crash risk: An analysis using the 100-car naturalistic driving study data.

Mullen, N., Charlton, J., Devlin, A., Bédard, M., 2011. Simulator Validity, Handbook of Driving Simulation for Engineering, Medicine, and Psychology. CRC Press.

Nurullah, A.S., Thomas, J., Vakilian, F., 2013. The prevalence of cell phone use while driving in a Canadian province. Transportation Research Part F: Traffic Psychology and Behaviour 19, 52-62.

Risto, M., Martens, M.H., 2014. Driver headway choice: A comparison between driving simulator and real-road driving. Transportation Research Part F: Traffic Psychology and Behaviour 25, 1-9.

Tison, J., Chaudhary, N., Cosgrove, L., 2011. National phone survey on distracted driving attitudes and behaviors.

Zheng Z., 2014. Recent developments and research needs in modeling lane changing. Transportation Research Part B 60, 16-32.