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Minimizing Truck-Car Conflicts on Highways

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<p>16. Abstract</p> <p>Trucks represent the predominant form of domestic freight movement. Due to the substantial increase in freight truck traffic on the nation's highways, its influence on traffic flow performance, safety, and quality of travel experience, is garnering increased attention. Several existing studies have addressed the impacts of trucks on highway traffic flow conditions and crashes. This research models the behavior of non-truck drivers vis-à-vis their interactions with trucks by associating a "discomfort level" with every non-truck driver. This discomfort of non-truck drivers in the vicinity of trucks is assumed to be affected by situational factors such as time-of-day, weather, and ambient traffic congestion.</p> <p>Stated preference surveys of non-truck drivers are used to elicit the factors that influence their behavior when interacting with trucks on highways. A fuzzy logic model using if-then rules is developed to characterize non-truck driver behavior near trucks. It is used to determine the non-truck driver discomfort level, and is constructed using survey data and insights from the preliminary analysis performed using a binary discrete choice model.</p> <p>The discomfort level is used in conjunction with a traditional car-following traffic flow model to generate a truck-following model. Similarly, a modified lane-changing model is constructed to account for car-truck interactions. This redresses a key methodological gap in the literature and provides a capability to analyze alternative strategies to reduce car-truck interactions. An agent-based freeway segment microscopic traffic simulator is constructed using the car-following and lane-changing logics embedded in the FRESIM microscopic simulator, and the truck-following and modified lane-changing models developed in this research. Simulation experiments using data from the Borman expressway (I-80/94) in northwest Indiana are used to analyze model sensitivity to the various parameters and evaluate the effectiveness of alternative mitigation strategies.</p>					
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Minimizing Truck-Car Conflicts on Highways

Introduction

Trucks represent the most frequently used transportation mode for domestic freight movement in terms of both shipment values and weight. The increase in the number of trucks and the distance traveled by trucks has been substantial over the past three decades. While the freight truck transportation sector is a key part of the economic lifeline of the nation, trucks also play a disproportionate role in the context of crashes, congestion, and infrastructure deterioration. In Indiana, this has been identified as a key issue in several heavily traveled commercial corridors characterized by a significant percentage of truck traffic. Also, drivers in some rural areas of Indiana have expressed concern about driving discomfort due to the presence of high percentages of truck traffic. While there is a rich body of literature on truck characteristics and crash data, and on models to understand truck safety issues, corresponding progress on the modeling to analyze traffic flow interactions with other vehicles has been rather limited. This highlights methodological gaps in terms of: (i) providing capabilities to analyze the difference in the behaviors of truck and non-truck drivers when they interact in a traffic stream, and how these interactions affect traffic performance, and (ii) analyzing the effectiveness of strategies to mitigate car-truck interactions. The study uses the terms “car” and “non-truck” interchangeably. Car-truck interactions are viewed here as the driving

actions of non-truck drivers in the vicinity of trucks due to psychological discomfort. The methodological limitations manifest as the non-consideration or cursory acknowledgement of truck characteristics and effects in analytical and traffic simulation models used in practice.

In this study, a fuzzy logic based modeling framework is proposed to capture car-truck interactions from a non-truck driver perspective using measurable variables. This is done by introducing the notion of “discomfort” in the vicinity of trucks, and using it to extend existing microscopic traffic flow modeling logic. A new parameter called driver discomfort level is proposed to incorporate the various factors that affect individual driver actions/interactions in this regard. Further, it is important to characterize the effects of these interactions at a system level to address real-world problems. Hence, there is a need to benchmark alternative mitigation strategies from the perspective of driver discomfort in addition to system performance and safety. Alternative supply-side strategies to mitigate car-truck interactions on freeways are identified and evaluated using an agent-based simulation platform. Insights are obtained using a case study involving the Borman Expressway (I-80/94) in northwest Indiana.

Findings

This research proposes models to capture car-truck interactions in a traffic stream to more robustly incorporate the impacts of non-truck driver actions in the vicinity of trucks, and to analyze the effectiveness of strategies to reduce car-truck interactions. It represents a first step in developing traffic flow

modeling components that are sensitive to the differential driver behavior/actions in the vicinity of trucks. Thereby, it bridges a key methodological gap in the traffic flow modeling arena where trucks are not differentiated from other vehicles, especially from a driver behavior perspective. It proposes some

methodological tools and modeling components for the next-generation of traffic simulation models that seek increased realism in modeling traffic flow. In this context, the fuzzy logic based approach can be advantageous as it can be calibrated using measurable data. Further, the explicit incorporation of driver behavior is a robust mechanism to address other modeling limitations in the traffic flow arena. For example, the influence of road geometry on driving actions is fundamentally based on driver behavior.

Non-truck driver behavior and actions in the vicinity of trucks are solicited through a survey. A majority of drivers believe that they would keep a wider gap with a truck ahead. This is a primary premise for the truck-following model developed in this study. Similarly, drivers state that they drive faster to overtake trucks implying that they prefer to avoid being in the vicinity of trucks, and hence move away from them as soon as possible. Also, drivers state that they are more likely to pass a truck than a car. This influences the lane-changing model when following a truck. The survey also seeks reasons for driver discomfort. More than half the survey respondents state that their discomfort towards trucks is due to trucks blocking the line of sight. Hence, a primary factor for non-truck driver discomfort to trucks is the physical characteristics of trucks. Other

reasons identified are the perceived discomfort due to truck driver blind spot and truck size. The various significant reasons for discomfort suggest that truck size and characteristics tend to increase the uncertainty in perceiving the traffic ahead by non-truck drivers, making them more cautious. This cautiousness is reflected through the “discomfort” in the vicinity of trucks, and motivates our hypothesis on driver discomfort.

Car-truck interaction mitigation strategies are analyzed for different congestion levels and truck percentages in the ambient traffic. Under low congestion levels and low truck percentages, restricting trucks to the right-most lane can significantly reduce car-truck interactions without negatively impacting traffic performance. Under high congestion levels and truck percentages, allowing trucks on all lanes may represent the best strategy for some traffic scenarios. For other scenarios, adding a new lane may represent the best strategy, though this entails significant monetary investment. A general caveat when seeking to reduce car-truck interactions is that trade-offs exist among the traffic performance, safety and monetary investment. This implies that the effectiveness of a strategy should be viewed more holistically than just focusing on reducing the discomfort level.

Implementation

The survey of INDOT personnel as part of this study suggests that interstate freeways, especially urban highways, are problematic from the perspective of car-truck interactions. The various locations identified are illustrated in the study. Since the transportation demand and supply conditions vary across problematic locations, INDOT should consider implementing the proposed procedure for specific segments of roadways where the problems are perceived to be acute. The geometric and demand characteristics of the specific segment, in conjunction with the characteristics inferred from the non-truck driver behavior survey conducted in this study, can be used to quantify

the level of car-truck interactions. The various mitigation strategies suggested and analyzed in the study may not all be feasible for all problematic segments. Hence, the implementation should first identify the feasible mitigation strategies for a specific location. Further, some strategies may require legislative approval and others may require significant monetary investments. In addition, the implementation should consider trade-offs among multiple performance measures in addition to the car-truck interaction aspects so as to ensure that the strategies implemented are sustainable.

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CHAPTER 1. INTRODUCTION

1.1. Background

Freight trucks are a key element of the national economy. They represent the transportation mode used most frequently for domestic freight movement in terms of both shipment values (71.7%) and weight (69.4%) (Bureau of Transportation Statistics, 2003). Trucks are also the leading freight movement mode for import and export with Canada and Mexico in terms of shipment values (Bureau of Transportation Statistics, 2003). The increase in the number of trucks has been substantial over the past three decades; registration of trucks increased from 4.6 million in 1970 to more than 8 million in 2000, an increase of about 74%. The distance traveled by trucks increased even more dramatically from 62 billion vehicle-miles in 1970 to 206 billion in 2000, an increase of about 232%, compared to the 148% increase for all vehicles (Bureau of Transportation Statistics, 2003). This indicates an expanding demand for trucking services. According to the projections of the Federal Motor Carrier Safety Administration, truck travel is expected to increase by about 20% in terms of vehicle miles over the next 10 years.

While the freight truck transportation sector is a key part of the economic lifeline of the nation, trucks can also play a disproportionate role vis-à-vis crashes, congestion, infrastructure deterioration, injuries and fatalities. They are more likely to be involved in accidents due to their physical and operational characteristics, such as size, weight, braking distance and turning radii. In 1998, trucks constituted three percent of all registered vehicles and 7% of all vehicle-miles traveled, but were involved in 12% of all passenger vehicle occupant deaths, and 23% of passenger vehicle occupant deaths in multi-vehicle crashes (Federal Highway Administration, 1999). In 1999, there were more than 452,000 traffic crashes involving large trucks. They accounted for 13% of all traffic related fatalities (5362 deaths) and 4% of all injuries. A key causal factor in this regard is the presence of large blind spots for

truck drivers, also labeled the “no-zone”. It refers to the road areas around trucks and other large vehicles (such as buses) where drivers have limited visibility, increasing the risk of a crash. The no-zone is so labeled because it represents the areas in the vicinity of trucks that other vehicles should avoid to the extent possible, and/or travel through as quickly and safely as possible to minimize the likelihood of collisions. Statistics suggest that potentially 36 percent of all two-vehicle crashes involving a truck and a passenger vehicle took place in the no-zone area (Longo, 1999).

Trucks also have a significant influence on traffic flow and pavement conditions. Past studies (Federal Highway Administration, 1999) emphasize the effects of the physical characteristics of trucks and their operational constraints on traffic performance. Other studies (Gillespie et al., 1993) highlight their disproportionate contribution to pavement deterioration vis-à-vis the distance traversed. Hence, trucks can have significant impacts on safety, performance and infrastructure deterioration. However, while there is a rich body of literature on models to understand truck safety issues, corresponding progress on the modeling of trucks to analyze traffic performance and flow interactions with other vehicles has been rather limited. For example, there exist several statistical models that analyze the causal factors for truck crashes. One study (Office of Motor Carrier Safety, 1999) analyzes statistical crash data from the U.S. Department of Transportation’s Fatality Analysis Reporting System and collision investigation reports from seven state law enforcement agencies to infer on the pre-crash actions of other vehicles in the vicinity of trucks. However, the effects of truck characteristics on traffic flow are represented rather inadequately, and typically in an indirect manner. A common approach in this regard, adopted by the Highway Capacity Manual (HCM) (Transportation Research Board, 2000), uses “passenger car equivalents” to estimate level of service by converting a truck into a proportional number of passenger cars for analysis. Such a strategy highlights significant methodological gaps in robustly capturing the effects of trucks on traffic performance: (i) truck physical dimensions and operational characteristics (such as, acceleration or deceleration limits) are well-

known but seldom used for analysis, (ii) partly as a consequence of (i), the constraints introduced by the geometric characteristics of roads are typically ignored in modeling, and (iii) the behavioral aspects arising due to the interactions of trucks with other vehicles on the road are mostly ignored. These methodological gaps manifest as the non-consideration or cursory acknowledgement of truck characteristics and effects in analytical and traffic simulation models used in practice. For example, most existing traffic simulation models (NGSIM, 2001) do not consider truck operational characteristics or the influence of road geometry on truck performance. Further, from a driver behavior standpoint, existing models do not differentiate between trucks and other vehicles on the road. That is, the driving behavior of truck drivers and non-truck drivers is assumed identical. As a consequence, the behavior of drivers for car-truck interactions is modeled no differently from that of car-car interactions, and this fallacy is reflected in the associated simulation and/or analytical models. Past studies (Yoo and Green, 1999) indicate that the headway when following a truck is wider than the headway when following a car. Beyond the flow modeling limitations, other studies (Peeta et al., 2000) suggest that truck and non-truck drivers can react differently when provided routing information as part of an advanced traveler information system (ATIS), primarily due to the physical/operational characteristics of trucks.

This study addresses driver behavior related to “car-truck conflicts” which may or may not cause car-truck collisions. However, the term “conflict” in traffic engineering commonly refers to a traffic event involving two or more road users, in which at least one user has to undertake an evasive maneuver to avoid collision with other road users. Therefore, using the label “car-truck conflicts” may be inconsistent with the traditional definition of a “conflict”. Hence, the phrase “car-truck interactions” is used in the report to illustrate the problem being addressed.

The study focuses on modeling the interactions between trucks and non-trucks from a behavioral perspective. Here, the term “truck” implies conventional combination trucks used for freight transportation, typically also called “eighteen-

wheelers”. The terms “car” and “non-truck” are used interchangeably in this report. Car-truck interactions can have negative impacts on traffic safety and performance. Hence, a primary objective of the study is to minimize car-truck interactions through various control strategies, primarily supply-side ones. The behavioral aspects of car-truck interactions are assumed to be reflected through the psychological discomfort of non-truck drivers in the vicinity of trucks on the roadway. This discomfort manifests in terms of the truck-following and lane-changing behaviors of non-truck drivers. As will be illustrated in the study, this “discomfort” has implications for traffic performance and safety. While interactions can also arise from the truck driver perspective, past studies in this domain emphasize the need for educating non-truck drivers on their driving actions in the vicinity of trucks by increasing their awareness of the truck no-zone through educational campaigns. Hence, interactions in the current study are viewed from the perspective of non-truck driver behavior.

Simulation experiments are conducted for a two-mile stretch of the Borman Expressway (I-80/94) in Northwest Indiana to analyze: (i) the sensitivity of non-truck driver discomfort to various causal factors, and (ii) the effectiveness of various strategies to mitigate car-truck interactions. The Borman Expressway provides an ideal test bed as it has a high percentage of trucks in the ambient traffic stream, ranging from 30% to 70% on a typical day. Ultimately, it is hoped that strategies to reduce car-truck interactions will positively impact traffic safety and/or performance by enabling non-truck drivers to be more comfortable when sharing the roadway with trucks.

1.2. Study Objectives

The primary objectives of this study are to qualitatively define car-truck interactions, identify their causal factors, develop methodological constructs to model these interactions, and evaluate strategies to mitigate them. This highlights the limitations in the state-of-the-art in the modeling of trucks vis-à-vis their influence on traffic flow, performance, and safety. A significant gap in this regard arises in

terms of the lack of the consideration of driver behavior or its limited treatment in the literature from the perspective of car-truck interactions. Specifically, the objectives of the study are to:

- 1) Provide a qualitative definition for car-truck interactions so as to analyze the factors that lead to such interactions and enable the development of modeling capabilities to derive insights on car-truck interactions.
- 2) Develop behavioral models for non-truck drivers by seeking to capture their discomfort levels in the vicinity of trucks. Non-truck driver surveys in the region of interest will be conducted to elicit behavioral tendencies with respect to trucks. This information will be used to develop driver discomfort models using discrete choice modeling and fuzzy logic constructs.
- 3) Develop truck-following components for use in traffic flow models. The driver behavior models in (2) will be incorporated into traditional traffic flow models to account for the influence of trucks on traffic flow and non-truck driver behavior. In this context, the car-following model in the microscopic freeway simulator FRESIM (Halati, 1991) will be extended to construct truck-following models. The car- and truck-following models in FRESIM, along with the modified lane-changing model, will be used to construct an agent-based freeway segment simulator to analyze car-truck interactions.
- 4) Evaluate alternative control strategies to mitigate car-truck interactions. The freeway segment simulator will be used to perform sensitivity analyses of the various attributes associated with the driver discomfort model in terms of traffic performance and safety. Then, alternative strategies to mitigate car-truck interactions will be evaluated to identify practical strategies and their effectiveness.

1.3. Report Organization

This report includes seven chapters. Chapter 2 briefly reviews relevant literature on truck-related issues including truck safety, truck characteristics, relevant driver behavior and mitigation strategies.

Chapter 3 discusses insights on car-truck interactions obtained through a survey of traffic engineers nationwide. The survey seeks to identify the characteristics of problematic locations, the characteristics of the interactions, and operational solutions for mitigating car-truck interactions.

Chapter 4 describes the concepts and methodologies used to characterize and analyze car-truck interactions. It first defines car-truck interactions and driver discomfort level. Then, it provides a conceptual overview of the methodology used to determine driver discomfort levels and evaluate alternative mitigation strategies. The methodological components including the stated preference survey, binary logit model for discrete choice analysis, and the fuzzy logic approach used to construct the driver discomfort level model, are discussed in detail. This is followed by a description of the car-following and lane-changing models in FRESIM, and their extensions to incorporate car-truck interactions.

Chapter 5 discusses the implementation of the methodology to a case study involving a 2-mile stretch of the Borman Expressway in Northwest Indiana. It provides details on the data collection and a preliminary analysis of the data. The associated insights are used to develop a fuzzy logic based non-truck driver discomfort model.

Chapter 6 introduces the SWARM environment and the construction of the agent-based microscopic freeway segment simulator. It then discusses the sensitivity analysis of the driver discomfort vis-à-vis various causal factors and model parameters. Then, it discusses the evaluation of alternative car-truck interaction mitigation strategies.

Chapter 7 provides some concluding comments by summarizing the study, highlighting its contributions, and identifying potential future directions for research.

CHAPTER 2. LITERATURE REVIEW

2.1. Introduction

This chapter surveys existing literature on the subject domains relevant to studying car-truck interactions from a non-truck driver behavior viewpoint. As stated in Chapter 1, there are significant modeling gaps in the traffic flow theory literature vis-à-vis adequately incorporating the influence of truck characteristics on traffic performance and non-truck driver behavior. A large body of literature exists on truck characteristics and related data. In addition, several studies address truck-related crashes and associated models based on empirical data. However, the existing studies are limited in their ability, especially from a modeling standpoint, to: (i) enable the evaluation of the impacts on traffic flow due to the influence of road geometry on truck performance, (ii) provide capabilities to analyze the behavior of truck and non-truck drivers when they interact in a traffic stream, and how these interactions affect traffic performance, and (iii) analyze the effectiveness of strategies to mitigate car-truck interactions. These limitations manifest in terms of the inadequacies in existing traffic simulation models, and the approximate and/or insufficient mechanisms adopted in the HCM. For example, the traffic flow logic in existing microscopic simulation models does not differentiate between car-following and truck-following. Similarly, the HCM uses passenger car equivalents to represent the effects of truck characteristics in an indirect manner.

The literature review in this chapter briefly summarizes the insights from studies on truck characteristics and truck-related crashes, and puts it in the context of the objectives addressed in this study. In addition, existing studies on driver behavior in the context of trucks are briefly discussed. Finally, the literature on strategies to mitigate the negative impacts of trucks on traffic performance is summarized.

2.2. Truck Characteristics

A comprehensive study (FHWA, 1999) by the Federal Highway Administration (FHWA) documents truck sizes and weights, and summarizes the different limitations of truck sizes/weights across various states. It classifies trucks into three general categories: Single Unit Trucks, Conventional Combination Vehicles, and Longer Combination Vehicles. The study also provides a comprehensive truck impacts assessment report on: infrastructure costs (pavements, bridges and road geometry), safety (crash rates, public perception, and vehicle stability/control), traffic operations (capacity), energy, environment, rail impacts and shipper costs. In addition, the study also proposes passenger car equivalents for different truck categories for rural and urban highways. As discussed earlier, the HCM also provides equations for computing passenger car equivalents for different situations. However, both the FHWA study and the HCM focus only on capturing the effects of the physical characteristic of trucks (such as length, acceleration/deceleration limitations). As mentioned earlier, the influence of trucks on non-truck driver behavior, and the resulting impacts, are not addressed. Another study (USECB, 1999) by the United States Economic Census Bureau (USECB) provides detailed statistics on truck categories and vehicle miles traveled; however it is purely a data collection study.

From a truck driver perspective, a key truck characteristic is its blind spots. Unlike regular passenger vehicles, trucks have deep blind spots directly behind them as well as on either side as illustrated in Figure 2.1. In addition, they also have a blind spot directly in front of them. These blind spots, also labeled “no-zone”, refer to the area where cars disappear from the truck driver’s line of vision (Longo, 1999). As discussed briefly in Chapter 1, the truck driver driving behavior is influenced significantly by the no-zone and road geometry. The predominant strategy suggested by studies focusing on truck driver driving constraints is an educational no-zone safety awareness campaign so as to aid other drivers to share the road more safely with trucks. In addition, trucks typically represent a relatively smaller percentage of

the traffic stream. Hence, this study focuses on exploring the influence of truck characteristics on non-truck driver behavior by capturing car-truck interactions.

2.3. Truck-related Crashes

A key aspect that highlights the influence of truck characteristics on vehicular road traffic is truck-related crashes. As discussed in Chapter 1, truck-related crashes can have disproportionate severity in terms of fatalities/injuries, property damage, and traffic delays. Hence, truck dimensions and safety repercussions are the primary factors that influence non-truck driver psychology in the vicinity of trucks. This emphasizes the need for the robust modeling of the interactions between non-trucks and trucks when they share the roadway, and potentially indicates the influence of trucks on traffic performance and safety. While there is a comprehensive literature on truck-related crashes and conflicts, interactions between trucks and non-trucks that may not lead to crashes or conflicts have not been adequately explored/modeled. Hence, this research focuses only on the behavior of non-truck drivers and their implications for traffic flow performance and traffic safety.

A comprehensive study (NHTSA, 1996) by the National Highway Traffic Safety Administration (NHTSA) discusses trends in truck crashes by truck categories. It summarizes vehicle miles traveled and fatalities involving truck for the period 1975-1995. An additional comprehensive source of data is the U.S. Department of Transportation's Fatality Analysis Reporting System.

There is a rich body of literature (NCSA, 2002) on identifying and analyzing the causal factors for truck-related crashes and conflicts. It employs varied methods based primarily on statistical tools to analyze data and derive insights on the causes of truck-related crashes and conflicts. While road geometry, truck characteristics, weather, and traffic conditions have been identified as some key factors, driver actions and behavior have also been emphasized as key causal variables. This further highlights the need to study car-truck interactions from the perspective of non-truck driver behavior.

2.4. Driver Behavior

A study (OMCS, 1999) by the Office of Motor Carrier Safety (OMCS) identifies acts of motorists in the vicinity of large trucks. It analyzes statistical crash data from the U.S. Department of Transportation's Fatality Analysis Reporting System, and collision investigation reports from seven states. It also surveys experts, truck drivers and officials to identify primary crash factors for which non-truck drivers are responsible. A relative rating instrument is developed to enable experts to assign values to each unsafe driving act with respect to how dangerous a behavior is, and how frequently it occurs. The study then recommends the development of training brochures for truck drivers, non-truck drivers, and law enforcement officers.

Another study (Kostyniuk et al., 2002) uses crash data to identify unsafe driving acts unlike the OMCS's use of expert judgment and experience. The first stage of the study involves the analysis of 94 driver-related factors. Using probability analysis techniques, the study determines the likelihood of the involvement of each factor based on the probability that the crash did or did not involve a truck. It reveals four factors which contribute more to car-truck crashes than car-car crashes. As before, this study also recommends the development of educational brochures only and does not suggest explicit strategies to proactively eliminate or mitigate the associated driver actions.

In summary, studies on driver behavior focus primarily on informational campaigns to reduce crashes rather than explicitly addressing interactions that may or may not lead to crashes or conflicts. The literature in this context is rather sparse. Yoo and Green (1999) explore car-following and truck-following behaviors by conducting experiments using a driving simulator. Sixteen drivers, who are the experimental subjects, follow cars by about ten percent closer than when they follow trucks. However, the study is observational only, and does not explore the factors that lead to the different behavior in the vicinity of trucks. That is, it does not provide insights on car-truck interactions from a behavioral perspective.

2.5. Truck-Related Traffic Strategies

Garber and Gadiraju (1991) use simulation to evaluate the effects of several truck-related strategies on traffic flow and safety on multilane highways. The strategies used are differential speed limit, truck right lane restriction, and combinations of them. However, they do not consider the influence of car-truck interactions on traffic flow. This is because existing simulation models do not differentiate between car-car and car-truck interactions. As discussed in Chapter 1, such a capability is essential for evaluating alternative mitigation strategies. Grenzeback et al. (1991) investigate the effects of large trucks on peak-period urban freeway congestion. They list strategies to reduce congestion from the supply and demand perspectives. The demand-side strategies relate to shipper and receiver actions. They test the strategies by considering technical, legal, and budgetary constraints. However, they do not address the strategies' effectiveness vis-à-vis mitigating car-truck interactions. In this study, relevant strategies are analyzed for mitigating car-truck interactions.

2.6. Summary

The literature review briefly summarizes the insights from studies on truck characteristics and truck-related crashes, and puts them in the context of the study objectives. However, past studies do not address the influence of truck characteristics and related safety issues on non-truck driver behavior. In addition, car-truck interactions that do not result in crashes/conflicts are not analyzed. Consequently, methodological gaps exist in the context of identifying strategies to mitigate the negative impacts of car-truck interactions. This study seeks to overcome this critical vacuum by postulating non-truck driver discomfort as the basis for the associated driver behavior under car-truck interactions.

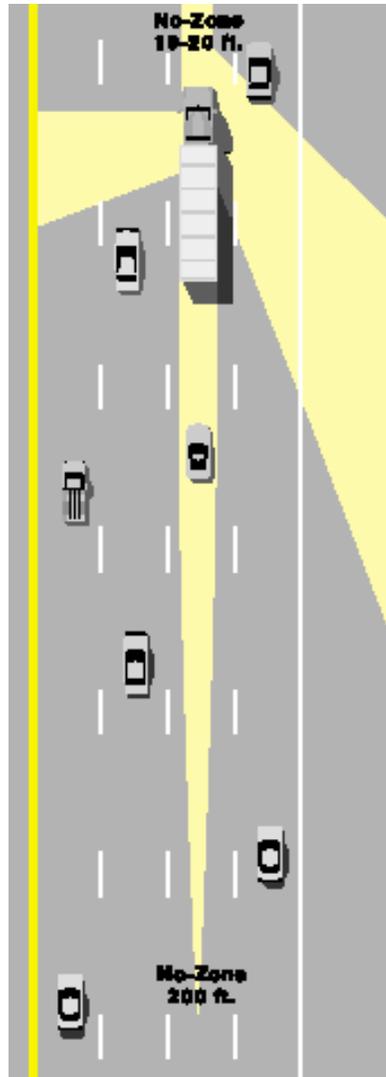


Figure 2.1 Truck Driver Blind Spots: No-zone

CHAPTER 3. CAR-TRUCK CONFLICTS SURVEY

The project was conducted in two stages. In the first stage, a nationwide and a state-level (INDOT) survey on car-truck conflicts were conducted. They were used to identify the characteristics of problematic locations in Indiana with high “car-truck conflicts”, the characteristics of these “conflicts”, and potential solution strategies. The term “car-truck conflicts” was used in this stage, and it included: (1) car-truck crashes; (2) traffic congestion caused by car-truck interactions; and (3) discomfort to non-truck drivers. As stated earlier, this phrase was specific to the first stage of the project, and is different from the one used in this report. The survey insights were useful for modeling car-truck interactions in the second stage of the project.

3.1. Survey Design and Data Collection

The objectives of the survey were to explore the primary reasons for car-truck conflicts, and to identify effective operational strategies to mitigate them. The INDOT survey on car-truck conflicts is illustrated in Appendix A. The nationwide survey on car-truck conflicts is shown in Appendix B. The surveys have identical structure and questions, except for the Indiana-specific questions in the INDOT survey to identify the associated problematic locations in Indiana.

The survey first seeks work-related information from the respondent. It then seeks the opinions of the respondents on the characteristics of car-truck conflicts for various road types and their potential causes. The road types specified include urban interstate highways, rural interstate highways, urban roads, and rural roads. The potential key causes of car-truck conflicts for the various road types are listed for each road type, and the survey respondents are asked to rank-order them by importance for the road types identified by them. In the INDOT survey, respondents are asked to identify specific problematic locations in this context. The final part of the survey lists potential mitigation strategies for car-truck conflicts on freeways and

non-freeways, and respondents are asked to rank-order them by potential effectiveness.

The survey was conducted in July, 2002. Ninety seven surveys were sent to INDOT personnel through email, and 23 responses were obtained. Ninety surveys were sent through email to Department of Transportation personnel of representative states in all geographical regions of the nation, and 21 responses were received.

3.2. Survey Results

Table 3.1 indicates that most INDOT respondents believe that the severity of car-truck conflicts is “high”. 13% respondents rank the severity of car-truck conflicts as “very high”, and none choose “low” or “very low”. This suggests that INDOT personnel feel car-truck conflicts as being problematic.

Table 3.2 rank-orders road types in terms of the level of concern of INDOT respondents vis-à-vis car-truck conflicts. It indicates that urban interstate highways concern them the most and highlights the need to analyze car-truck conflicts on urban interstate highways. Hence, the Borman Expressway was chosen as the representative location for the project.

Table 3.3 identifies the problematic locations with car-truck conflicts on Indiana freeways. The Borman Expressway area is frequently mentioned in the survey as one of the problematic locations. Table 3.4 lists the problematic locations with car-truck conflicts on non-freeways in Indiana as per INDOT personnel.

Table 3.5 ranks the reasons for car-truck conflicts on urban locations. “Speeding of trucks and cars”, “unsafe driving behavior of passenger vehicle drivers”, and “unsafe driving behavior of truck drivers” were identified as the top three reasons; all of them relate to driver behavior. Therefore, this study seeks to explore the influence of driver behavior on car-truck conflicts.

Table 3.6 ranks the reasons for car-truck conflicts on rural locations. “Unsafe driving behavior of truck drivers”, “speeding of trucks and cars and “unsafe driving behavior of passenger vehicle drivers” again rank as the top three reasons. It

suggests that unsafe driving behavior of truck drivers is perceived to have an important role in car-truck conflicts on rural locations.

Table 3.7 rank-orders operational strategies for mitigating car-truck conflicts on freeways based on the survey. “Truck-only lanes at certain locations”, “restrict trucks to certain lanes”, and “design special truck routes which will mostly/solely be used by trucks” are the top three strategies suggested for mitigating car-truck conflicts. It can be observed that the suggested most effective strategies seek to separate trucks from cars; however, they do not consider benefit-cost aspects and focus solely on mitigating conflicts. In this study, we quantify “car-truck interaction” and explore its influence on traffic performance. This provides the foundation for the benefit-cost analysis of the mitigation strategies.

Table 3.8 lists the suggested strategies for non-freeways. “Improve geometric features based on truck needs”, “design special truck routes”, and “prohibit trucks from entering certain busy roads” are the top three strategies suggested. These strategies are different from the ones suggested for freeways. They focus on the geometric features of non-freeways and the need to limit truck access to busy routes.

Table 3.1 Severity of Car-Truck Conflicts (Survey: INDOT Engineers)

	Total	Very High	High	Average	Low	Very Low
Greenfield	3	0	2	1	0	0
LaPorte	9	2	5	2	0	0
Vincennes	3	0	3	0	0	0
Fort Wayne	2	1	1	0	0	0
Seymour	2	0	2	0	0	0
Crawfordsville	3	0	1	2	0	0
Central Operation Office	1	0	0	1	0	0
Total	23	3	14	6	0	0
Percentage	100%	13%	61%	26%	0	0

Table 3.2 Car-truck Conflicts on Different Road Types

Rank	Road Type
1	Car-truck conflicts on urban interstate highways
2	Car-truck conflicts on rural interstate highways
3	Car-truck conflicts on urban roads
4	Car-truck conflicts on rural roads

Table 3.3 Problematic Locations in Indiana (Freeway)

Freeway	Details
I-80/94 (Borman Expressway)	Illinois State Line to SR 51/I-90 Interchange
I-69	I-469 North to the South junction of I-469
I-65 & I-70	Marion County/Downtown & East
I-65	Henryville (SR 160) North to Seymour (US 50)
I-65 & I-70	I-70/I-65 South to North Split, Marion County
I-465, I-65 & I-70	Near Indianapolis
I-70/I-65	I-70 from SR 39 to Marion/Hendricks County Line
I-64	Mile Marker 40-50
I-65	Near the Kankakee River Rest Area
I-65	Exits at US 231 and SR 114 from I-65
I-65	Mile Marker 200 to Mile Marker 240
I-465 & SR-37	I-465 at SR 37 South Side

Table 3.4 Problematic Locations in Indiana (Non-freeway)

Non-freeway number	Detail locations
US 24, US 30, US 6, US 20	I-469 to Ohio Line on US 24 I-69 to SR 19 on US 30 Ohio line to SR 19 on US 6 Ohio line to SR 15 on US 20
SR 61	Coal truck haulage from mine to power plant
US 30, US 31, US 41	
US 50, US 231, SR 57	US 50 - SR 57 to SR 37 US 231 - Kentucky State Line to SR 54 SR 57 - I-64 to SR 67
SR 9	Madison, Hancock and Shelby Counties
US 50	SR 101 west to I-65
SR 912	
US 31	US 31 in Greenfield District
US 36	US 36 from Danville to Indianapolis
US 30, US 31, US 41	Kosciusko & Whitley Counties
SR 37	From I-465 to Monroe/Lawrence County Line
US 20	
US 231	From Kentucky State Line to SR 66
US 41	South of SR 10 on the Southbound lane
US 41	Kentucky State Line to SR 57
US 231 & SR 114	
SR 10	From SR 49 to Illinois State Line
SR 114	From US 231 to I 65
SR 2	From Illinois State Line to US 231
SR-37 & Thompson Road	
SR 16	Between US 35 - US 31
US 421	Between SR 25 - SR 26
SR 18	Between US 31 - US 421
US 35	Between US 24 - US 31
US 24	Between I-65 - US 35
SR 32	Noblesville

Table 3.5 Primary Causes (Urban)

Rank	Causes
1	Speeding of trucks and cars
2	Unsafe driving behavior of passenger vehicle drivers
3	Unsafe driving behavior of truck drivers
4	Number of lanes
5	The weight and length of trucks
6	The width of lanes
7	The width of the shoulder
8	Horizontal and vertical curvature
9	The truck scheduling and routing plans of freight companies

Table 3.6 Primary Causes (Rural)

Rank	Causes
1	Unsafe driving behavior of truck drivers
2	Speeding of trucks and cars
3	Unsafe driving behavior of passenger vehicle drivers
4	The weight and length of trucks
5	The width of lanes
6	Number of lanes
7	Horizontal and vertical curvature of the roadway
8	The width of the shoulder
9	The truck scheduling and routing plans of freight companies

Table 3.7 Effective Strategies on Freeways

Rank	Strategies
1	Truck-only lanes at certain locations
2	Restrict trucks to certain lanes
3	Design special truck routes
4	Toll truckways
5	Improve geometric features based on truck needs
6	Improve driver education programs
7	Prohibit trucks from entering certain busy roads
8	Create local and express lanes
9	Provide more traffic information to truck companies
10	Allow through trucks to go on the left lanes
11	Truck diversion
12	Increase/decrease toll fees for trucks
13	Reduce truck speed limit
14	Increase truck speed limit

Table 3.8 Effective Strategies on Non-freeways

Rank	Strategies
1	Improve geometric features based on truck needs
2	Design special truck routes
3	Prohibit trucks from entering certain busy roads
4	Build by-pass roads
5	Improve driver education programs
6	Restrict trucks to certain lanes
7	Truck diversion
8	Provide more traffic information to truck companies
9	Reduce truck speed limit
10	Allow through trucks to go on the left lanes
11	Increase truck speed limit

CHAPTER 4. METHODOLOGY

This chapter introduces the concept of car-truck interactions and describes the methodologies used in the study. It provides a conceptual definition of car-truck interactions and discusses the methodology used to determine these interactions. Stated preference surveys and fuzzy logic modeling are used to capture non-truck driver discomfort towards trucks. These discomfort levels are used in conjunction with microscopic simulation modeling to generate truck-following and modified lane-changing models. These simulation modeling components are used to infer the degree of car-truck interactions in the ambient traffic stream. The interactions are used to evaluate the effectiveness of alternative mitigation strategies.

4.1. Car-truck Interactions

4.1.1. Definition of Car-truck Interactions

We define car-truck interactions as the driving actions (decisions) of non-truck drivers due to their discomfort in the vicinity of trucks in the ambient traffic stream. This is primarily manifested when non-truck vehicles follow trucks.

We assume that non-truck drivers have psychological discomfort to different degrees in the vicinity of trucks, and that the resulting driving actions are influenced significantly by this discomfort.

It is reasonable to expect the non-truck driver behavior to vary across drivers based on their socio-economic characteristics, past experience, and innate behavioral tendencies. In addition, these driving actions are also dependent on situational factors such as weather, time-of-day and ambient traffic (congestion) conditions. From a traffic flow modeling standpoint, these driving actions manifest in terms of the truck-following actions and the lane-changing logic when following a truck.

4.1.2. Level of Discomfort Towards Trucks

Based on our definition of car-truck interactions, the mechanism to identify and quantify car-truck interactions entails the measurement of the level of discomfort for a non-truck driver when following a truck. As discussed in Section 4.1.1, this quantifiable discomfort level (DL) depends on a driver's socioeconomic characteristics, innate behavioral tendencies and situational factors. This implies that different drivers in the same traffic stream may have different DL s due to differences in their behavioral tendencies. By contrast, drivers with similar socioeconomic characteristics may have different DL s if their situational factors are different. This implies that all non-truck drivers have discomfort to varying degrees in the vicinity of trucks, and that these discomfort levels are dynamic. Hence, when a non-truck driver follows a non-truck vehicle, there is no car-truck interaction. Also, even when a non-truck driver follows a truck, there may be no discomfort if the space/time headway between them is sufficiently large that the non-truck driver does not feel the discomfort. From a traffic flow modeling perspective, this implies that the truck-following behavior is not triggered. This is akin to the logic of traditional car-following models where car-following behavior is not triggered unless the headway is below a threshold value. We assume DL to take values from 1 through 5 consistent with the survey discussed in Section 4.3.1. Here, 1 represents no discomfort and 5 implies maximum discomfort.

4.1.3. Identification of a Car-truck Interaction

The notion that discomfort may not exist even when a non-truck driver follows a truck implies the need to define when such an event represents a car-truck interaction and when it does not. In this study, we base this on a threshold time gap. Figure 4.1 shows two scenarios (a) and (b) that represent “no interaction” and “interaction” cases, respectively. Let L_T denote the space gap between the truck and the non-truck vehicle based on the truck-following model (discussed in Section 4.4). Let L_2 represent the space gap from the end of the truck to a point two seconds away

based on the current speed of the non-truck vehicle. We assume that if $L_T > L_2$, the two vehicles do not interact as they are sufficiently apart. However, if $L_T \leq L_2$, we assume that the two vehicles interact, in which case the DL is obtained for the non-truck driver using the procedure in Section 4.3.3. The 2-second threshold time gap is based on the recommended safe time gap in the Indiana driving manual. Presumably, if the two vehicles are at least two seconds apart, they are sufficiently far from each other that the non-truck driver actions are not influenced by the truck ahead. It is important to note here that the study methodology is independent of the threshold time gap used. A more conservative outlook implying a stricter interpretation of car-truck interactions would entail a larger threshold time gap. From the perspective of a traffic engineer addressing the car-truck interaction problem in a region using mitigation strategies, this implies lesser tolerance for such interactions. By contrast, a smaller value for the threshold time gap implies a more lenient view of such interactions. In an actual situation, the threshold time gap is based on the traffic engineer's tolerance level unless a standard value is mandated by state/federal guidelines.

4.1.4. Degree of Car-truck Interactions for a Roadway Segment

The “discomfort level” discussed in the previous sections is a disaggregate parameter specific to an individual driver. However, it is not sufficient to enable the primary practical objective of the study, the evaluation of the effectiveness of alternative car-truck interaction mitigation strategies. This motivates the need for an aggregate measure of the degree of car-truck interactions for a roadway segment. We define the average aggregate discomfort level ($AADL$) for a roadway segment in this context. It is the time-averaged aggregated sum of the discomfort levels of all vehicles on a roadway segment for a pre-specified duration averaged over all vehicles. The procedure to determine $AADL$ is described in Section 4.4.3. From a practical standpoint, a higher $AADL$ value implies a greater degree of car-truck

interactions, and vice versa. Hence, the *AADL* provides a convenient quantifiable tool to evaluate alternative mitigation strategies.

4.2. Methodological Framework

This section provides a brief overview of the conceptual framework for the methodology vis-à-vis addressing the car-truck interactions problem. As stated earlier, the primary application domain for this study is the ability to analyze the effectiveness of alternative strategies to mitigate car-truck interactions.

Figure 4.2 illustrates the methodological framework used to determine the discomfort levels of drivers. A non-truck driver behavior survey is conducted in the region of interest to identify factors that contribute to driver discomfort level. A preliminary analysis of the survey data is conducted to identify the significant factors that affect the individual discomfort level vis-à-vis following a truck. The survey data and a fuzzy logic modeling approach are then used to determine the *DL* for each non-truck driver. The *DL* is used to extend the car-following logic of a microscopic simulator to obtain a truck-following model. In addition, it is used to modify the lane-changing logic. This leads to a microscopic traffic flow simulator that is modified to incorporate the car-truck interactions logic.

Figure 4.3 highlights the application of the *DLs* to evaluate alternative mitigation strategies. First the car-truck interaction mitigation strategy is identified. Let the time duration of interest be discretized into intervals, $t = 1, 2, 3, \dots, \tau$. The time counter is set to 1 and the modified traffic simulator is initiated. The network topology, road geometry, demand, weather, and time-of-day are inputs to the traffic simulator. The demand consists of trucks and non-truck vehicles for that time interval. The non-truck driver behavior characteristics are based on the survey data. The number of vehicles in interval t in the road segment (network topology of interest) is denoted by $K(t)$. It includes vehicles in that road segment at the end of the previous time interval and the new demand entering that segment in interval t . The vehicle counter k ($k = 1, 2, \dots, K(t)$) is set to 1. If vehicle k is a non-truck vehicle

following a truck, the DL level is determined and L_T is determined. If $L_T \leq L_2$, an interaction is identified. Then, DL is used to obtain the modified lane-changing model. If $L_T > L_2$, no interaction occurs and the lane-changing logic is not used. If vehicle k is a truck or a non-truck vehicle following a non-truck vehicle, the standard car-following and lane-changing models are applied to determine the action of that vehicle in interval t . If $k \leq K(t)$, the inner loop logic in Figure 4.3 is repeated. If $k > K(t)$, the relevant traffic performance measures are computed for interval t . In addition, the $AADL$ is computed for t . If $t \leq \tau$, the outer loop in Figure 4.3 is repeated. If $t > \tau$, the procedure is ended.

4.3. Description of Methodology Components

This section discusses the data collection methodology, the mechanism for the preliminary analysis of the data using discrete choice modeling, and the details of the fuzzy logic modeling approach to determine DL .

4.3.1. Data Collection: Non-Truck Driver Behavior Survey

As discussed earlier, the factors that contribute to driver discomfort in the vicinity of trucks can be categorized into socioeconomic characteristics, inherent behavioral tendencies and situational factors. The socioeconomic characteristics can include variables such as age, gender, education, household size, and frequency of freeway usage. The situational factors include weather conditions (rain, snow), time-of-day (day time or night time) and congestion levels (low, medium, high). The former tend to be static variables whereas situational factors are dynamic. Hence, the discomfort levels of drivers depend on the time-dependent actual situations encountered by them when driving in a traffic stream. However the behavioral tendencies of drivers are latent variables and cannot be measured directly. Hence, the non-truck driver discomfort when following a truck cannot be measured trivially and needs to be inferred through empirical data. Ideally, it is desirable to obtain data based on the revealed actions of drivers in actual situations or in a quasi-revealed manner through driving simulators. This is known as revealed preference (RP) data

in the choice modeling literature. However, RP data entails significant labor and monetary investment. Hence, we use a stated preference (SP) survey to elicit potential driver actions in hypothetical scenarios to infer on the discomfort characteristics of each survey respondent. As is well-known in the literature, the SP data may not be consistent with a driver's actions in an actual situation.

We use an on-site SP survey of non-truck drivers to infer on driver discomfort levels. The survey is conducted in the Borman Expressway corridor in Northwest Indiana. This site represents the case study for our experiments discussed in Chapter 5 and Chapter 6. The survey questionnaire is illustrated in Appendix C. The first set of questions address the socioeconomic characteristics of the respondents. These include age, gender, education level, household size, and frequency of freeway usage.

The second set of questions relate to discomfort under various situational factors. To obtain detailed insights, respondents are asked to convey their degree of discomfort using a Likert scale from 1 to 5 (where 1 represents no discomfort and 5 represents the most discomfort) under two scenarios relative to the truck: (i) following a truck, and (ii) driving parallel to a truck. The situational factors considered are bad weather, night driving, and three levels of traffic congestion (low congestion, medium congestion with smooth flow, and high congestion with low speeds).

The last set of questions is oriented towards eliciting driver behavior and actions vis-à-vis discomfort in the vicinity of trucks. It seeks specific information about driver actions when following a truck or a non-truck. This is used to infer on difference in driving actions when following trucks. Additional questions seek to identify the reasons for the discomfort.

4.3.2. Preliminary Analysis of Survey Data

The proposed methodology to obtain driver DL is a fuzzy logic based model. This is amenable to the use of a Likert scale to quantify the discomfort level. However, it is important to identify the variables with significant explanatory power

vis-à-vis driver discomfort in the vicinity of trucks. To identify these variables, a preliminary analysis is performed using discrete choice modeling. To minimize computational effort, a choice model with only two alternatives (low discomfort or high discomfort) is analyzed. The binary logit model (Ben-Akiva and Lerman, 1985) is used, with the probability of individual k having low discomfort (choice i) as:

$$P_k(i) = \frac{1}{1 + e^{-(V_{ik} - V_{jk})}} \quad 4.1$$

where,

$P_k(i)$ = the probability of an individual k having choice i (low discomfort)

V_{ik} = systematic component of the utility of choice i (low discomfort) for individual k

V_{jk} = systematic component of the utility of choice j (high discomfort) for individual k

The structure of the binary logit model estimated using the survey data is:

$$V = (V_{ik} - V_{jk}) = \alpha_0 + \sum_{l=1}^5 \alpha_l X_k^l + \sum_{m=1}^5 \gamma_m Y_k^m \quad 4.2$$

where,

α_0 = alternative specific constant

α_l = coefficient for socioeconomic variable l

X_k^l = categorical value of socioeconomic variable l for driver k (shown in Table 5.4)

γ_m = coefficient for situational variable m

Y_k^m = dummy explanatory variable for situational variable m for driver k (shown in Table 5.4)

Based on the potential set of explanatory variables, the detailed expression for the binary logit model is:

$$V = (V_{ik} - V_{jk}) = \alpha_0 + \alpha_1 X_k^G + \alpha_2 X_k^A + \alpha_3 X_k^E + \alpha_4 X_k^H + \alpha_5 X_k^F + \gamma_1 Y_k^W + \gamma_2 Y_k^T + \gamma_3 Y_k^{LC} + \gamma_4 Y_k^{MC} + \gamma_5 Y_k^{HC} \quad 4.3$$

where,

X_k^G = categorical variable based on gender of driver k

X_k^A = categorical variable based on age of driver k

X_k^E = categorical variable based on educational level of driver k

X_k^H = household size of driver k

X_k^F = categorical variable based on frequency of freeway trips of driver k

Y_k^W = dummy explanatory variable for bad weather

Y_k^T = dummy explanatory variable for night driving

Y_k^{LC} = dummy explanatory variable for low congestion

Y_k^{MC} = dummy explanatory variable for medium congestion and smooth flow

Y_k^{HC} = dummy explanatory variable for high congestion and low speeds

To enable the consistency between the Likert scale (1-5) of the survey data for DLs and the binary logit model, different combinations of the survey responses are considered to obtain the dependent variable value for the model estimation. In the case study addressed in this report, different combinations were estimated using the LIMDEP 7.0 estimation software. Based on the analysis, the following combination had the best ρ^2 value implying the best fit:

$$\varepsilon_k = \begin{cases} \text{low discomfort,} & \text{if the stated } DL \leq 3 \\ \text{high discomfort,} & \text{if the stated } DL = 4 \text{ or } 5 \end{cases} \quad 4.4$$

That is, the grouping in which DLs 1, 2 and 3 were assumed to represent low discomfort, and DLs 4 and 5 represent high discomfort provided the best fit for the survey data. In general, this procedure should be applied to the specific case study to identify the best grouping of the DL values.

4.3.3. Fuzzy Logic Modeling Approach

The fuzzy logic approach is the modeling mechanism in this study to estimate the level of discomfort of non-truck drivers to trucks. Fuzzy logic seeks to formalize the human capacity for imprecise or approximate reasoning. Such reasoning represents the human ability to reason approximately and judge under uncertainty (Ross, 1995). Ross (1995) also suggests that there are two kinds of situations where fuzzy logic can be successfully employed: (i) very complex models where understanding is strictly limited, and (ii) processes where human reasoning, perception, or decision-making are inextricably involved.

Peeta and Yu (2002) propose a fuzzy logic approach to estimate the pre-trip and en-route decisions of drivers under information provision. The associated model is compared with a binary discrete choice model using survey data to build both models. The fuzzy logic model is shown to be more robust as it has higher choice prediction rates. Gonzalez-Rojo et al. (2002) use a fuzzy logic approach to model car-following to estimate the parameters in the associated equations. Wu et al. (2000) develop a microscopic simulation model using fuzzy logic, called the fuzzy logic motorway simulation model (FLOWSIM). Hamad and Kikuchi (2002) develop a measure of traffic congestion using the fuzzy logic approach.

As discussed in the previous section, the preliminary analysis is used to identify significant factors that contribute to the discomfort levels of drivers. After identifying these factors, the fuzzy logic approach is used to combine their contributions to estimate the level of discomfort for a non-truck driver. The fuzzy logic approach is a robust tool for this problem due to the subjectiveness in characterizing driver discomfort and some causal factors. The fuzzy logic modeling approach used in this study is based on the approach employed by Peeta and Yu (2002).

The structure of the fuzzy logic based *DL* model in this study can be expressed as:

$$\begin{aligned}
DL_{k,t} = & w_1\Omega_G(X_k^G) + w_2\Omega_A(X_k^A) + w_3\Omega_E(X_k^E) + w_4\Omega_H(X_k^H) \\
& + w_5\Omega_W(Z_t^W) + w_6\Omega_T(Z_t^T) + w_7\Omega_C(Z_t^C)
\end{aligned}
\tag{4.5}$$

where:

$DL_{k,t}$ = discomfort level for non-truck driver k in interval t

X_k^l = value of socioeconomic variable l for driver k

Z_t^m = value of situational factor m at time t

$\Omega_G(\cdot)$ = transformation function that generates a crisp value for gender

$\Omega_A(\cdot)$ = transformation function that generates a crisp value for age

$\Omega_E(\cdot)$ = transformation function that generates a crisp value for education

$\Omega_H(\cdot)$ = transformation function that generates a crisp value for household size

$\Omega_W(\cdot)$ = transformation function that generates a crisp value for weather

$\Omega_T(\cdot)$ = transformation function that generates a crisp value for time-of-day

$\Omega_C(\cdot)$ = transformation function that generates a crisp value for congestion level

w_j = weight associated with attribute (explanatory variable) j

The explanatory variables used in the fuzzy logic model are the variables identified as significant by the preliminary analysis using discrete choice modeling. The socioeconomic variables (X) and the situational factors (Z) are used to determine the DL values. The $\Omega(\cdot)$ represent the fuzzy logic approach based transformation functions to determine the crisp values corresponding to the specific explanatory variable. The fuzzy logic procedure to obtain the crisp values using the transformation functions is described hereafter. It consists of the following steps: (i) construction of if-then rules, (ii) construction of membership functions, (iii)

application of the implication operator, (iv) defuzzification, and (v) adjustment of the weights of if-then rules. We use the “education” variable to illustrate these steps.

4.3.3.1. If-then rules

In the proposed approach, a non-truck driver’s discomfort to trucks is assumed to be based on some simple rules. Natural language is perhaps the most powerful form of conveying information that humans possess for any problem or situation that requires reasoning (Peeta and Yu, 2002). Also, in the field of artificial intelligence, a common mechanism to represent human knowledge is to form it into natural language expressions of if-then rules, such as:

IF premise (antecedent), THEN conclusion (consequent).

This is commonly known as the if-then rule-based form. It typically expresses an inference such that if we know a fact (premise, hypothesis, antecedent), then we can infer, or derive, another fact called a conclusion (consequent) (Ross, 1995).

Consistent with the rule-based fuzzy logic approach, the individual discomfort level to trucks is assumed to be based on a set of rules that relate it to the driver socioeconomic characteristics and situational factors. The rules are based on the variables identified as significant in the preliminary analysis and/or those identified based on the insights from previous studies in the related driver behavioral domain.

For generality, a rule i is defined in the form of “if x is A_i then y is B_i ”. The left hand side (LHS) of a rule deals with driver characteristics and situational factors, while the right hand side (RHS) represents the degree of discomfort to trucks. For example, “if the driver is well-educated, the discomfort is high” is one rule related to education that is used in the study. Here, x represents education, a relevant characteristic for the driver. A_i represents the fuzzy set of the term “well-educated”. y represents discomfort, and B_i represents the fuzzy set of the term “discomfort is high”.

However, the description of the education factor for a specific driver may not completely match the associated rule. As stated earlier, the fuzzy logic approach is a

tool to account for such linguistic subjectivity in describing the driver characteristics. For example, if the education variable input for a driver is “some college”, it does not directly match the if-then rule: “if the driver is well-educated, the discomfort is high”. Nor does it completely match the rule: “if the driver is less-educated, the discomfort is low”. Hence, there is a need to determine to what extent each of these two rules corresponds to “some college”. This is done through a procedure known as implication which is discussed in Section 4.3.3.3, and illustrated in Figure 4.4.

Hence, the if-then rule matching can be described as follows. If an actual input and the LHS of rule i are approximately matched, a consequence may be inferred as follows:

$$\begin{array}{lll}
 \text{If } x \text{ is } A_i & \text{then } y \text{ is } B_i & \rightarrow \text{Generic if-then rule} \\
 x \text{ is } A_i^* & & \rightarrow \text{Input value for driver} \\
 \hline
 y \text{ is } B_i^* & & \rightarrow \text{Implication value for driver}
 \end{array}$$

Here, everything above the line is known, and below the line is unknown. For example, the generic “education” rules described above are known, and a specific driver’s education “some college” is the input which represents A_i^* . The implication value of B_i^* is computed based on the composition of A_i^* and an implication relation R for each of the two “education” rules, as described in Section 4.3.3.3.

An aggregation mechanism is used to combine the implication values for all “education” rules into one fuzzy set based on the input for the driver, “some college”. This output fuzzy set is then transformed into a crisp value through a process called defuzzification, as illustrated in Figure 4.5. This crisp fuzzy value would represent the $\Omega_E(X_k^E)$ value for driver k in the Equation 4.5. The procedure is repeated for the other variables in Equation 4.5.

The construction of the if-then rules is the most critical step in the fuzzy logic approach. The actual set of if-then rules used in our Borman Expressway case study is discussed in Chapter 5. After the if-then rules are constructed, they are translated into a graphical form, called membership functions, for enabling the remainder of the fuzzy logic approach.

4.3.3.2. Membership Functions

The membership function of a fuzzy variable is a mapping between the fuzzy variable values and the set $[0, 1]$, where the value in set $[0, 1]$ indicates the possibility of each variable value. The possibility of a fuzzy variable is a function with a value between 0 and 1 indicating the degree of evidence or belief that a certain element belongs to a set. It is a mathematical representation of linguistic information. It focuses on the imprecision intrinsic in language and quantifies the meaning of events (Peeta and Yu, 2002). The construction of the membership functions is a key step in the fuzzy logic approach. Generally, the methods for determining membership functions are heuristic and can be subjective. In our study, the membership functions are constructed consistent with the survey data based on the preliminary analysis using the discrete choice model, and based on insights from past studies. Typically, the triangle and trapezoid shapes are popular for membership functions because of their computational efficiency and ease of construction. We use these shapes in our study.

We use the “education” variable example to illustrate the construction of the membership functions. Figure 4.6 illustrates the membership functions for “well-educated” and “less-educated” categories. Based on the study survey in Appendix C, there are four categories specified for education: high school or less, some college, college graduate, and postgraduate. They are represented by 1, 2, 3, and 4, respectively in Figure 4.6. In the membership function for well-educated, “postgraduate” is identified as “well-educated” with possibility 1, and “high school or less” is identified as “well-educated” with possibility 0. Similarly, the membership function for less-educated has a possibility 0 if the driver response is “college graduate” or “postgraduate” as both of these are generally not considered as “less-educated”. Using similar reasoning, the membership functions for “low discomfort” and “high discomfort” are constructed, as shown in Figure 4.6. As will be discussed in Section 4.3.3.5, the membership functions are constructed through intuitive reasoning as well as survey data. The approach is to tweak these functions

so that the weights of the attributes in Equation 4.5 reflect their significance to explaining driver discomfort based on the preliminary analysis.

4.3.3.3. Implication Operator

As discussed in Section 4.3.3.1, the inferred value of B_i^* is computed based on the input of A_i^* and an implication relation R . The relation can be represented as follows:

$$B_i^* = A_i^* \circ R \quad 4.6$$

where R is the implication relation from A_i to B_i . Several implication operators can be used to infer B_i^* . We use the Larson Product implication operator (Peeta and Yu, 2002), defined as:

$$\mu_{B_i^*}(y) = \gamma_i \cdot \mu_{B_i}(y), \quad 4.7$$

where γ_i is the degree of overlap between A_i and A_i^* , and is given by:

$$\gamma_i = \max_{x \in X} \min(\mu_{A_i^*}(x), \mu_{A_i}(x)) \quad 4.8$$

where X is the overlap between A_i and A_i^* .

B_i^* , the fuzzy set representing the discomfort based on the input A_i^* , can be obtained using this implication operation. Figure 4.4 illustrates the logic of the Larson Product implication operation. The membership function ($\mu_{A_i^*}(x)$) of input A_i^* has overlap with the membership function ($\mu_{A_i}(x)$). From this γ_i can be obtained as the highest value of the overlap, as expressed in Equation 4.8. Then, Equation 4.7 is used to imply the membership function of B_i^* using the known B_i membership function, as illustrated in Figure 4.4. This operation is illustrated in the context of the “education” variable in Figure 4.5. B_1^* and B_2^* are the fuzzy sets computed for rules 1 and 2, respectively, using the implication operator.

4.3.3.4. Defuzzification Method

After using the implication operator to determine the fuzzy set B_i^* for if-then rule i , the process is repeated for all if-then rules that are fired based on the rule category. As shown in Figure 4.5, for the “education” variable and driver input “some college”, both rules in the education category, discussed in Section 4.3.3.1, are fired. They generate fuzzy sets B_1^* and B_2^* . Defuzzification is the mechanism to transform these fuzzy outputs to a crisp value. This is done by using a defuzzification method to process the aggregated output B^* , which is the union of B_1^* and B_2^* in Figure 4.5.

The Center of Sums (COS) method is used to defuzzify the fuzzy output B^* . The COS seeks to find the center of B^* , and is obtained as:

$$y^* = \frac{\int_Y y \cdot \sum_{i=1}^n \mu_{B_i}(y) dy}{\int_Y \sum_{i=1}^n \mu_{B_i}(y) dy} \quad 4.9$$

where:

Y = the range of discomfort level (1 to 5)

n = number of rules in the category

$\mu_{B_i}(y)$ = possibility value of y in fuzzy set B_i

y^* = crisp value from defuzzification.

In the context of the “education” variable for driver k (with input “some college”), the crisp value from defuzzification, y_k^{*E} , is equal to 2.79, as shown in Figure 4.5. Hence, the fuzzy transformation function output in Equation 4.5 specifies a crisp value for the corresponding category. For example, for education, we have:

$$\Omega_E(X_k^E) = y_k^{*E} \quad 4.10$$

where:

X_k^E = “some college” for driver k ,

$y_k^{*E} = 2.79$ (from Figure 4.5) for driver k .

Based on this approach, seven crisp values are generated for the seven explanatory variables in Equation 4.5 that represent the fuzzy logic based DL model. The final step in the fuzzy logic approach is to determine the importance of each attribute category (such as education, gender, time-of-day etc.) in contributing to the DL value.

4.3.3.5. Adjustment of the Weights of If-then Rules

The discomfort level of a driver k in interval t , DL_k^t , is computed by obtaining the crisp values for each fuzzy explanatory variable (attribute). Each attribute is represented as a set of if-then rules. To determine the DL_k^t , the contribution (weight) of each attribute to it is necessary. This implies that some attributes (and their associated if-then rules) may be more important than others in determining the DL value. As shown in Equation 4.5, the DL for driver k and in interval t can be represented as:

$$DL_k^t = \sum_{j=1}^{N_A} w_j y_k^{*j} \quad 4.11$$

where:

y_k^{*j} = the crisp value obtained for attribute j using the fuzzy logic approach

N_A = the number of attributes

The weighted sum approach of Equation 4.11 is reasonable because the importance and contribution of each attribute can be different. The weights of various attributes can be determined using the survey data. The survey provides the stated DL values for different situations for each respondent. Hence the attribute values and DL values are known for each respondent k . The y_k^{*j} values are computed using the fuzzy logic approach discussed heretofore. Hence, the unknowns are the weights w_j for the attributes $j = 1, \dots, N_A$. We solve a set of $N+1$ simultaneous equations, where N is the number of observations from the SP survey. The additional equation is the normalizing constraint $\sum_{j=1}^{N_A} w_j = 1$. An additional requirement, which

provides N_A constraints, is that all weights w_j should be greater than or equal to zero. Once the w_j values are determined, the fuzzy logic based DL model (Equation 4.5) can be used to predict the DL value for a specific driver. As discussed in Section 4.3.3.2, the membership functions are adjusted such that the obtained w_j values are consistent with the survey data and the preliminary analysis. Hence, a more significant attribute has a higher weight.

As discussed in Section 4.2, the DL values are then used to modify the traffic simulation components on car-following and lane-changing. This is discussed next.

4.4. Adaptation of Car-truck Interaction Logic to Traffic Flow Models

As discussed in Chapter 1 and 2, existing traffic flow models and simulators do not account for car-truck interactions. To the extent that these interactions are manifest at the individual driver level, existing microscopic flow modeling components are extended to incorporate the interactions. We extend the car-following and lane-changing logics in the FRESIM (Halati, 1991) microscopic freeway simulator to obtain a truck-following model and a modified lane-changing model. Hence, the car-truck interaction modeling in this study is applicable to freeways only. However the methodological framework is not restricted to the freeway domain only. While such models can be developed for the non-freeway context as well, their significance vis-à-vis mitigation strategies is not as apparent. This is because supply strategies such as lane restrictions to reduce car-truck interactions are not as meaningful for arterial streets when trucks have to use specific routes to reach their destinations. In such instances, road geometry constraints would likely represent the primary factors affecting traffic performance rather than car-truck interactions.

The strategic goal for the models developed in this study is to provide a realistic modeling component vis-à-vis car-truck interactions for the next generation of traffic simulation models (NGSIM, 2001) that seek greater traffic flow modeling realism. In the interim, we modify the associated modeling components in the FRESIM

simulator. However, modifying the source code of commercial software may not be possible due to copyright restrictions or the significant effort involved. Hence, we develop an agent-based traffic flow simulator for freeway segments using the modified FRESIM modeling logic. The agent-based simulator incorporates the discomfort levels for non-truck drivers obtained from the fuzzy modeling approach in Section 4.3.3 to replicate the traffic flow movement for freeway segments.

4.4.1. Relevant FRESIM Modeling Components

FRESIM (Halati., 1991) is part of the CORSIM corridor simulation model (Owen, 2000) developed by the FHWA. It is chosen as the base model for this study based on the insights from a study by Aycin and Benekohal (1999) which compares several popular car-following models. They conclude that the FRESIM car-following model more closely replicates the field data compared to the other models when the driver sensitivity factors are robustly calibrated. However, FRESIM is not as robust under stop-and-go traffic conditions. We now briefly describe the car-following and lane-changing models embedded in FRESIM.

4.4.1.1. Car-following model

The FRESIM car-following model updates vehicles sequentially in the simulation using its leader-follower logic. First, the leader is moved to its new position and then the follower is placed at a position consistent with the car-following logic. That is, the follower vehicle's speed and position are determined after updating its leader's position for the current time step. The Pitts car-following model, developed by the University of Pittsburgh is used for this purpose (Halati, 1991). Using this model, the space headway between the leader and the follower vehicle is given by:

$$H = L + 10 + qv_l + bq(u_l - v_l)^2 \quad 4.12$$

where:

H = space headway (ft)

L = lead vehicle length (ft)

q = driver sensitivity factor for the follower vehicle

v_t = speed of the follower vehicle at time t (ft/s)

u_t = speed of the lead vehicle at time t (ft/s)

b = calibration constant defined as:

$$b = \begin{cases} 0.1, & u_t < v_t \\ 0, & \text{otherwise} \end{cases} \quad 4.13$$

Based on the above formula, the follower vehicle acceleration for any simulation scanning interval δ is determined as:

$$a = \frac{2 \{x_{t+\delta} - y_t - L - 10 - v(q + \delta) - bq(u_{t+\delta} - v_t)^2\}}{\delta^2 + 2q\delta} \quad 4.14$$

where:

$x_{t+\delta}$ = lead vehicle position at time $t + \delta$

y_t = follower vehicle position at time t

q = driver sensitivity factor for the follower vehicle

4.4.1.2. Lane-changing logic

In FRESIM, discretionary lane-changing refers to lane changes performed to bypass other slow-moving vehicles, to obtain a more favorable position, and/or to attain a higher speed. The discretionary lane change logic quantifies the driver decision to perform the lane change based on the behavioral factors “motivation” and “advantage”.

Motivation refers to the desire (denoted in percentage units) to perform the discretionary lane change which is a function of a vehicle’s present speed and the driver’s behavioral characteristics. The model assigns to each vehicle an “intolerable” speed level below which the driver is highly motivated to perform the lane change. The “intolerable” speed (v_{int}) is computed as:

$$v_{int} = v_{ff} \left[\frac{50 + 2c}{100} \right] \quad 4.15$$

where:

v_{int} = tolerance threshold speed for lane changer

v_{ff} = desired free-flow speed (ft/s)

c = driver type factor (a randomly assigned number between 1 to 10 with 10 representing the most aggressive driver and 1 representing the most timid driver)

The desire to perform a discretionary lane change (D) is then modeled as:

$$D = \begin{cases} 100, & v \leq v_{int} \\ 100 \left[1 - \frac{v - v_{int}}{v_{ff} - v_{int}} \right], & v_{int} < v < v_{ff} \\ 0, & v \geq v_{ff} \end{cases} \quad 4.16$$

where:

D = desire to perform a discretionary lane change (percent)

v = speed of the lane changer

Figure 4.7 illustrates the definition of the desire to perform a discretionary lane change in FRESIM. Once a driver has the desire to perform a lane change because of the slow vehicle ahead, the gaps on the adjacent lanes are evaluated (Halati, 1991). After confirming that a vehicle desires a lane change and the gaps on other lanes permit a lane change, the advantage gained by shifting to other lanes is computed to determine whether such an advantage is significant enough for that driver.

Advantage refers to the benefits gained by performing the lane change and is modeled in terms of the “lead factor” (F_l) representing the disadvantage of remaining in the current lane and the “putative factor” (F_p) which represents the potential gain in moving to a new lane. The lead factor is computed in terms of the vehicle’s current headway with respect to its current leader using:

$$F_l = \begin{cases} 1, & h \leq h_{min} \\ 1 - \frac{h - h_{min}}{h_{max} - h_{min}}, & h_{min} < h < h_{max} \\ 0, & h \geq h_{max} \end{cases} \quad 4.17$$

where:

h_{min} = minimum time headway (default value of 2 seconds)

h_{max} = maximum time headway (default value of 5 seconds)

h = existing time headway in the current lane computed as:

$$h = \frac{s - F_s v_d}{v} \quad 4.18$$

where:

s = separation distance between the vehicle and its leader in the current lane

F_s = speed threshold factor (default value is 2 seconds)

v_d = speed differential between the vehicle and its leader

The algorithm for computing the putative factor is identical to that for the lead factor with the exception of the headway computation, which is performed with respect to the putative leader in the target lane. The “advantage” for discretionary lane change is computed as the difference between the putative factor and the lead factor. The lane change is permitted if this difference exceeds the advantage threshold which has a value of 0.4.

4.4.2. Modified Simulation Model to Incorporate Car-Truck Interactions Logic

As discussed earlier, akin to other existing traffic models, the FRESIM car-following and lane-changing components are limited by their inability to account for car-truck interactions. The non-truck driver behavior survey discussed in Section 4.3.1 and Chapter 5 suggests that drivers prefer to overtake a truck ahead than a car ahead when all other conditions are identical. This implies that the desire to perform a discretionary lane change is higher when following a truck. In addition, as discussed in Section 2.4, Yoo and Green (1999) conclude that headway when following a car is lower than when following a truck. Based on these insights and other factors discussed in Chapter 2, the FRESIM models are extended to develop a truck-following model and a modified lane-changing model.

4.4.2.1. Truck-following Model

The discomfort level for non-truck driver i , $DL(i)$, is used to reflect the interactions with a truck ahead. To reflect the greater spacing when the vehicle ahead is a truck, the FRESIM car-following model (Equation 4.12) is extended by

including a term to represent the additional contribution due to the discomfort of the following driver with respect to a truck ahead. This leads to the truck-following model:

$$H = L + 10 + qv_t + bq(u_t - v_t)^2 + \beta \times (DL - 1) \quad 4.19$$

and the acceleration rate of the follower will be:

$$a = \frac{2 \{x_{t+\delta} - y_t - L - 10 - v(q + \delta) - bq(u_{t+\delta} - v_t)^2 - \beta \times (DL - 1)\}}{\delta^2 + 2q\delta} \quad 4.20$$

where β is coefficient for DL .

In the Equations 4.19 and 4.20, the DL is subtracted by one. This is to ensure consistency between the definition of DL and its computation using the fuzzy logic approach. As discussed in Section 4.3.3, the fuzzy logic model generates values between 1 and 5, where 1 represents no discomfort. Since the discomfort level does not contribute to the headway when there is no discomfort, DL is subtracted by 1 to ensure a consistent interpretation for Equations 4.19 and 4.20.

The coefficient of the discomfort level term β , represents the weight of the contribution of the discomfort to the space headway. A variable value for β implies less conservative (lesser value for β) or more conservative (greater value for β) drivers in terms of the additional space that they would maintain with the truck ahead. We assume that β is identical across all non-truck drivers. The value of β can be calibrated using field data or a driving simulator. Due to the lack of either resource, we use the results of the study by Yoo and Green (1999). They used sixteen subjects with a driving simulator and found that the subjects followed cars about ten percent closer than they did for trucks. The socioeconomic characteristics of the subjects from that study were used to compute their DL values using our fuzzy logic approach. The ten percent increase in headway and the DL values were used to compute the β_i for each of the sixteen drivers. An average of these individual β_i values generated the β value. Based on this procedure, the β value of 8.15 was used in our study experiments in Chapters 5 and 6.

4.4.2.2. Modified lane-changing model

As discussed earlier, the non-truck driver behavior survey indicates that these drivers are more willing to change lanes when they follow a truck. This implies that truck characteristics induce non-truck followers to overtake the truck even if the truck is not slow enough to exceed the tolerance level of the follower. Based on this, the FRESIM lane-changing logic “desire” component (Equation 4.16) is modified. The desire to perform a discretionary lane change for non-truck drivers when following a truck is then modeled as:

$$D_{truck} = \begin{cases} 100 & v \leq v_{int} \\ \min \left(100 \left[\left(1 - \frac{v - v_{int}}{v_{ff} - v_{int}} \right) + \omega \cdot (DL - 1) \right], 100 \right) & v_{int} < v < v_{ff} \\ \omega \cdot (DL - 1) \cdot 100 & v \geq v_{ff} \end{cases} \quad 4.21$$

where ω is the desire coefficient associated with DL .

Figure 4.8 illustrates the desire to perform a discretionary lane change of non-truck drivers when following a truck.

Akin to the truck-following, the discomfort level term is subtracted by 1 to ensure consistency with the lane-changing logic. D_{truck} is used to represent lane-changing desire (unit in percent) when following a truck. The coefficient ω has an interpretation similar to that of β for the truck-following model. We assume that ω is identical across all non-truck drivers. Its value can be calibrated using field data or a driving simulator. In the study experiments, we assume a value 0.1 so that a driver with discomfort level 3 has a 20% probability of desiring to change lanes even when the truck ahead travels at free-flow speed.

4.4.2.3. Modified Traffic Simulator Logic

Figure 4.9 illustrates the modified simulator logic to account for driver discomfort when following a truck. It is used to develop the agent-based traffic simulation model for freeway segments. As illustrated by the figure, at each time step, each non-truck vehicle is examined to check whether it follows a truck. If it does not follow a truck, the FRESIM car-following and lane-changing models are

used to update its speed and position. If the non-truck vehicle follows a truck, the truck-following model is used to determine the space headway and acceleration rate. If the space gap is less than or equal to a 2-second time gap, interaction is identified and the modified lane-changing logic is used. If the space gap is greater than the 2-second time gap threshold, it is inferred that a car-truck interaction does not exist. Then, the FRESIM lane-changing model is used to determine the desire to change lanes. This procedure is repeated for all non-truck vehicles.

4.4.3. Computation of the AADL

As discussed in Section 4.1.4, the *AADL* is a performance measure that can be used to infer on the degree of car-truck interactions on a roadway segment. The *DL* values are obtained from the fuzzy logic approach as discussed in Section 4.3.3. The modified simulation model is used to determine whether a non-truck vehicle following a truck interacts with it. Based on this data, the average aggregate discomfort level for time interval t is computed as:

$$AADL(t) = \frac{\sum_{k=1}^{N(t)} \xi_{k,t} \cdot DL_{k,t}}{N(t)} \quad 4.22$$

where:

$N(t)$ = number of non-truck vehicles on the roadway segment of interest during

interval t

$DL_{k,t}$ = discomfort level of individual k in interval t

$$\xi_{k,t} = \begin{cases} 1, & \text{if } k \text{ has interaction with truck ahead in interval } t \\ 0, & \text{if } k \text{ does not have interaction with truck ahead in} \\ & \text{interval } t \end{cases} \quad 4.23$$

Hence, *AADL*(t) represents the average degree of car-truck interactions over the entire roadway segment for interval t .

For evaluating car-truck interactions mitigation strategies, it is more meaningful to obtain the average of the *AADL*(t) values over a pre-specified time duration. This

average aggregate discomfort level averaged over τ time intervals is denoted by $AADL_\tau$ and is expressed as:

$$AADL_\tau = \frac{\sum_{t=1}^{\tau} AADL(t)}{\tau} \quad 4.24$$

The $AADL_\tau$ is the primary performance measure used to evaluate alternative mitigation strategies evaluated through the study experiments in Chapter 6.

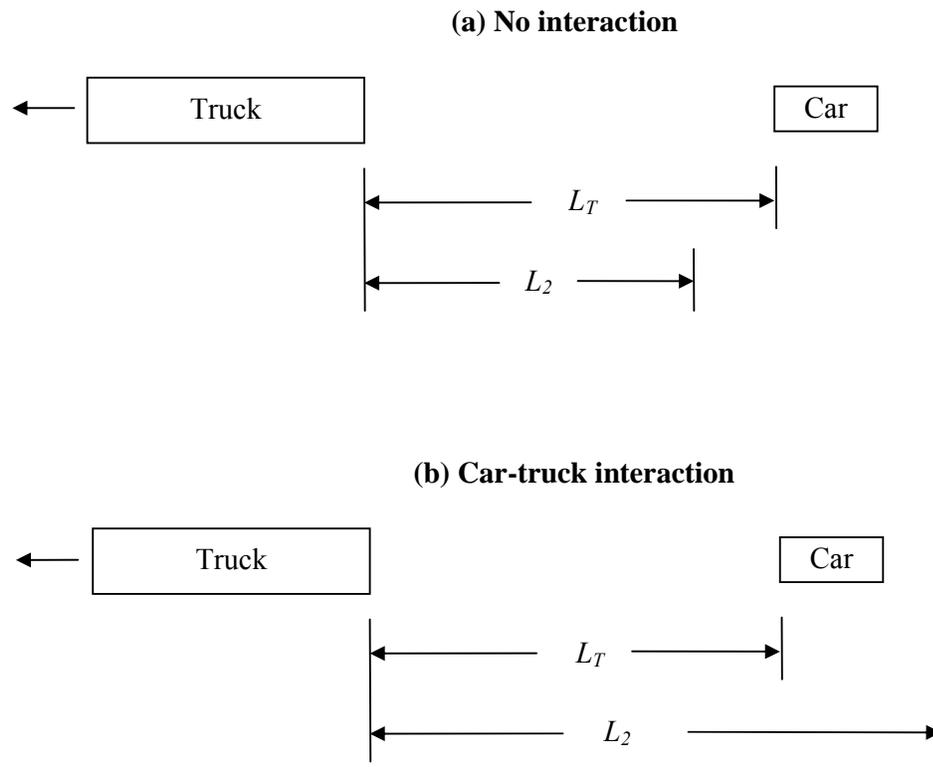


Figure 4.1 Identification of a Car-truck Interaction

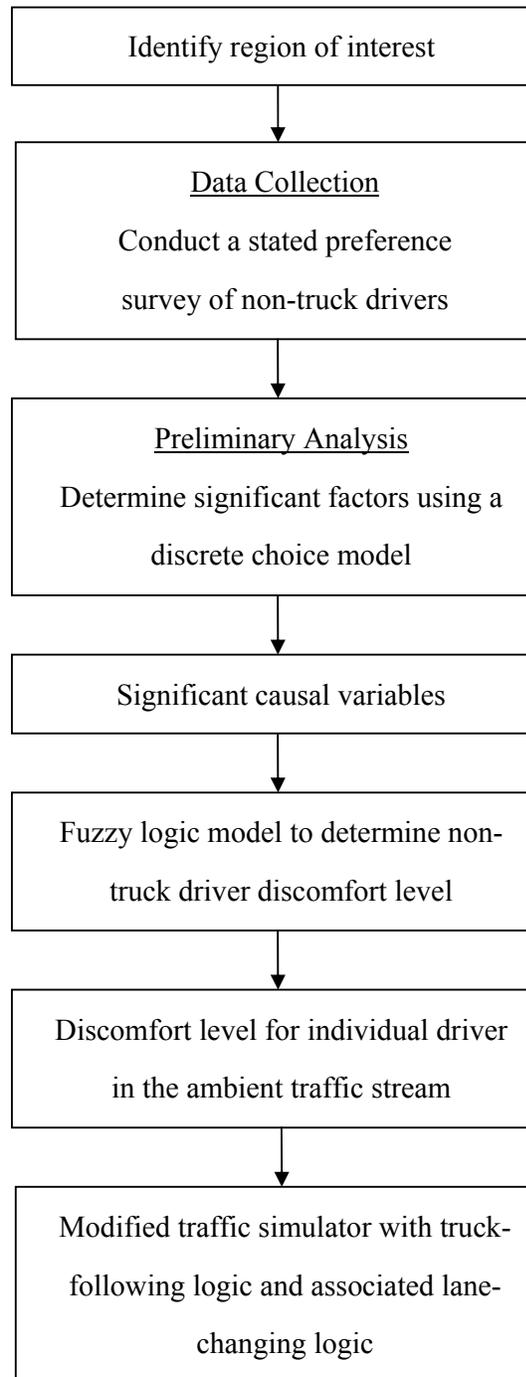


Figure 4.2 Conceptual Framework To Determine Driver Discomfort Level

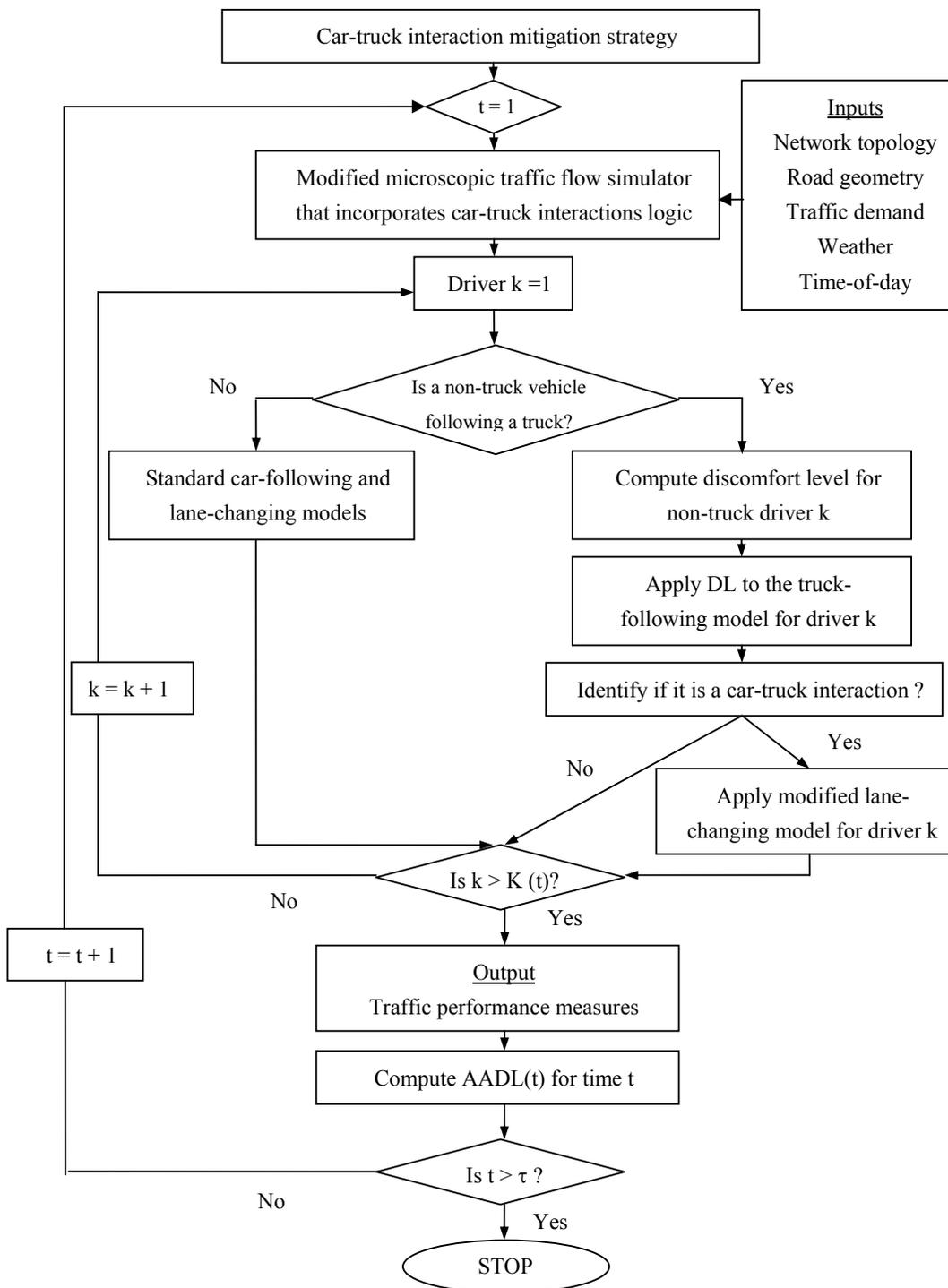


Figure 4.3 Application of Discomfort Levels to Evaluate Car-truck Interaction Mitigation Strategies

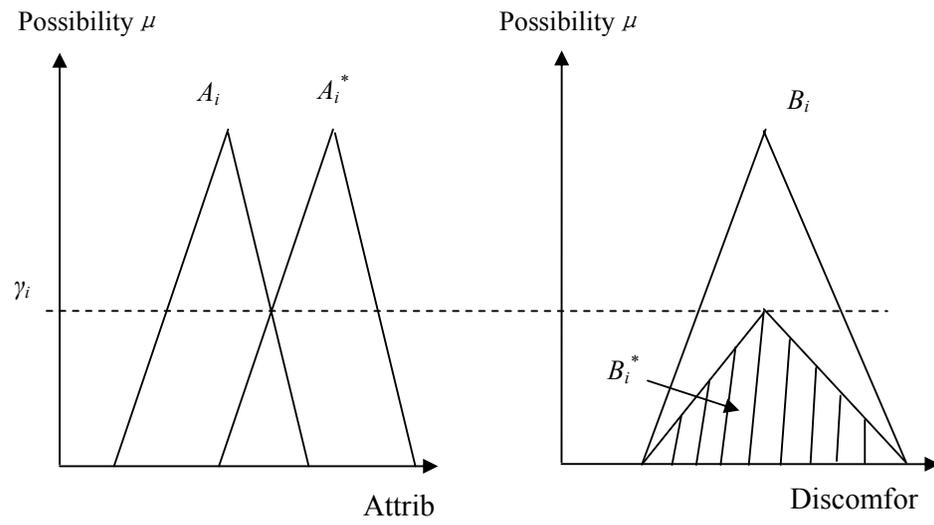
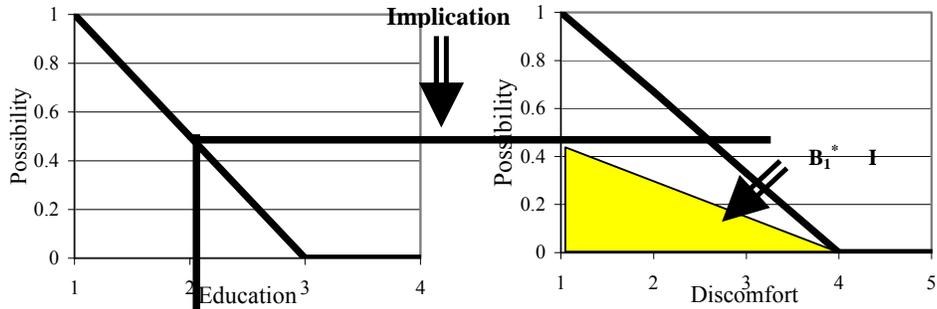
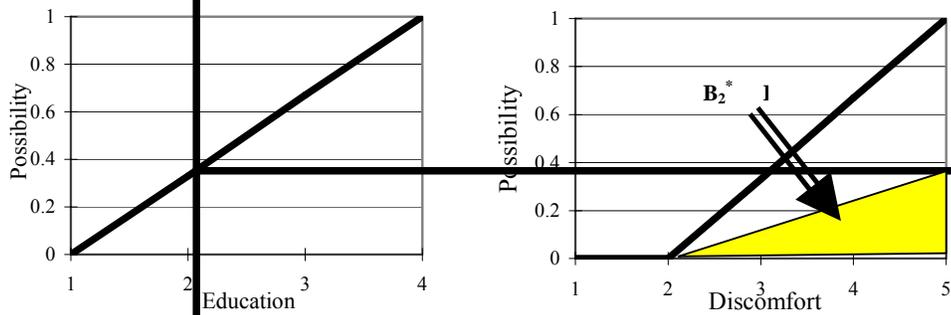


Figure 4.4 Implication Operator

Rule 1: If driver is less-educated, then the discomfort is low

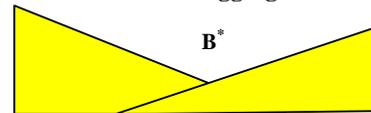


Rule 2: If driver is well-educated, then the discomfort is high



INPUT: "Some College"

Aggregation



Defuzzification

OUTPUT: Crisp Value: 2.79

Figure 4.5 Computation of Crisp Values Using IF-THEN Rules

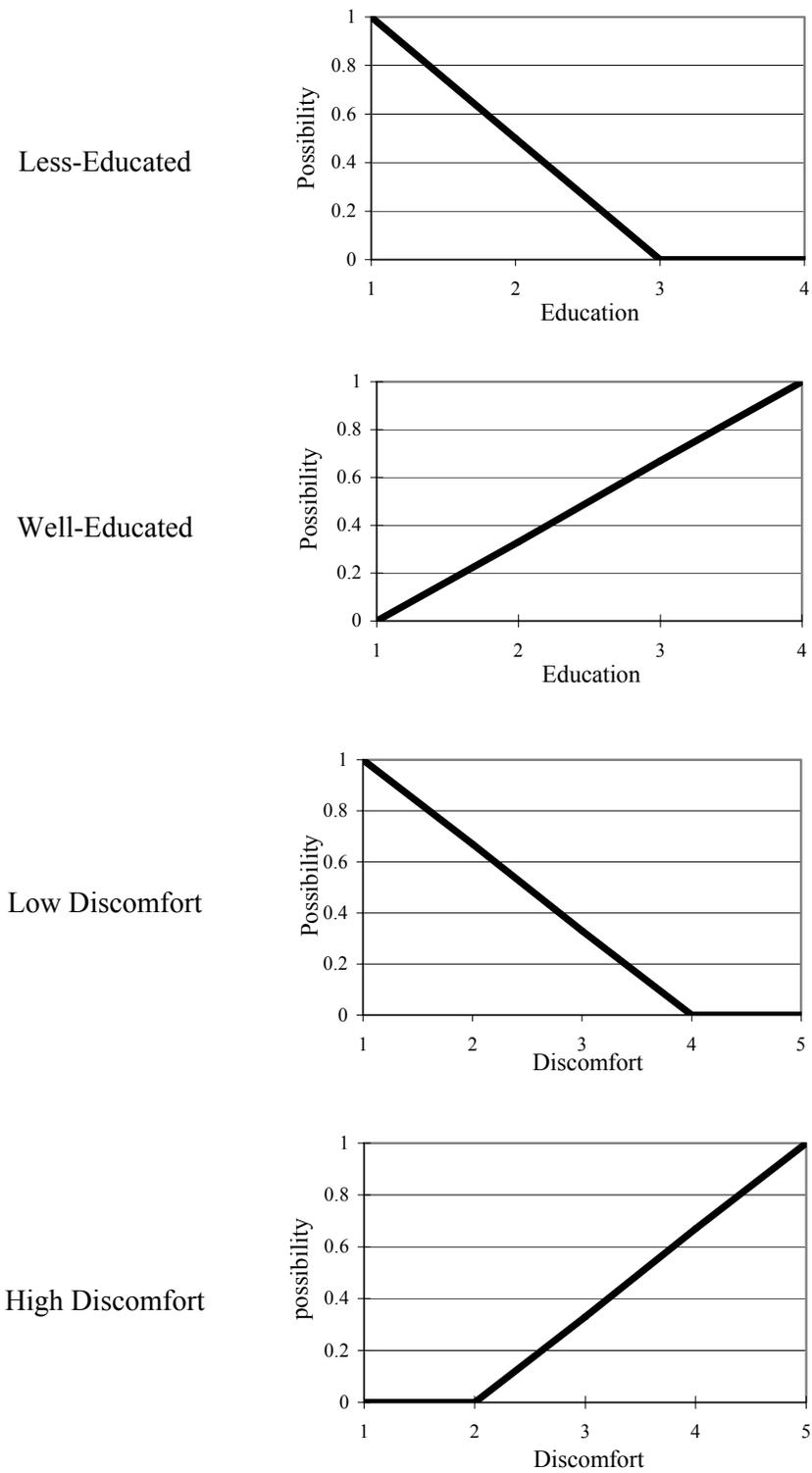


Figure 4.6 Determination of Membership Functions

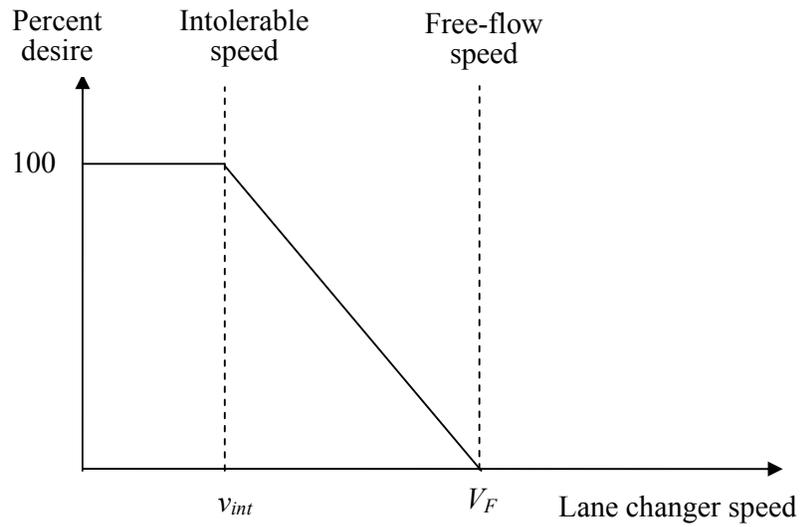


Figure 4.7 Desire to Perform a Discretionary Lane Change When Car-Following

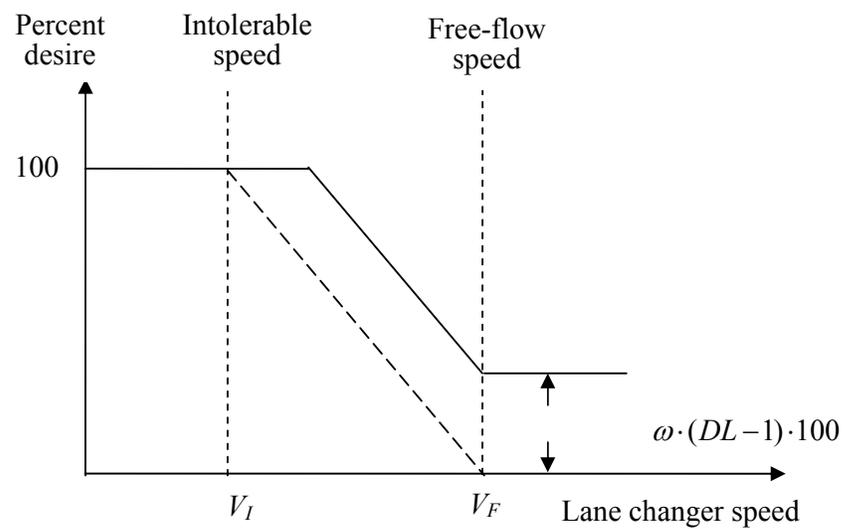


Figure 4.8 Desire to Perform a Discretionary Lane Change When Truck-Following

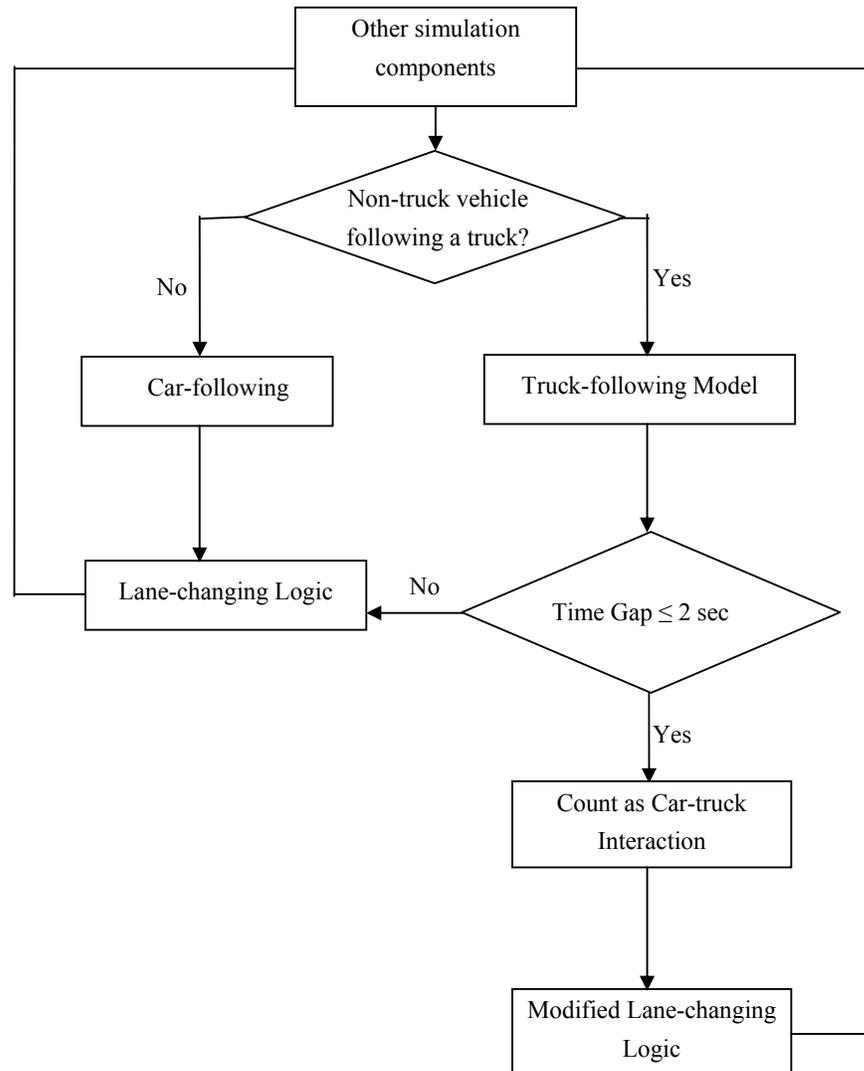


Figure 4.9 Modified Traffic Simulator Logic

CHAPTER 5. CASE STUDY

This chapter discusses the implementation of the survey, preliminary analysis of survey data, and construction of the fuzzy logic based *DL* model for the Borman Expressway case study. The preliminary analysis is performed by estimating binary logit models. The construction of the *DL* model involves the identification of the if-then rules, the construction of the membership functions for the attributes, and the determination of the weights of the attributes.

5.1. Case Study: Borman Expressway

The Borman Expressway region in Northwest Indiana is used as a case study to analyze car-truck interactions in this study. It consists of the Borman Expressway which is a sixteen-mile segment of I-80/94, the surrounding arterials, and nearby interstates, I-65 and I-90. The Borman Expressway network is shown in Figure 5.1. Besides connecting the Indiana and Illinois tollways, the Borman is also part of the Gary-Chicago-Milwaukee (GCM) corridor. This corridor connects the northwestern part of Indiana, the Chicago area, and Wisconsin, making it one of the most heavily traveled expressways in the nation. The GCM is one of the four “Priority Corridors” established by the United States Congress in the Intermodal Surface Transportation Efficiency Act (ISTEA) of 1991 to support ITS technologies and provide an operational test bed for long-term research and evaluation of ITS (Ramos, 2000).

The Borman Expressway represents an ideal testbed to analyze car-truck interactions. This is because while the average daily traffic on it is over 140,000 vehicles, truck traffic represents 30% of the total volume during peak periods, and up to 70% at nights. This makes the Borman Expressway one of the busiest commercial routes in the nation.

5.2. Data Collection and Analysis

5.2.1. Non-Truck Driver Survey

The non-truck driver behavior survey seeks to elicit driver behavioral tendencies vis-à-vis car-truck interactions for the drivers who use the Borman Expressway. However, there are no rest areas on the Borman Expressway to conduct on-site surveys. Hence, rest areas on major freeways (I-65 and I-94) that lead to the Borman Expressway are used to survey non-truck drivers. As shown by the thick circles in Figure 5.2, one rest area is located on northbound I-65 about 25 miles south of the Borman Expressway. The other rest area is on westbound I-94 about 25 miles east of the Borman Expressway. The survey respondents at these locations are highly likely to use the Borman Expressway. Using the survey questionnaire of Appendix C, responses were obtained from 159 drivers over a four-hour period at each location. The refusal rate for this on-site survey was about fifty percent.

5.2.2. Analysis of Survey Data

Table 5.1 shows the socioeconomic characteristics of the 159 non-truck drivers. About 62% of the respondents were male and 38% were female. The distribution of the respondents in terms of age groups is not uniform. Only about 28% of the respondents are less than 40 years old. It is likely that most of the drivers stopping at the rest area are on non-work or personal trips as the survey was conducted on a Monday afternoon. Also, older drivers are more willing to spend the time required to fill the survey questionnaire. The lower percentage of younger drivers may reflect the traffic stream robustly; however if it does not, the influence of age attribute can be skewed. In terms of education, 44% of the survey respondents have some college experience or lesser education, and 56% received at least one college degree. 45% have a household with 3 or more members including themselves. Most of the respondents (about 79%) are frequent users of interstate freeways.

The discomfort level of non-truck drivers when following a truck under different situations is summarized in Table 5.2. The responses were obtained in the

form of a 5-point Likert scale where 1 represents no discomfort to trucks and 5 implies the most discomfort. The results suggest that under normal conditions, the inherent discomfort level to trucks tends to be relatively low. More than 82% respondents choose a discomfort level less than or equal to 3. But under bad weather, night driving, and congestion, the level of discomfort increases. This discomfort is especially pronounced for bad weather, where only 56% of the respondents choose a discomfort level less than or equal to 3. For night driving, this percentage is 80%, implying that time-of-day may not be a significant factor. However, this can be an artifice of SP surveys whereby drivers may act differently in an actual night driving situation. In terms of congestion levels, the discomfort is the least when no congestion exists. For medium and high congestion levels, the discomfort is higher, especially under medium congestion. However, aggregate statistics can provide only a rudimentary tool to analyze trends. Hence, discrete choice modeling is used to perform a more in-depth analysis.

The third set of survey questions seek to elicit driver behavior and actions in the vicinity of trucks and the reasons for discomfort. The associated survey responses are summarized in Table 5.3. To explore the specific driving actions in the vicinity of trucks, four statements are provided (questions 5) in the survey questionnaire. The evaluation is based on the 5-point Likert scale where 1 represents “strongly disagree” and 5 represents “strongly agree.” A majority of the respondents agree with the first three statements. That is, a majority of drivers believe that they would keep a wider gap with a truck ahead. This is a primary premise for the truck-following model in this study. Similarly, drivers driving faster to overtake trucks suggest that they prefer to avoid being in the vicinity of trucks, and hence move away from them as soon as possible. The third action indicates that drivers are more likely to pass a truck than a car. This influences the lane-changing model when following a truck, which is reflected in our modified lane-changing model. In summary, the survey responses to these three statements reveal that there is a feeling of discomfort towards trucks. The responses to the fourth statement indicate that

most drivers do not avoid driving on a freeway simply because it has significant truck traffic. That is, since freeways typically are faster routes to the destinations, the travel time attribute tends to dominate other factors such as the percentage of truck traffic.

The survey also seeks reasons for driver discomfort by identifying four potential causes. About 54% of the survey respondents state that their primary discomfort towards trucks is due to trucks blocking the line of sight. Hence, a primary factor for non-truck driver discomfort to trucks is the physical characteristics of trucks. The response for this statement and others in Question 6 is based on an ordinal ranking where the driver allocates the ranking 1 to the most important reason and 4 to the least important reason. Other reasons identified as important include the perceived discomfort due to truck driver blind spot and truck size. This is reinforced by the fact that over 86% of the respondents are aware of the truck no-zone. The various significant reasons for discomfort suggest that truck size and characteristics tend to increase the uncertainty in perceiving the traffic ahead by non-truck drivers, making them more cautious. This cautiousness is reflected through the “discomfort” in the vicinity of trucks.

5.3. Preliminary Analysis using Logit Model

The binary logit model discussed in Section 4.3.2 is used to estimate the significant factors vis-à-vis discomfort level using the survey data. Of the 159 responses, 105 are used to estimate the model and the remaining ones are used for analyzing the model prediction capabilities. As stated in Chapter 3, the LIMDEP 7.0 software is used to estimate the parameters of Equation 4.2. The two choice alternatives are “low discomfort” (corresponding to survey discomfort levels 1-3) and “high discomfort” (corresponding to survey discomfort levels 4-5).

Table 5.4 illustrates the variables used to estimate the binary logit models. All attributes are included in the initial model procedure to estimate the coefficients using the survey data (6 situations \times 105 respondents = 630 pooled observations, 6

situations include general situation, bad weather, night driving, no congestion, congested traffic with smooth flow, and congested traffic with stop-and-go situation). However, variables estimated to be insignificant in the initial model are omitted in the next stage. Based on updated model, the estimation results of the binary logit model are shown in Table 5.5.

The alternative specific constant, *ONE*, has a positive value which implies that drivers choose low discomfort to trucks when situational factors and socioeconomic characteristics are not considered. *GEN* and *HHS* are the two socioeconomic characteristics found to be significant in the initial model, and are hence considered in this model. Gender has a negative coefficient implying that females have more discomfort to trucks than males. The household size coefficient is positive implying that drivers with larger families tend to have lower discomfort to trucks. This could possibly be because larger families tend to have more trips, reducing the discomfort levels for the associated drivers. That is, more trips or experience in the vicinity of trucks may lead to the driver being more comfortable.

WEA, *TOD*, *NCO*, *MCO*, and *HCO* are situational factors that are represented as dummy variables in the model. Bad weather contributes significantly to an increase in driver discomfort as illustrated by the negative sign and the level of significance for the variable *WEA*. Bad weather has a tendency to inherently increase driving discomfort, irrespective of whether a vehicle is following a truck. However, trucks can splatter water, grime and dirt on the windshields of cars in their vicinity under bad weather (rain, snow, etc.). This magnifies the effect of reduced sight for the non-truck drivers, increasing their discomfort substantially.

The variable *HCO* is also significant and has a negative sign indicating that discomfort increase with stop-and-go traffic. This could be because stop-and-go traffic corresponds to the unstable traffic regime and entails inherent uncertainty in driving conditions for drivers. The possibility that ambient traffic speeds in the vicinity of the driver can oscillate between zero and some medium speed value substantially reduces the driver's anticipatory aspect vis-à-vis future traffic

conditions. This is especially so when non-truck drivers have trucks ahead of them that block the line of sight. Also, under stop-and-go traffic, the non-truck vehicles are in close proximity of trucks, which could enhance the sense of discomfort as drivers may feel intimidated by the truck size. Further, trucks have reduced operational characteristics (speeds, acceleration, deceleration, etc.) compared to non-truck vehicles; these tend to get magnified under stop-and-go traffic.

There is a possibility that the driver discomfort under stop-and-go traffic is not actually higher compared to that for the medium congestion case. This is because speeds tend to be lower in such situations. This is partly substantiated by the survey (Table 5.2 indicates lower discomfort for high congestion compared to medium congestion when responses 1 and 2 are considered). However, this difference is not significantly high. This can be due to a key limitation of SP surveys where driver's stated discomfort is higher than the revealed discomfort. This is possible because higher congestion has a negative connotation in a driver's mind and that may be transferred to the notion of discomfort in the vicinity of trucks though speeds would be significantly lower under stop-and-go traffic. The inconsistency can also be due to the aggregation of *DLs* in the binary logit model using Equation 4.4, where stated *DLs* 1, 2, and 3 are grouped as "low discomfort". Hence, in this study, we go with the latter viewpoint based on the insights from the survey data which suggests that higher congestion implies medium discomfort. It also suggests that under the congested traffic case with smooth flow, the discomfort is high as speeds are significantly higher.

The situational factors *TOD*, *NCO* and *MCO* are not significant as their t-statistics are low, especially for *TOD* and *NCO*. In reality, time-of-day can have significant influence on driver discomfort and the survey data may simply represent an artifice of SP surveys. Similarly, different congestion levels can influence driver discomfort. However, since these are situational factors, their influence is more robustly elicited through revealed preference data rather than SP data. Hence, we retain these variables in the fuzzy model discussed in the next section.

It can be noted that *NCO*, *MCO* and *HCO* represent three levels of traffic congestion. Hence, the model in Table 5.5 can be modified to have a single variable for congestion, labeled *CON*. The coefficients for *NCO*, *MCO* and *HCO* in Table 5.5 are -0.341, -0.519 and -0.882, respectively indicating that discomfort to trucks increases with congestion level. To ensure that congestion with smooth flow (*MCO*) denotes the default situation in most freeway traffic streams, it is assigned a value 0 in the modified model. Based on this, *CON* is assigned a value -1 for no congestion and a value 1 for high congestion with stop-and-go traffic to ensure consistency in the interpretation of *DL* under congestion.

Table 5.6 illustrates the modified binary logit model estimated with the single variable for congestion level, *CON*. The t-statistic value indicates that this variable is significant. Its coefficient is negative indicating increased discomfort with congestion. This forms the basis for the “congestion” related if-then rules in the fuzzy logic model. It should be noted here that the survey itself suggests slightly higher discomfort under medium congestion compared to high congestion, as illustrated in Table 5.2. The potential error is because of the use of Equation 4.4 to group stated *DLs* 1,2, and 3 as low discomfort, and 4 and 5 as high discomfort in the binary logit model.

Hence, based on the preliminary analysis, the variables *GEN*, *HHS*, *WEA*, *TOD*, and *CON* are found to be significant vis-à-vis discomfort levels.

5.4. Fuzzy Logic Based Discomfort Level Model

This section discusses the if-then rules and the membership functions for the fuzzy logic modeling approach for the case study. This is based on the methodology discussed in Section 4.3.3. The variables considered for the *DL* model are highlighted in Equation 4.5. They include the socioeconomic characteristics age, gender, education and household size. In addition, weather conditions, time-of-day and congestion levels represent the situational factors. Past studies (NHTSA, 1998) on driver behavior suggest that age and education can have a perceptible influence

on driving actions. In general, younger people, whose reaction times are lower, tend to be more aggressive while driving and maintain lower headways with vehicles ahead. Similarly, better-educated drivers are likely to employ greater caution while driving. Hence, age and education are included in the *DL* model.

Table 5.7 highlight the if-then rules employed in the fuzzy logic based *DL* model for the case study. They are based on the survey insights and the preliminary analysis. As discussed in Section 4.1.2, the socioeconomic variables are constant or relatively unchanged. However, the situational factors are time-dependent. Hence, non-truck driver discomfort levels are dynamic variables to capture the effects of weather, time-of-day and congestion in the actual driving situation.

As discussed in Section 4.3.3.1, the variables represented by the if-then rules are fuzzy in nature. Hence, membership functions are constructed for them. Figure 5.3 shows the membership functions used in the case study. The x-axis represents the fuzzy variables and the y-axis has denotes the possibility value.

As discussed in Section 4.3.3.5, a set of simultaneous equations are solved to estimate the weights associated with the crisp values for the fuzzy variables in Equation 4.5. The weights for the seven attributes are 0.2566, 0.0007, 0.0004, 0.1701, 0.4051, 0.0277, 0.1394, respectively, for gender, age, education, household size, weather, time-of-day and congestion level. These weights are consistent with the survey data and the preliminary analysis. As can be seen, the contributions due to age and education are negligible, consistent with survey insights. These weights are used in the study experiments discussed in Chapter 6.

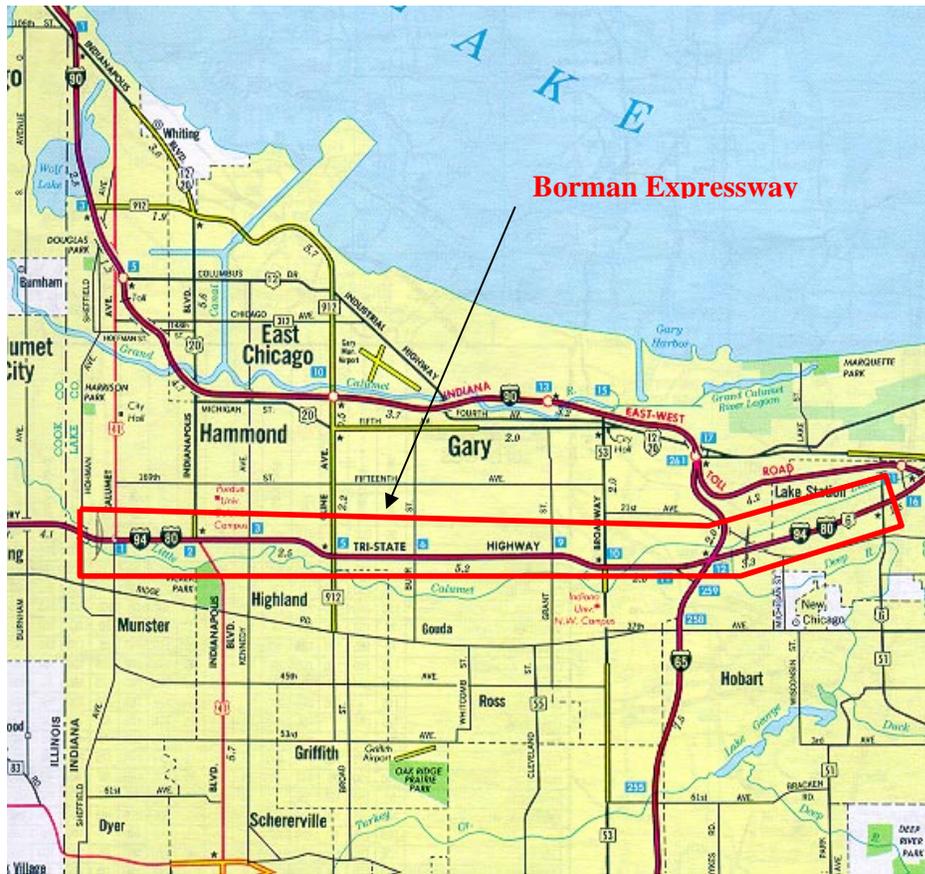


Figure 5.1 Borman Expressway Network (Source: Ramos, 2000)



Figure 5.2 Non-Truck Driver Survey Locations

Table 5.1 Socioeconomic Characteristics of Survey Respondents

Attribute	Grouping	Non-truck Drivers (%)
Gender	Male	99 (62.3%)
	Female	60 (37.7%)
Age Group	<20	3 (1.9%)
	20-29	19 (11.9%)
	30-39	23 (14.4%)
	40-49	34 (21.4%)
	50-64	49 (30.8%)
	≥65	31 (19.5%)
Education Level	High school or less	29 (18.2%)
	Some college	41 (25.8%)
	College graduate	41 (25.8%)
	Postgraduate	48 (30.2%)
Persons in Household	1	22 (13.8%)
	2	65 (40.9%)
	3	24 (15.1%)
	≥4	48 (30.2%)
Freeway Usage	Very frequent	48 (30.2%)
	Frequent	77 (48.4%)
	Neutral	21 (13.2%)
	Not frequent	8 (5.0%)
	Seldom	5 (3.2%)

Table 5.2 Influence of Situational Factors

Situation		Discomfort level when following a truck				
		1	2	3	4	5
1	No specific situation (normal conditions)	47 (29.6%)	41 (25.8%)	44 (27.7%)	20 (12.6%)	7 (4.4%)
2	Bad weather (rain or snow)	16 (10.1%)	30 (18.9%)	43 (27.0%)	46 (28.9%)	24 (15.1%)
3	Night driving	41 (25.8%)	45 (28.3%)	42 (26.4%)	19 (11.9%)	12 (7.6%)
4	Low congestion	59 (37.1%)	41 (25.8%)	42 (26.4%)	11 (6.9%)	6 (3.8%)
5	Medium congestion (with smooth flow)	33 (20.8%)	33 (20.8%)	52 (32.7%)	26 (16.3%)	15 (9.4%)
6	High congestion (with stop-and-go traffic)	45 (28.3%)	38 (23.9%)	33 (20.8%)	26 (16.3%)	17 (10.7%)

Table 5.3 Driver Behavior and Actions

Question 5	1	2	3	4	5
I prefer to keep a wider gap with a truck ahead than a car ahead when following it	22 (13.8%)	26 (16.4%)	44 (27.7%)	28 (17.6%)	39 (24.5%)
The speed at which I drive to pass a truck ahead is faster than the speed of passing a car ahead	17 (10.7%)	32 (20.1%)	37 (23.3%)	42 (26.4%)	31 (19.5%)
I am more likely to pass a truck than a car	31 (19.5%)	27 (17.0%)	25 (15.7%)	41 (25.8%)	35 (22.0%)
The presence of significant truck traffic influences my decision to avoid driving on a freeway	54 (34.0%)	35 (22.0%)	27 (17.0%)	22 (13.8%)	21 (13.2%)

Question 6	1	2	3	4	None
Blocks your sight; you cannot see the traffic in front of the truck	86 (54.1%)	31 (19.5%)	21 (13.2%)	7 (4.4%)	14 (8.8%)
Speed of trucks is slow	17 (10.7%)	29 (18.2%)	32 (20.1%)	54 (34.0%)	27 (17.0%)
The truck driver cannot see me	35 (22.0%)	45 (28.3%)	41 (25.8%)	16 (10.1%)	22 (13.8%)
Feel intimidated by truck size	35 (22.0%)	25 (15.7%)	28 (17.6%)	44 (27.7%)	27 (17.0%)

Question 7	Yes	No
Have you heard of the huge “blind spot” for truck drivers	138 (86.8%)	21 (13.2%)

Question 8	1	2	3	4	5	None
Discomfort on Borman Expressway	25 (15.7%)	28 (17.6%)	51 (32.1%)	29 (18.2%)	17 (10.7%)	9 (5.7%)

Question 9	
More comfortable with the same speed limit for trucks	67 (42.1%)
More comfortable with the lower speed limit for trucks	92 (57.9%)

Table 5.4 Explanatory Variables

Explanatory Variable	Mnemonics
Alternative Specific Constant	ONE
Gender =1, if male =2, if female	GEN
Age =1, if ≤ 20 =2, if 21-30 =3, if 31-40 =4, if 41-50 =5, if 51-64 =6, if ≥ 65	AGE
Education =1, if high school or less =2, if some college =3, if college graduate =4, is postgraduate	EDU
Household Size =n, if the household size is n	HHS
Freeway Experience =1, if very frequent user of freeways =2, if frequent user of freeways =3, if neutral user of freeways =4, if not frequent user of freeways =5, if seldom user of freeways	FRQ
Bad Weather Situation (dummy variable)	WEA
Night Driving Situation (dummy variable)	TOD
No Congestion (dummy variable)	NCO
Congested Traffic with Smooth Flow (dummy variable)	MCO
Congested Traffic with Stop-and-go Situation (dummy variable)	HCO

Table 5.5 Binary Logit Model from Non-truck Driver Behavior Survey Data

Variable	Model Coefficient (t-statistic)
ONE	1.731 (3.886)
GEN	-0.568 (-2.842)
HHS	0.313 (4.047)
WEA	-1.624 (-4.727)
TOD	-0.213 (-0.564)
NCO	-0.341 (0.821)
MCO	-0.519 (-1.425)
HCO	-0.882 (-2.500)
Sample size	630
L(0)	-436.68
L(β)	-310.67
ρ^2	0.289

Table 5.6 Modified Binary Logit Model with Single Attribute for Congestion

Variable	Model Coefficient (t-statistic)
ONE	1.682 (4.388)
GEN	-0.567 (-2.841)
HHS	0.313 (4.047)
WEA	-1.576 (-6.103)
TOD	-0.165 (-0.545)
CON	-0.299 (-3.551)
L(0)	-436.68
L(β)	-311.03
ρ^2	0.288

Table 5.7 If-then Rules for Case Study DL Model

Category	LHS	RHS
Gender	If driver is a man	Discomfort is low
	If driver is a woman	Discomfort is high
Age	If driver is young	Discomfort is low
	If driver is old	Discomfort is high
Education	If driver is less-educated	Discomfort is low
	If driver is well-educated	Discomfort is high
Household Size	If driver has a big family	Discomfort is low
	If driver has a small family	Discomfort is high
Weather	If weather is good	Discomfort is low
	If weather is bad	Discomfort is high
Time of Day	If driving during day	Discomfort is low
	If driving during night	Discomfort is high
Congestion	If the traffic is not congested	Discomfort is low
	If the traffic is highly congested	Discomfort is medium
	If the traffic is congested with smooth flow	Discomfort is high

Figure 5.3.a Driver is young

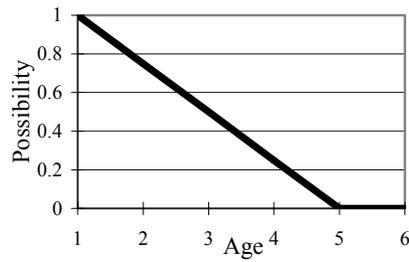


Figure 5.3.b Driver is old

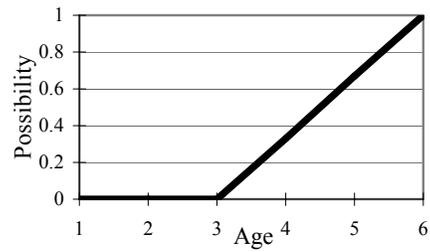


Figure 5.3.c Driver is less-educated

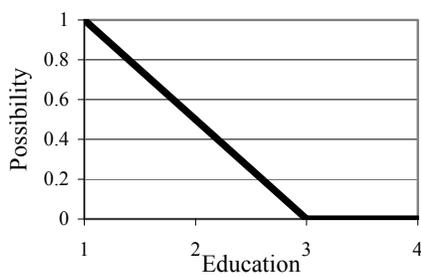


Figure 5.3.d Driver is well-educated

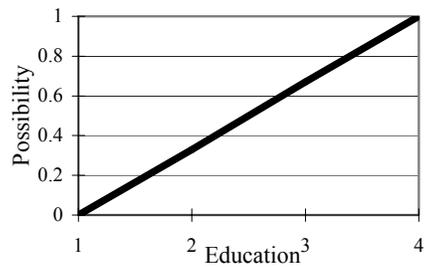


Figure 5.3.e Small household

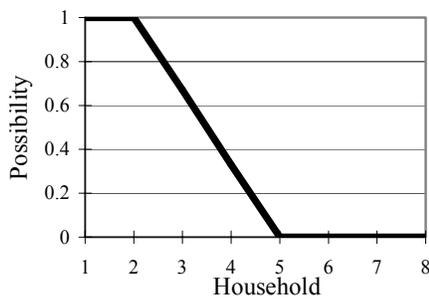


Figure 5.3.f Large household

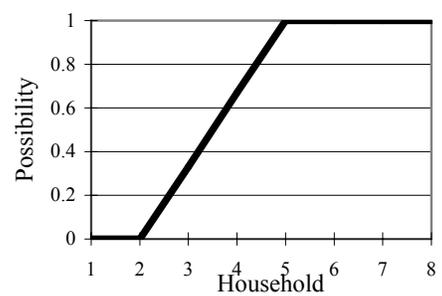


Figure 5.3.g Discomfort is low

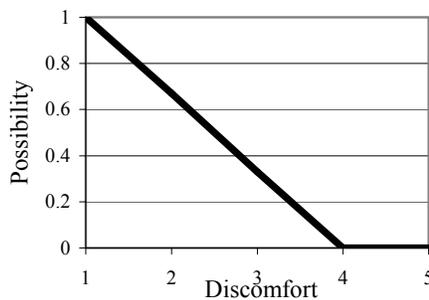


Figure 5.3.h Discomfort is high

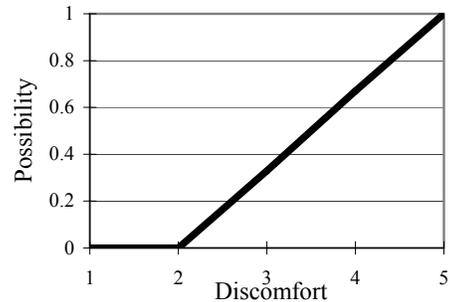


Figure 5.3 Membership Functions for the Fuzzy Variables for Which If-then Rules are Constructed

CHAPTER 6. SIMULATION EXPERIMENTS

This chapter discusses the simulation experiments conducted for the case study to perform sensitivity analyses on the model parameters and evaluate the effectiveness of alternative mitigation strategies. The results from the sensitivity analyses and evaluation of strategies are used to derive insights on the characteristics and impacts of car-truck interactions.

6.1. Simulation Model Setup

6.1.1. Environment

The simulation experiments are conducted using the agent-based simulation model discussed in Section 4.4. The simulation model is coded in the SWARM (Daniels, 1999) programming environment. SWARM, a program development environment based on Objective C or Java languages, is a collection of software libraries which provide support for simulation programming. It is especially designed for agent-based simulation. It is a free software and can be obtained at www.swarm.org.

Agent-based modeling in the SWARM environment is used to build the microscopic traffic flow simulator for freeway segments consistent with the modified FRESIM logic discussed in Section 4.4.2. Each vehicle in the simulator, truck or non-truck, is an agent with specific socioeconomic characteristics (age, gender, educational level and household size) that are assigned consistent with the survey data as discussed in Section 6.1.3.2. Each vehicle interacts with other vehicles every time step, which is one second in the simulator. The discomfort level towards trucks for each non-truck driver encountering a truck ahead is computed for the relevant time steps using the fuzzy logic approach based on the agent socioeconomic characteristics and the situational factors encountered by that agent.

The *AADL* is computed every simulation second using the procedure in Section 4.4.2.3. It is used as a key performance measure to infer on car-truck interactions.

6.1.2. Demand Generation and Loading

The simulator mimics a 2-mile long freeway section, illustrated in Figure 6.1. A demand profile and the associated loading factor, discussed in Section 6.1.3.1, are used to generate vehicles for a 30-minute duration. The vehicles generated include trucks and non-trucks based on the percentage of trucks in the traffic stream. As shown in Figure 6.1, the vehicles are generated to a single loading stack queue, assigned randomly to a lane, and discharged sequentially. Hence, the loading queue can be viewed as a single-lane entrance ramp or the boundary for the space domain for which car-truck interactions analysis is desired. The speed of the vehicle at the beginning once it enters a lane is set as the average speed for that lane in that time interval. However, the determination of when a vehicle enters the assigned lane is based on the car-following or truck-following space headway requirements. If sufficient space headway consistent with the following logic does not exist for a vehicle assigned in the current interval, it is randomly assigned to another lane if it is not constrained by lane restrictions and discharged in the same interval. If it cannot be assigned to another lane due to lane restrictions, it is held back till the next interval and the loading logic is repeated. It should be noted that vehicles cannot jump the queue; that is, a vehicle behind another vehicle in the queue cannot be assigned a lane till the vehicle ahead is discharged from the queue to one of the lanes. Hence, after discharging the first vehicle, sequentially the next vehicle in the demand loading queue is randomly assigned to a lane. This process is repeated till the queue is empty. Note that at low demand levels, a loading queue may not exist. That is, a vehicle may be generated and discharged in the same scanning interval. Conversely, long loading queues may exist for heavy demand loads.

6.1.3. Simulation Parameters

6.1.3.1. System Parameters

6.1.3.1.1. Loading factor and profile

Loading factor is an indicator to benchmark the demand intensity and to compare alternative demand loads. Typically, the loading factor for the base case is set to 1. In this study, the base case entails a uniform demand 2000 vph and is benchmarked as loading factor 1. Hence, a loading factor 2 represents twice the base case demand and implies a demand of 4000 vph. Figure 6.2 illustrates the three loading factors (1, 2, 2.5) considered under the uniform demand profile. Figure 6.3 shows the two loading profiles (uniform and peaking) considered in the experiments for loading factor 1. A peaking profile can generate greater intensity of congestion, and in a time-dependent manner. Since most analyses are relevant for peak periods, this analysis can be insightful.

6.1.3.1.2. Truck percentage

Truck percentage in the ambient traffic stream can significantly influence car-truck interactions. Also, in the context of the case study, truck percentage can vary from 30% to 70% on the Borman Expressway. The experiments consider four truck percentages for analysis (10%, 30%, 50% and 70%). However, 70% may represent too high a fraction of truck traffic in most instances. Even on the Borman Expressway, a 70% truck volume is obtained only during off-peak periods. Hence the 70% case is considered only for low to medium road congestion situations in the case study. The study base case considers a 20% truck volume in the traffic stream.

6.1.3.1.3. Lane Assignment Scheme

The lane assignment scheme states the lanes on which trucks are allowed on the freeway. It is the basis for many supply-side strategies to mitigate car-truck interactions. Since the freeway segment has three lanes, the three strategies considered are: truck restricted to right lane, truck restricted to right two lanes, and

trucks allowed on all three lanes. The base case, representing the current strategy on the Borman Expressway, restricts trucks to the right two lanes on the freeway segment.

6.1.3.2. Agent Parameters

As stated earlier, socioeconomic characteristics are specified for each vehicle agent consistent with the SP survey data. These characteristics are maintained unchanged for all the simulation experiments.

6.1.3.2.1. Gender

For each driver, gender is randomly generated consistent with the survey data in Table 5.1. Hence, more male drivers are generated for the study.

6.1.3.2.2. Age

The age of an agent is in the range 16-80 years, and is generated randomly consistent with the survey data in Table 5.1.

6.1.3.2.3. Household size

The household size of an agent is in the range 1-8. It is randomly generated consistent with the survey data in Table 5.1.

6.1.3.2.4. Education

The education level of an agent is randomly generated from the four possibilities (high school or less, some college, college graduate, and postgraduate) consistent with Table 5.1.

6.1.3.2.5. Driver type

Driver type factor is a parameter in FRESIM that represents the aggressiveness of drivers. It is a uniform random number between 1 to 10, with 10 representing the most aggressive driver and 1 representing the most timid driver. Another factor in FRESIM, the driver sensitivity factor, is determined by the driver type factor as shown in Table 6.1.

6.1.3.2.6. Free-flow speed

In the simulator, each vehicle is assigned a free-flow speed based on the vehicle type. For non-truck drivers, free-flow speed is uniformly distributed from 60 mph (96.6 kmph) to 70 mph (112.7 kmph). Free-flow speed for truck drivers is uniformly distributed from 55 mph (88.5 kmph) to 65 mph (104.6 kmph). This represents the speed differences among vehicle types along the Borman Expressway, which has a speed limit 55 mph (88.5 kmph). The free-flow speeds for trucks are slightly lower (by 5mph) based on Indiana speed limits.

6.1.4. Simulation Base Case

Based on the description of the various simulation parameters, Table 6.2 summarizes the values of the parameters in the simulation base case. The base case represents the benchmarking scenario to which most experiment outcomes are compared. Here, low congestion demand (2000 vph) with 20% trucks by volume is assumed to represent the base case. In terms of lane restriction scheme, the current scheme on the Borman Expressway which restricts the trucks to the right two lanes is assumed to represent the benchmarking scenario. The socioeconomic characteristics are assumed to be consistent with the distributions obtained through the SP data, and summarized in Table 5.1.

6.1.5. Computational Statistics

6.1.5.1. Duration for Computing Statistics

The freeway segment simulator has a 30-minute demand generation period. The simulator begins when the first vehicle is generated and ends when the last vehicle leaves the 2-mile freeway segment. Hence, the simulation duration is the time difference between these two events. But, such as approach inherently introduces start-up and end-time effects to reflect the durations required to fill the 2-mile segment at the start of the simulation and empty the 2-mile segment towards the end of the simulation, respectively. Hence, the start-up and end-time effects can artificially skew the performance measures. The standard approach to circumvent

this issue is to eliminate the statistics for these periods and compute the performance measures based on the simulation output for the intermediate duration. This is illustrated in Figure 6.4. T_c denotes the intermediate duration for which simulation statistics are computed. T_b is the time duration to populate the freeway section. It is the time at which the first vehicle leaves the freeway segment. However, in this study, it is conservatively set at a constant value of 150 seconds. t_2 denotes the time at which the last generated vehicle enters the freeway segment. This time value depends primarily on the level of demand congestion. If a highly congested demand scenario exists, vehicles can spend a significant amount of time in the queue. Hence, t_2 is partly an indicator of the demand loading level. T_c denotes the time duration between when the last generated vehicle enters the freeway segment and the last vehicle leaves it. Therefore, the simulation statistics (performance measures) are computed for the duration:

$$T_c = T_s - T_b - T_e \quad 6.1$$

6.1.5.2. Performance Measures

The simulation statistics used to analyze different scenarios are the primary performance measures computed for the duration T_c . They include *AADL*, number of car-truck interactions, average speed, average travel time, average lane speed differentials. They are briefly defined hereafter.

AADL: The *AADL* is the primary indicator of the degree of car-truck interactions. It is computed for the duration T_c using the procedure discussed in Section 4.4.3.

Number of car-truck interactions: This measure is another indicator for the level of car-truck conflicts. It is computed for the duration T_c using the logic discussed in Section 4.1.3 to identify car-truck interactions. While *AADL* provides a quantitative measure for level of discomfort, the number of car-truck interactions is a directly inferable measure that can provide additional insights.

Average speed: The average speed for the simulation is obtained by averaging the average freeway segment speeds over all time steps for the duration T_c .

Average travel time: The average travel time for the simulation is obtained by averaging the travel times of all vehicles in the duration T_c . The travel time for a vehicle is defined as the time duration between when a vehicle enters the loading queue and when it leaves the freeway segment.

Average lane speed differential: The average lane speed differential is the average of the differences in the average speeds for adjacent lanes over the duration T_c . Average lane speed differentials are a reasonable proxy for safety in the freeway segment. This is because past studies suggest greater safety issues when speed differentials are higher.

In summary, the performance measures (i) and (ii) are indicators of the level of car-truck interactions; the performance measures (iii) and (iv) related to traffic network performance; and (v) is a proxy for safety.

6.2. Simulation Experiments

Simulation experiments are conducted using the case study and the simulation parameters discussed in earlier sections. Before addressing the study objectives, the validity of the microscopic freeway segment agent-based traffic simulator is analyzed. This is done by plotting the fundamental traffic flow relationships between speed, density and flow using an initial set of runs on the traffic simulator. The parameters for the base case are used for this purpose, except for demand which is varied from 1000 to 8000 vph. The simulation statistics are collected for the duration T_c . Next, the sensitivity analyses and evaluation of alternative car-truck interaction mitigation strategies are performed by varying the appropriate simulation parameters.

6.2.1. Validity of the Agent-Based Simulator

The microscopic freeway segment agent-based simulator based on the modified logic of the relevant FRESIM components is tested to analyze its validity vis-à-vis realistic traffic flow replication. Traffic flow realism entails that the simulation flow

statistics comply with the fundamental traffic flow relationships. This is done by plotting these relationships for the FRESIM model without the car-truck interaction logic and the modified microscopic agent-based simulator. Figure 6.5 and Figure 6.6, respectively, show these plots.

The plots for the fundamental traffic flow relationships in Figure 6.5 and Figure 6.6 are obtained using 10 simulation runs for the base case with various loading factors ranging from 0.5 to 4. In each run, six time snapshots (at 5 minutes, 10 minutes, 15 minutes, 20 minutes, 25 minutes, and time t_2 in Figure 6.4) are obtained for the various traffic flow parameters. Hence, sixty time snapshots are plotted on each figure. The plots show that both the FRESIM model and the modified simulator are realistic in terms of replicating the fundamental relationships between speed, density, and flow. There is a slight deterioration in performance due to car-truck interactions, as highlighted by the speed-density plots at the higher densities in Figure 6.6 compared to Figure 6.5. With this validation, the modified agent-based simulator is used to analyze the study objectives.

6.2.2. Sensitivity Analyses

6.2.2.1. Situational Factors

Figure 6.7 illustrates the impacts of truck percentage in the ambient traffic stream, night-time driving, and bad weather on the driver discomfort levels represented by *AADL* for loading factor 2. The figure illustrates the *AADL* for the duration T_c for varying truck percentages. The *AADL* increases with truck percentage. This is intuitive because the likelihood of car-truck interactions increases with truck percentage. Hence, as the number of interactions increase, the *AADL* increases as well when other conditions (such as loading factor) are identical. This is also aided by the fact that the number of non-truck vehicles decrease with increasing truck percentage, as illustrated by Equation 4.22.

The impacts of bad weather and night-time driving are consistent with the survey data. Both the preliminary analysis and the fuzzy attribute weights suggest that bad weather significantly affects the *AADL* while night-time driving has a marginal effect on it. This is reflected by the significant increase in the *AADL* values under bad weather. By contrast, the *AADL* values for night-time driving are not significantly different from those for the normal driving conditions (good weather, day-time driving). Hence, bad weather is an important factor that affects driver discomfort to trucks.

6.2.2.2. Congestion (Density)

The impacts of congestion on *AADL* are evaluated by tracking its proxy, density, as shown in Figure 6.8. At low to medium densities, the *AADL* increases with density. However, as we move from medium to high density levels, the *AADL* decreases. This trend illustrates a significant characteristic of driver discomfort towards trucks vis-à-vis congestion that is consistent with driver behavior realism. It is reasonable that drivers have greater discomfort towards trucks when speeds are higher along with density. However, when speeds are low along with high density, drivers would feel more in control of the driving situation, and consequently, may not exhibit high *AADL*.

At low congestion levels, speeds are higher but density is lower, reducing the likelihood of car-truck interactions. Hence, *AADL* is low for low densities. For medium congestion levels, the speeds are relatively higher, but so is the density. Hence, drivers are more tightly packed together in the traffic stream, though the flow itself is smooth and speeds are relatively high. This increases the likelihood of car-truck interactions based on the logic of Section 4.1.3 to identify car-truck interactions. Therefore, driver discomfort is high for medium congestion levels, as illustrated in Figure 6.8. At high congestion levels, vehicles are tightly packed together in the traffic stream. This reduces speeds based on driver psychology of being cautious when moving in tightly packed streams. Based on the logic for car-

truck interactions in Section 4.1.3, this reduces the likelihood of car and trucks interacting as the 2-second time gap threshold may not be breached as often as under medium congestion. These trends are also consistent with the survey data shown in Table 5.2, where respondents have lesser discomfort under stop-and-go traffic compared to the congestion with smooth flow scenario.

Another clear trend in Figure 6.8 is the greater variance in *AADL* at lower densities. This is because car-truck interactions tend to be random under low congestion levels. As congestion increases, vehicles tend to be packed closer together, reducing the randomness in car-truck interactions.

6.2.2.3. Vehicle Destination

The destination of a vehicle traveling on the freeway can influence the degree of car-truck interactions. This is especially so for non-truck vehicles as they are constrained to shift to the right-most lane to exit. Figure 6.9 shows the exit ramp for the freeway segment being analyzed here. The exit ramp is assumed to be exactly at the end of the 2-mile segment. It is assumed that there is a sign in the middle of the segment (that is, one mile from the end of the segment) that warns of the impending arrival of the associated exit number. Ten percent of the drivers entering the freeway segment are assumed to exit at the end of it. This implies the need to shift to the right-most lane, if necessary, before the exit ramp is reached. These vehicles are assumed to have a 100% desire to perform a lane change after reaching the warning sign. The *AADL* is recorded for these drivers before and after the exit warning sign. The simulation results show that the *AADL* is lower before the warning sign (1.35) and higher (1.46) after it. These *AADL* values are based on 3 runs of the simulator for a loading factor 2. This analysis indicates the significance of vehicle destination to the driver discomfort levels.

6.2.2.4. Incidents

Incidents can severely deteriorate traffic conditions. Hence, they can significantly influence *AADL* depending on their characteristics. This is because all

vehicles blocked by an incident need to shift lanes, which increases the potential for car-truck interactions. To explore the impacts of incidents under incidents, the left-most lane is blocked between the 1.0 mile and 1.5 mile markers for the entire simulation duration, as shown in Figure 6.10. Vehicles on the left-most lane have a 100% desire to perform a lane change on the first half of the freeway segment. The lead factor, which denotes the disadvantage of remaining in the current lane is set to 1 for the left-most lane upstream of the bottleneck. The *AADL* is plotted under different levels of congestion (loading factors 0.5 to 4) for the first and second halves of the freeway segment. Figure 6.11 plots the *AADL* values for each half for different loading factors. The *AADL* is higher for the first half as non-truck vehicles shift to the middle lane, increasing the potential for car-truck interactions. The *AADL* values increase with congestion levels up to medium congestion levels, similar to the trends in Figure 6.8. Consequently, the difference in *AADLs* between the first and second halves of the segment increases with demand load up to some point, and decreases beyond it.

6.2.2.5. Demand Loading Profile

The shape of the demand loading curve can also impact *AADL*. As discussed earlier, the two loading profiles considered are the uniform and peaking profiles. They are illustrated in Figure 6.3. For the same number of vehicles generated, a peaking profile can lead to worse traffic congestion due to the high loading rates for some duration. The simulation results for the various loading factors confirm this trend for car-truck interactions as well, as illustrated in Figure 6.12. The *AADL* values for the peaking profile are lower. This is consistent with insights from the sensitivity analysis for congestion levels discussed in Section 6.2.2.2. At high congestion levels, the *AADL* reduces. Since the peaking profile generates relatively higher congestion levels compared to the uniform loading profile, the *AADL* is lower for the peaking profile.

6.3. Operational Strategies to Mitigate Car-Truck Interactions

Operational strategies can be used to reduce car-truck interactions. As part of the study, a nationwide survey of traffic engineers was conducted to identify potential implementable strategies in this context. The surveys of Indiana DOT and other state DOTs are shown in Appendix A and B, respectively. Table 6.3 shows the top ten strategies suggested by traffic engineers nationwide. However, some of these strategies are not relevant for freeways, and others are not applicable to the Borman Expressway case study. Based on these considerations, four strategies are analyzed and compared to the base case which represents the current situation. They are evaluated for various demand loading levels (congestion levels) and truck percentages.

6.3.1. Description of Mitigation Strategies

The base case for the analysis of alternative mitigation strategies is described in Section 6.1.4. It is illustrated in Figure 6.13 in terms of the current operational strategy. In the current strategy, trucks are allowed on the two right lanes. The other strategies are described hereafter:

Strategy 1: Restrict trucks to the right-most lane

This strategy allows trucks on the right-most lane only, as illustrated in Figure 6.14. It fits within the commonly identified strategy in Table 6.3 of restricting trucks to specific lanes. While this strategy does not entail monetary investment, it may require legislation. A priori, it seems reasonable that restricting trucks to one lane will reduce the number of car-truck interactions. However, the level of service on the right-most lane may deteriorate due to the lane restriction.

Strategy 2: Allow trucks on all lanes

In this strategy, trucks are allowed on all three lanes, as shown in Figure 6.15. This strategy potentially increases the number of car-truck interactions since trucks are allowed on all lanes. However, the speed differential between lanes is expected to decrease as trucks are present on all lanes.

Strategy 3: Add one lane

This strategy adds one more lane to the freeway segment, as shown in Figure 6.16. Trucks are then allowed to travel on the two right lanes as in the base case. While the addition of a lane increases capacity, it requires significant monetary investment, and may generate additional traffic in the long-term due to system-level interactions of demand and performance. So, while the potential to reduce *AADL* exists, there are significant trade-offs to consider.

Strategy 4: Truck diversion

Unlike the other three strategies which are based solely on supply-side solutions, this strategy is more broad-based. That is, truck demand is diverted before it reaches the freeway segment of interest. Strategies such as “truck-only routes” “toll truckways” and “express lanes” seek to proactively reduce or eliminate interactions between trucks and non-truck vehicles. However, this strategy requires the presence of a viable alternative to route trucks, either through diversion or truck-only routes. Hence, this strategy may involve significant additional monetary investment. It should be noted here that if truck diversion is the strategy employed, then the traffic conditions on the diversion route may deteriorate. Here, we do not consider that aspect and only focus on the effects of diversion on the freeway segment of interest.

In the summary, while operational strategies may focus on reducing *AADL*, there are ramifications of such strategies for traffic performance, safety and monetary investment. Hence, the effectiveness of a specific strategy should be determined based on analyzing the trade-offs in terms of alternative performance measures rather than focusing car-truck interactions only. A key contribution of the study is that it enables the consideration of car-truck interactions in addition to the other performance measures in making operational decisions.

6.3.2. Results and Insights

Table 6.4 through Table 6.7 summarize performance statistics obtained through simulation for the first three strategies and the base case for different demand loads

(2000 vph, 3500 vph, 5000 vph, and 6000 vph) and truck percentages (10%, 30%, 50%, and 70%). As discussed in Section 6.1.3.1.2, the 70% truck percentage case is not considered for high demand loads (5000 vph and 6000 vph). The tabulated simulation results illustrate the trade-offs among average travel time, average lane speed differential, and *AADL* for the various strategies.

6.3.2.1. Impacts of Truck Percentage

The tables indicate that the number of interactions involving trucks and non-trucks increases with truck percentage up to a certain point and reduces beyond that point, especially for the low demand loadings (2000 vph and 3500 vph). This trend is also valid for most higher demand loading scenarios as well. This is illustrated in Figure 6.17 which plots the number of interactions for different truck percentages under the three strategies for demand 2000 vph. This indicates the interplay between the number of non-truck vehicles in the traffic stream and the potential for interactions with trucks. Hence, when truck percentages are very high, there are fewer non-truck vehicles on the freeway segment, and this effect dominates the potential for car-truck interactions, especially for lower congestion levels. At higher congestion levels (5000 vph, 6000 vph), the tight packing of vehicles in the traffic stream can reduce this effect at times. However, under all loading levels, the *AADL* mostly increases with truck percentage. This is illustrated in Figure 6.18. This is because truck free-flow speeds are slight lower than for non-trucks, leading to lower average speeds with increasing truck traffic. Since driver discomfort levels increase with congestion up to the medium-high congestion level, the *AADLs* typically increase with truck percentages. However, the trend of decreasing *DLs* with increased congestion at high congestion levels still holds across increasing demand loadings.

6.3.2.2. Lane Restriction Strategies

When truck percentages are relatively low (10% and 30%) and demand loads are not very high, the strategy restricting trucks to the right-most lane is a good

strategy vis-à-vis mitigating car-truck interactions without deteriorating the traffic performance (average travel time). Figure 6.19 illustrates this aspect by plotting the *AADLs* and number of interactions with increasing demand loads. However, the average lane speed differential increases.

When truck percentages are high (50% and 70%) and the demand is high to very high, restricting trucks to the right-most lane makes this lane highly congested leading to significant performance deterioration. Then, Strategy 1 is not a good solution to the car-truck interactions problem. For the same reason, the associated strategy is not realistic and has no statistics in Tables 6.5 through 6.7 for higher truck percentages. Allowing trucks on all lanes can improve the *AADL* to a small extent, especially under very high demand loads. But, in most cases, the number of car-truck interactions increase leading to significantly higher *AADLs* compared to even the base case. Also, the average speed on the left-most lane decreases significantly due to the presence of trucks on it.

6.3.2.3. Addition of a Lane

The addition of a lane to the existing section increases freeway capacity, involves significant monetary investment, disrupts traffic during the construction, and attracts more demand in the long run. Hence, it adds value only under high demand loads with high truck percentages. That is, the choice of adding a lane should be based primarily in terms of reducing congestion rather than some benefits in terms of *AADL* reduction. Figure 6.20 illustrates this point for a demand load of 6000 vph, where the demand load exceeds capacity. It shows that while adding a lane can aid substantially in reducing congestion effects, the influence on *AADL* may be minimal.

6.3.2.4. Truck Diversion

Table 6.8 shows the impacts of different levels of truck diversions on car-truck interactions. The lane assignment is based on the base case, while the demand load is 4000 vph, and 20% of the vehicles are trucks. The *AADL* is 1 when all trucks are

diverted, implying zero discomfort. Also, as higher percentages of trucks are diverted, *AADL* reduces. Hence, while truck diversion is a good strategy from the perspective of improving traffic performance and reducing car-truck interactions, it is constrained by the need for viable alternative routes for trucks.

6.3.3. Trade-offs and Insights from Mitigation Strategies

Table 6.9 illustrates the trade-offs between traffic performance (average travel time), safety (average lane speed differential), and car-truck interactions (*AADL*) for different truck percentages (10% and 50%) under the various mitigation strategies for an intermediate demand load of 3500 vph. In general, *AADL* values increase with truck percentage, as discussed in Section 6.3.2.1. The *AADLs* for low truck percentages (10%) and low to medium congestion (3500vph) are almost identical across the various strategies. In such a situation, allowing trucks on all lanes is beneficial as the average lane speed differential decreases substantially without affecting travel times. That is, the decision is based from a safety perspective rather than from the viewpoint of car-truck interactions or traffic performance. Under high truck percentages (50%), the strategies that are effective are restricting trucks to right-most lane and adding a lane, as both tend to reduce *AADL*. However, the reduction is much higher for Strategy 1 compared to Strategy 3. Since the average lane speed differentials under both strategies are not that different, and average travel times are similar, Strategy 1 is preferred. It becomes the only preferred strategy if the cost to build an additional lane is factored in.

In summary, there are trade-offs in terms of performance and safety, which typically tend to represent the primary criteria for selecting a strategy. That is, strategies that reduce car-truck interactions should also be cognizant of their effects on travel delays and traffic safety.

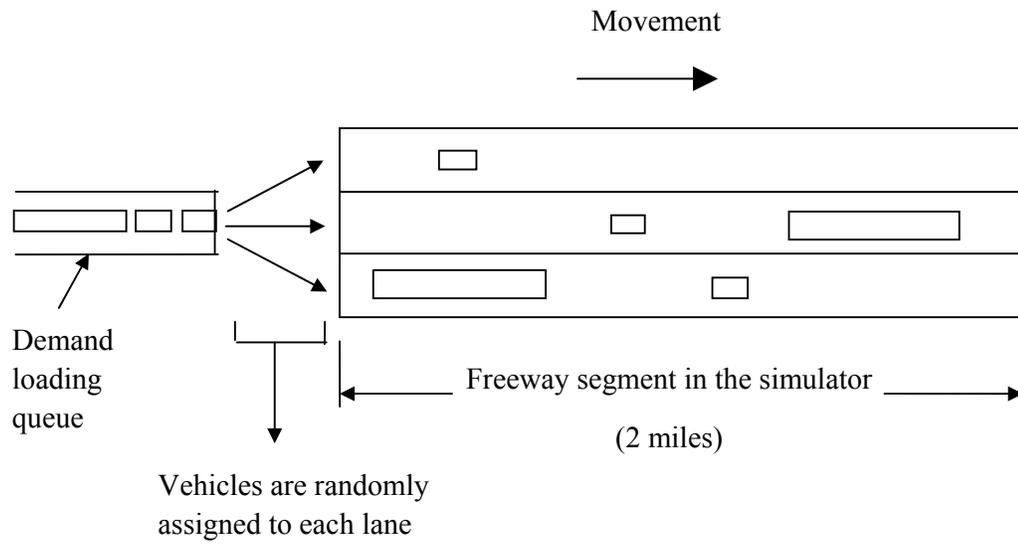


Figure 6.1 Freeway Segment in the Simulator

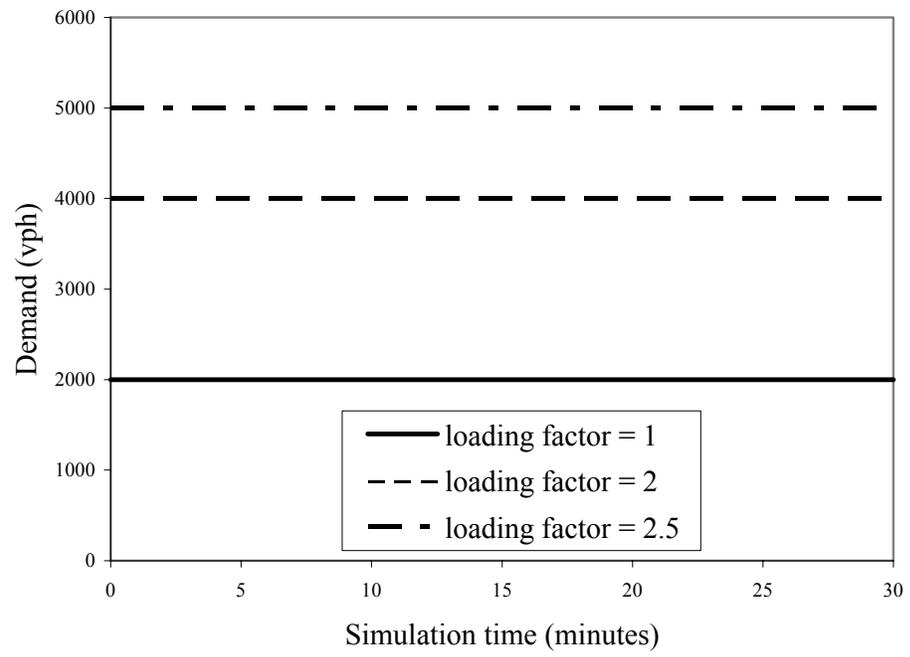


Figure 6.2 Demand Loading Factors

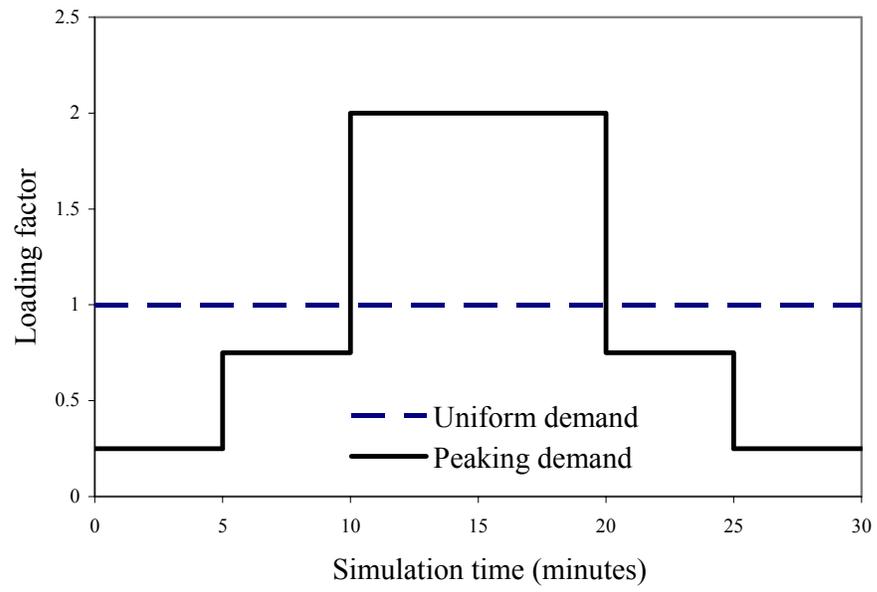


Figure 6.3 Demand Profiles

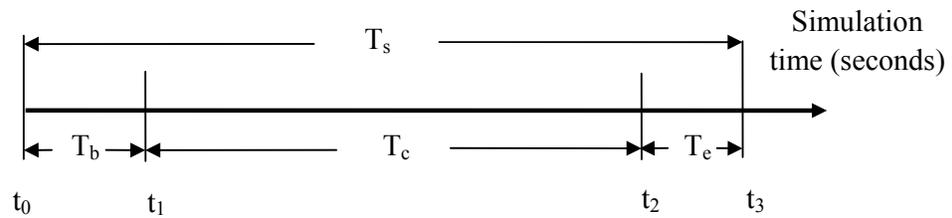
Table 6.1 Sensitivity Factor Assignment based on Driver Type

Driver type factor	1	2	3	4	5	6	7	8	9	10
Sensitivity factor	1.25	1.15	1.05	0.95	0.85	0.75	0.65	0.55	0.45	0.35

* Source: TSIS 5.1

Table 6.2 Simulation Parameters for the Base Case

Simulation parameters	Value
Loading Factor	1
Truck Percentage	20%
Lane Assignment	Three lanes; trucks on the right two lanes
Gender	Randomly distributed based on Table 5.1
Age	Randomly distributed in the range 16-80 based on Table 5.1
Education	Randomly distributed into four categories based on Table 5.1
Household Size	Randomly distributed between 1-8 based on Table 5.1
Driver Type Factor	Uniformly distributed from 1-10
Free-Flow Speed	For trucks: uniformly distributed in the range 55-65 mph (88.5-104.6 kmph) For non-trucks: uniformly distributed in the range 60-70 mph (96.6-112.7 kmph)



t_0 : the time at which the first vehicle is generated

t_1 : 150 seconds after t_0

t_2 : the time at which the last generated vehicle enters the freeway section

t_3 : the time at which the last vehicle leaves the freeway section

T_s : simulation time

T_b : 150 seconds

T_c : time duration for which statistics are computed

T_e : the time duration between the time the last generated vehicle enters the freeway section and the time at which the last vehicle leaves the freeway section

Figure 6.4 Simulation Duration for Which Statistics are Computed

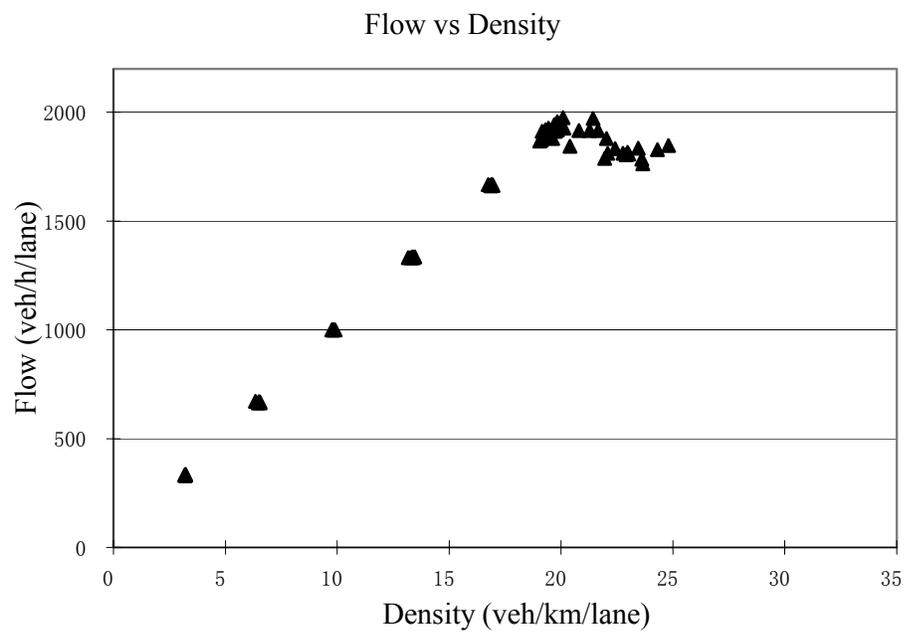
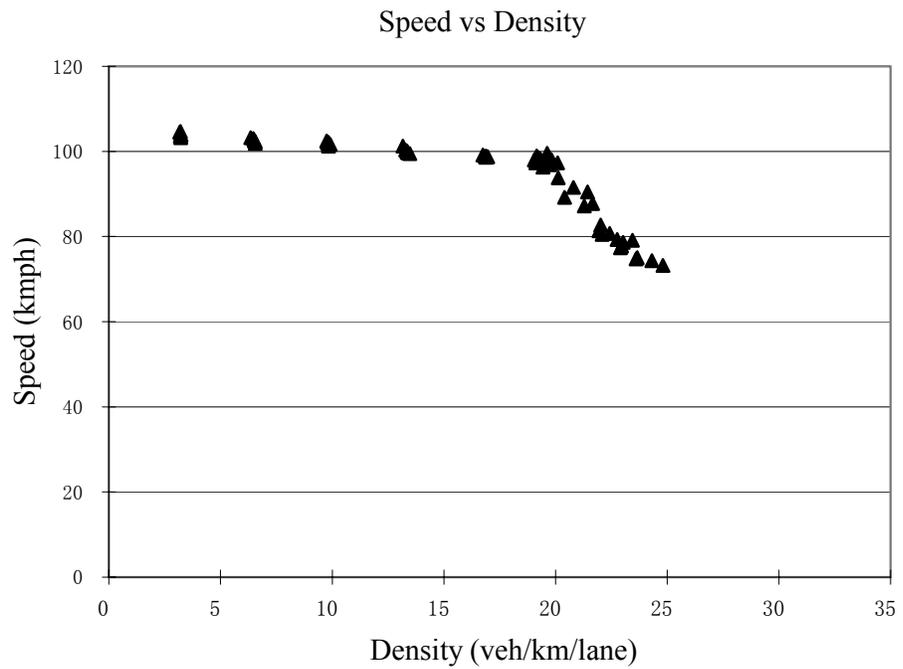


Figure 6.5 Traffic Flow Relationships when Car-Truck Interactions Logic is Excluded

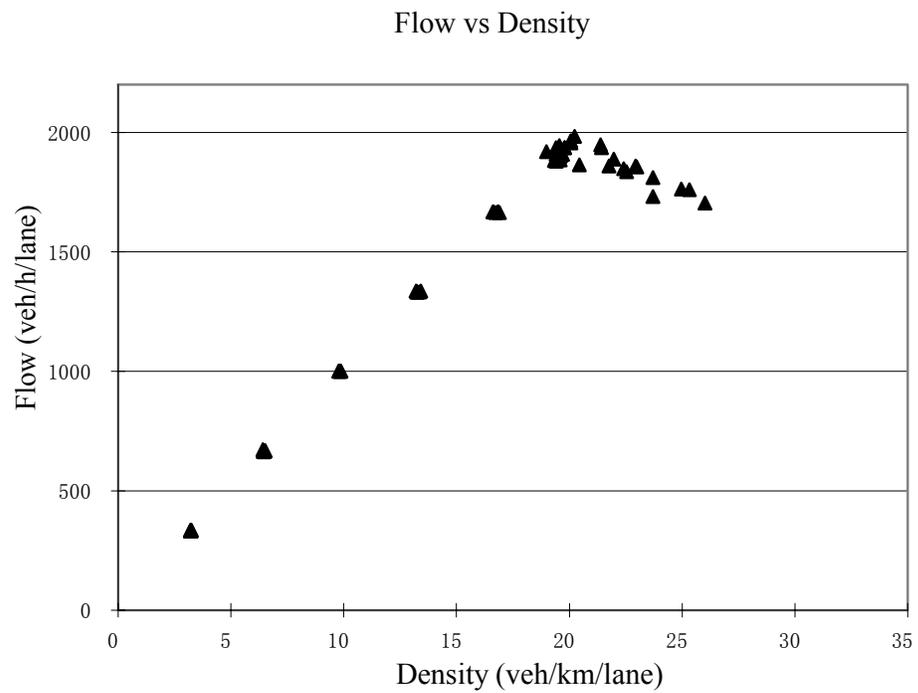
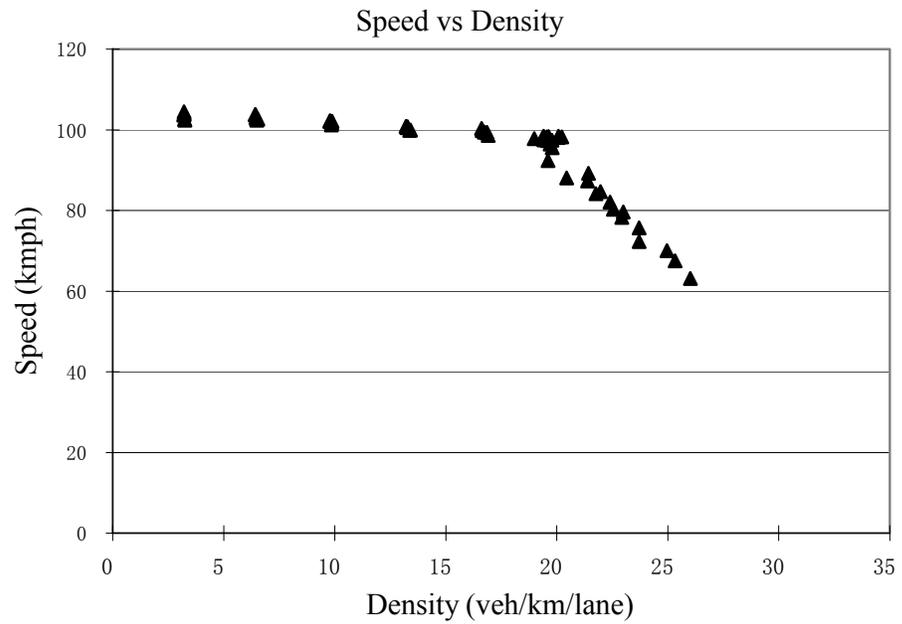


Figure 6.6 Traffic Flow Relationships when Car-Truck Interactions Logic is Included

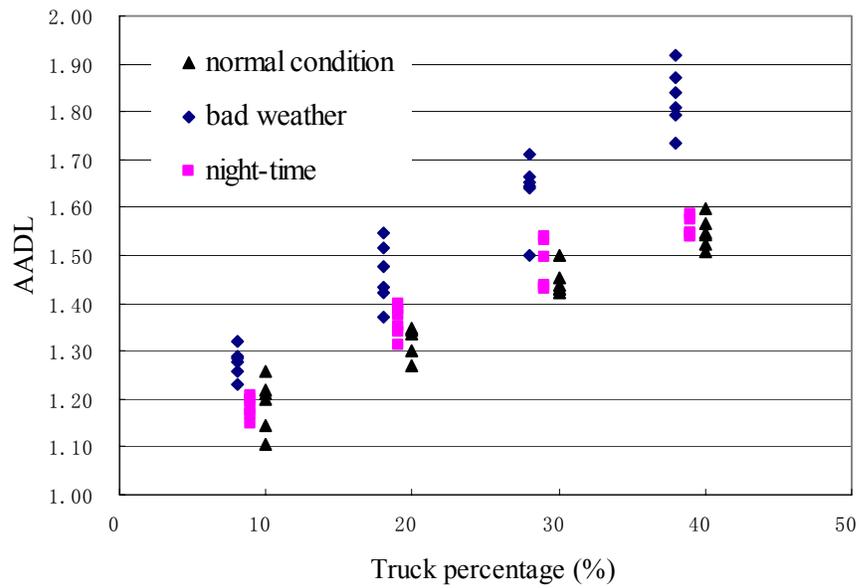


Figure 6.7 Impacts of Situational Factors

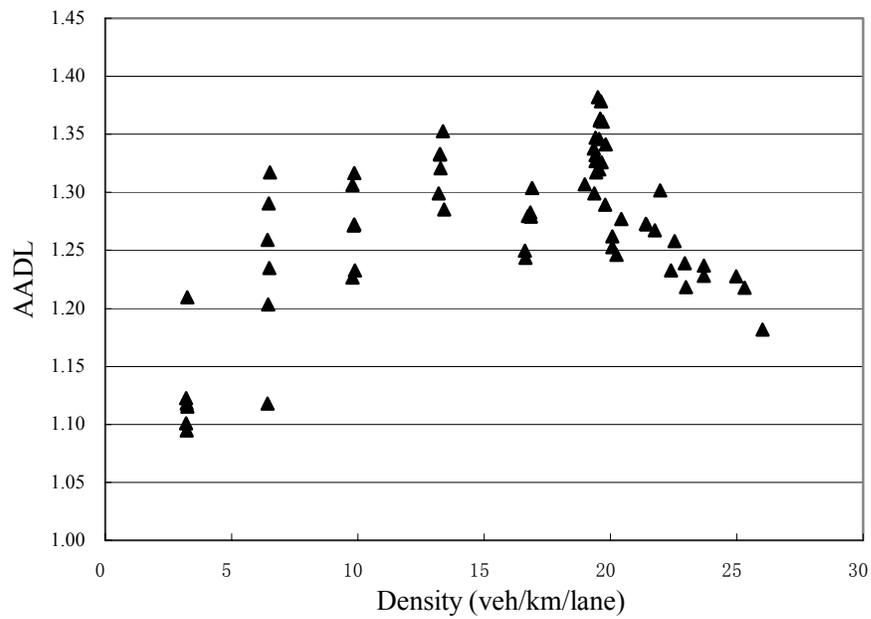


Figure 6.8 Impact of Traffic Density (Proxy for Congestion Level)

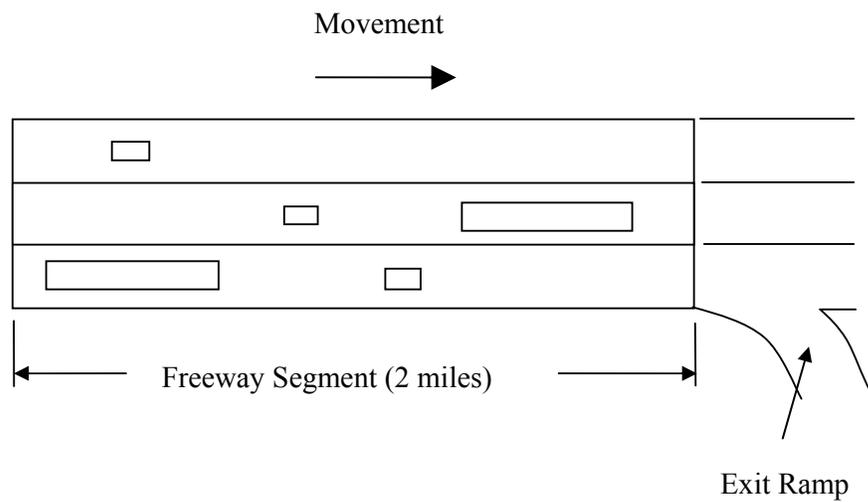


Figure 6.9 Exit Ramp Setup

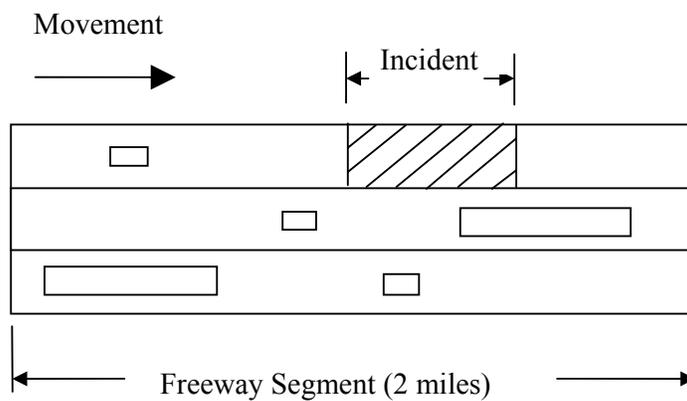


Figure 6.10 Incident Location

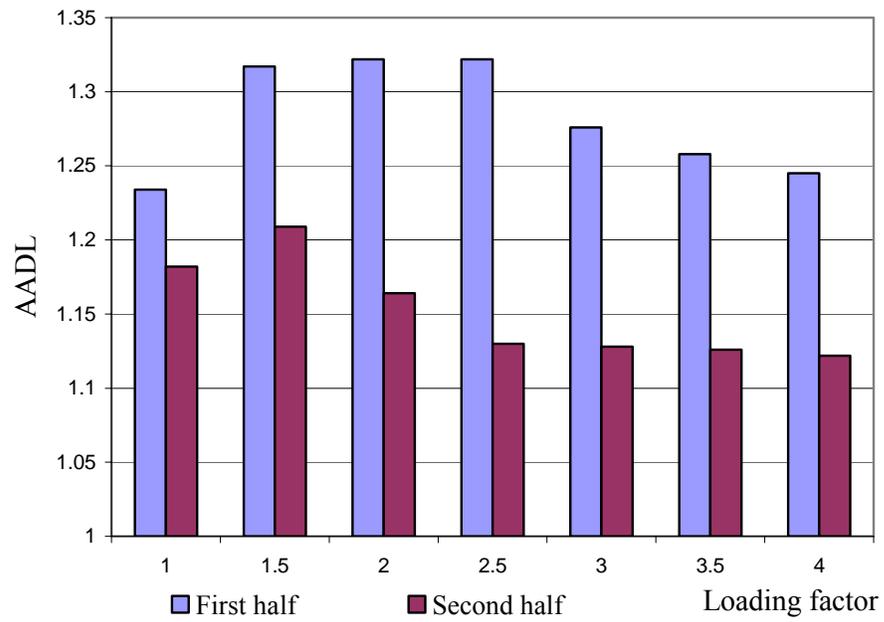


Figure 6.11 Impacts of Incidents

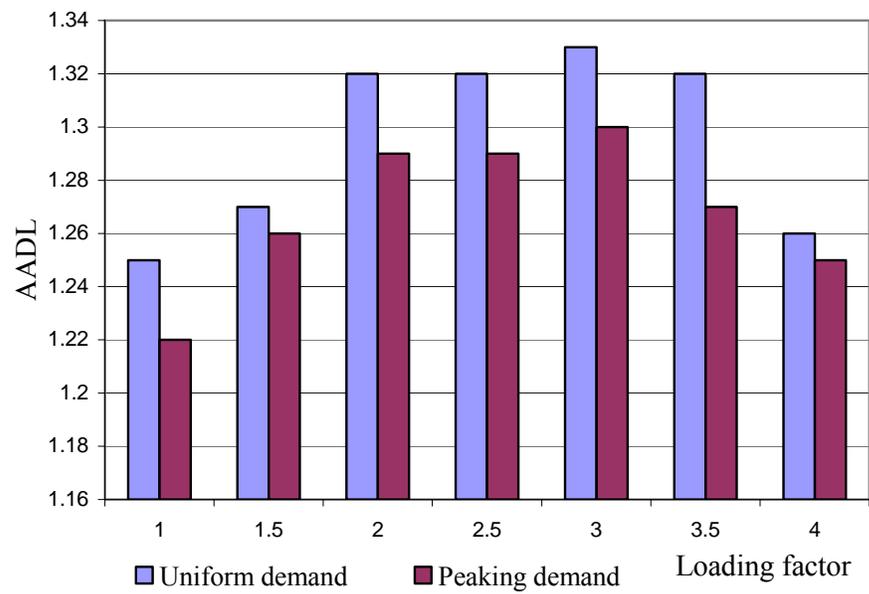


Figure 6.12 Impacts of demand loading profile

Table 6.3 Strategies Identified to Reduce Car-truck Interactions

Rank	Strategy
1	Truck-only lanes at certain locations
2	Restrict trucks to certain lanes
3	Design special truck routes which will mostly/solely be used by trucks
4	Toll truckways
5	Improve geometric features based on truck needs for some highway sections
6	Improve driver education programs
7	Prohibit trucks from entering certain busy roads/sections
8	Create local and express lanes
9	Provide more traffic information to truck companies/operators/drivers
10	Allow through trucks to go on the left lanes

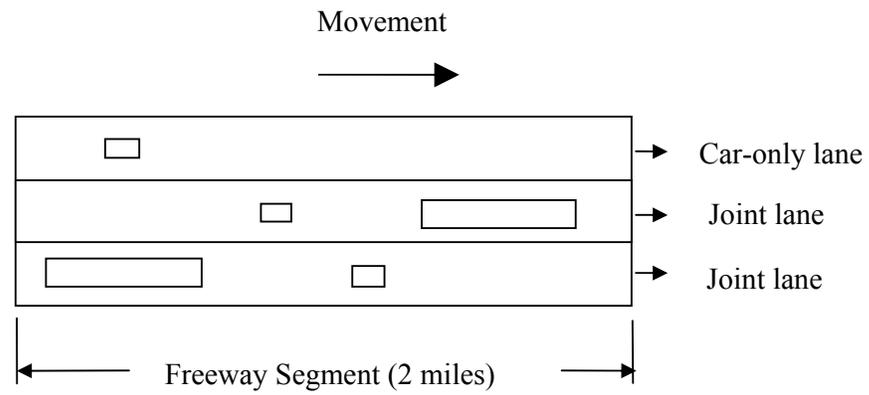


Figure 6.13 Lane Assignment for the Base Case

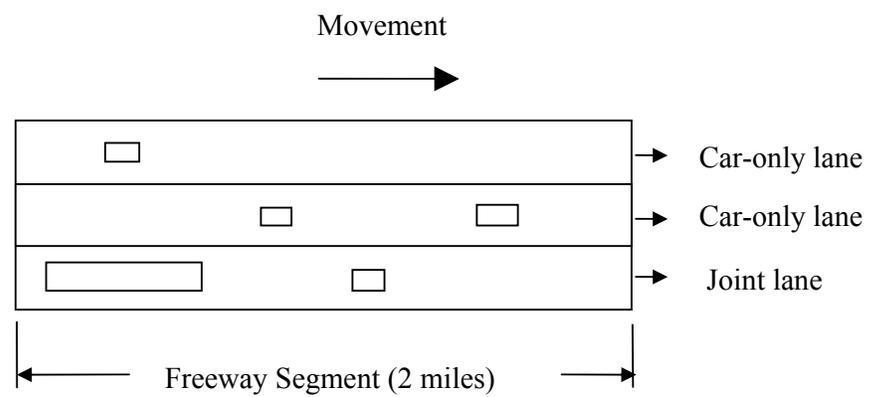


Figure 6.14 Lane Assignment for Strategy 1

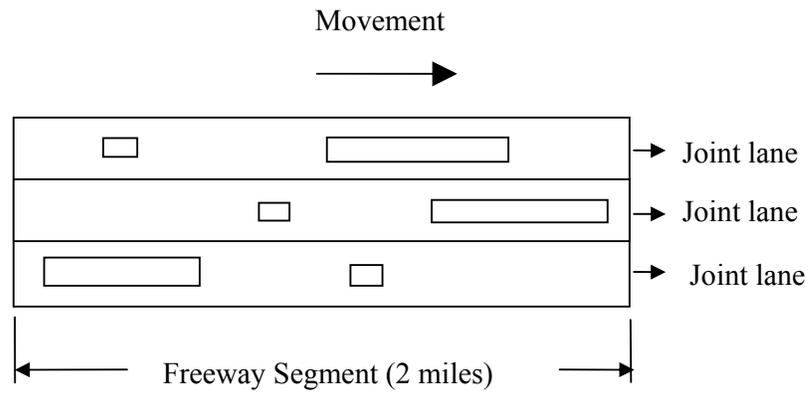


Figure 6.15 Lane Assignment for Strategy 2

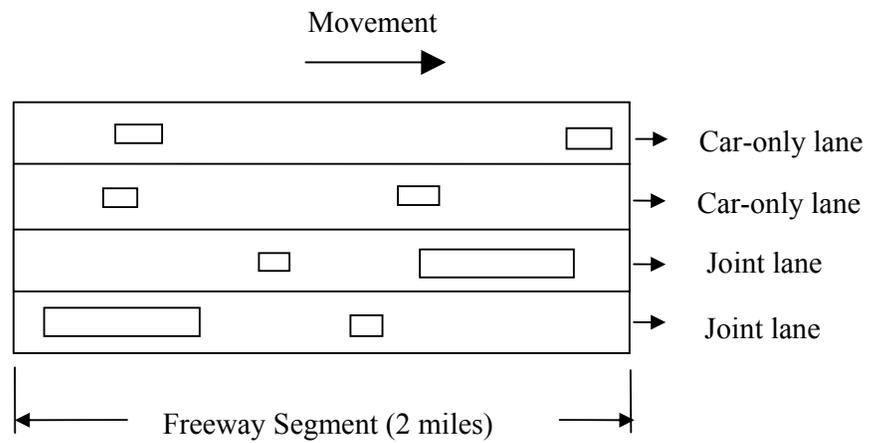


Figure 6.16 Lane Assignment for Strategy 3

Table 6.4 Simulation Results for Mitigation Strategies (2000 vph)

		Base Case	Restrict trucks to the right lane	Allow trucks on all lanes	Add one lane
10% Trucks	AADL	1.16	1.09	1.16	1.09
	Number of interactions	124.00	69.00	120.00	82.00
	Average speed	103.86	104.57	103.47	106.00
	Average travel time	111.57	110.81	111.98	109.32
	Speed-right lane	100.36	98.97	101.39	101.83
	Speed-middle lane	103.08	106.22	103.80	102.82
	Speed-left lane	109.07	109.07	105.23	109.18
	Speed-new lane				111.70
	Travel time-car	110.30	109.80	110.90	108.10
	Travel time-truck	121.90	121.10	120.90	122.00
30% Trucks	AADL	1.36	1.22	1.38	1.26
	Numer of interactions	233.00	115.00	244.00	178.00
	Average speed	101.28	101.94	100.51	102.71
	Average travel time	114.41	113.67	115.28	112.82
	Speed-right lane	98.54	94.59	99.30	98.86
	Speed-middle lane	98.65	106.11	101.94	98.10
	Speed-left lane	108.74	109.07	100.51	108.96
	Speed-new lane				111.81
	Travel time-car	111.10	109.40	112.60	108.70
	Travel time-truck	122.10	123.70	121.50	121.60
50% Trucks	AADL	1.47	1.25	1.50	1.45
	Number of interactions	232.00	68.00	283.00	202.00
	Average speed	99.19	98.86	98.65	99.74
	Average travel time	116.81	117.20	117.46	116.17
	Speed-right lane	95.79	92.72	98.21	95.35
	Speed-middle lane	96.89	106.55	99.74	96.45
	Speed-left lane	109.07	109.18	98.43	108.63
	Speed-new lane				111.70
	Travel time-car	111.00	108.70	114.00	109.90
	Travel time-truck	122.50	125.30	121.00	122.70
70% Trucks	AADL	1.61	1.16	1.74	1.39
	Number of interactions	176.00	26.00	257.00	117.00
	Average speed	96.67	95.68	96.45	97.44
	Average travel time	119.86	121.10	120.14	118.92
	Speed-right lane	94.15	91.62	96.23	94.59
	Speed-middle lane	94.91	106.77	97.22	94.59
	Speed-left lane	108.63	109.07	96.23	109.29
	Speed-new lane				111.81
	Travel time-car	111.50	108.40	115.10	108.60
	Travel time-truck	123.60	126.40	122.00	123.30

* Units: speed (kmph); travel time (seconds)

Table 6.5 Simulation Results for Mitigation Strategies (3500 vph)

		Base Case	Restrict trucks to the right lane	Allow trucks on all lanes	Add one lane
	AADL	1.17	1.15	1.20	1.13
10% Trucks	Number of interactions	198.00	151.00	219.00	178.00
	Average speed	102.71	103.36	101.72	105.45
	Average travel time	112.82	112.10	113.92	109.89
	Speed-right lane	99.30	97.22	99.85	100.07
	Speed-middle lane	101.17	105.23	102.60	102.27
	Speed-left lane	108.41	108.63	102.82	108.96
	Speed-new lane				111.81
	Travel time-car	111.70	110.90	113.00	108.70
	Travel time-truck	122.20	122.30	121.70	121.20
	AADL	1.48	1.21	1.48	1.34
30% Trucks	Number of interactions	397.00	159.00	449.00	356.00
	Average speed	99.52	100.84	97.99	102.27
	Average travel time	116.43	115.05	118.25	113.30
	Speed-right lane	96.01	93.05	97.00	96.34
	Speed-middle lane	96.34	105.12	100.07	97.55
	Speed-left lane	108.30	108.52	97.33	108.74
	Speed-new lane				111.81
	Travel time-car	113.50	110.40	116.60	109.70
	Travel time-truck	123.30	125.10	122.40	122.80
	AADL	1.62	1.07	1.76	1.52
50% Trucks	Number of interactions	400.00	34.00	554.00	321.00
	Average speed	97.22	98.10	96.12	98.65
	Average travel time	119.19	135.42	120.55	117.46
	Speed-right lane	93.93	90.75	95.68	93.93
	Speed-middle lane	94.15	105.67	96.78	93.60
	Speed-left lane	107.97	108.96	96.12	108.52
	Speed-new lane				111.81
	Travel time-car	114.20	125.80	118.30	110.60
	Travel time-truck	124.50	145.00	123.00	124.40
	AADL	1.69		2.07	1.52
70% Trucks	Number of interactions	255.00		461.00	174.00
	Average speed	94.48		94.37	95.46
	Average travel time	122.65		122.79	121.38
	Speed-right lane	92.17		94.70	91.95
	Speed-middle lane	92.17		94.70	91.95
	Speed-left lane	108.30		93.49	108.41
	Speed-new lane				111.81
	Travel time-car	114.40		120.50	110.00
	Travel time-truck	126.20		123.80	126.30

* Units: speed (kmph); travel time (seconds)

Table 6.6 Simulation Results for Mitigation Strategies (5000 vph)

		Base Case	Restrict trucks to the right lane	Allow trucks on all lanes	Add one lane
AADL		1.17	1.15	1.17	1.17
10% Trucks	Number of interactions	257.00	208.00	252.00	259.00
	Average speed	101.28	102.05	99.19	104.13
	Average travel time	114.41	113.55	116.81	111.28
	Speed-right lane	97.44	95.13	98.32	97.77
	Speed-middle lane	98.65	104.24	100.62	100.29
	Speed-left lane	107.64	108.19	98.97	108.52
	Speed-new lane				111.70
	Travel time-car	113.40	112.40	116.20	110.00
	Travel time-truck	122.90	123.70	122.70	122.30
AADL		1.42	1.17	1.50	1.40
30% Trucks	Number of interactions	495.00	171.00	628.00	472.00
	Average speed	97.99	99.96	95.57	100.62
	Average travel time	118.25	161.22	121.24	115.16
	Speed-right lane	94.26	90.75	95.24	93.82
	Speed-middle lane	94.04	104.68	97.00	94.91
	Speed-left lane	107.75	108.41	94.91	108.52
	Speed-new lane				111.81
	Travel time-car	115.70	156.20	120.10	111.10
	Travel time-truck	124.40	173.00	123.80	124.40
AADL		1.59		1.78	1.45
50% Trucks	Number of interactions	467.00		831.00	340.00
	Average speed	95.02		89.54	97.44
	Average travel time	130.94		129.41	118.92
	Speed-right lane	90.96		85.92	91.95
	Speed-middle lane	91.40		91.62	91.73
	Speed-left lane	108.08		90.09	108.41
	Speed-new lane				111.81
	Travel time-car	116.60		129.30	111.00
	Travel time-truck	127.40		129.60	126.60

* Units: speed (kmph); travel time (seconds)

Table 6.7 Simulation Results for Mitigation Strategies (6000 vph)

		Base Case	Restrict trucks to the right lane	Allow trucks on all lanes	Add one lane
10% Trucks	AADL	1.15	1.07	1.13	1.17
	Number of interactions	272.00	446.00	562.00	322.00
	Average speed	100.07	69.79	63.09	103.36
	Average travel time	125.59	274.64	201.35	112.10
	Speed-right lane	95.90	41.59	60.13	97.55
	Speed-middle lane	97.66	103.36	64.63	98.10
	Speed-left lane	107.53	107.86	63.31	108.08
	Speed-new lane				111.81
	Travel time-car	124.80	259.40	200.40	110.90
	Travel time-truck	133.20	426.20	209.00	122.90
30% Trucks	AADL	1.42		1.32	1.38
	Number of interactions	698.00		1304.00	505.00
	Average speed	93.27		56.51	99.63
	Average travel time	216.24		261.05	116.30
	Speed-right lane	93.16		51.90	92.50
	Speed-middle lane	85.15		68.03	92.94
	Speed-left lane	107.75		82.08	108.19
	Speed-new lane				111.81
	Travel time-car	212.30		259.85	112.30
	Travel time-truck	225.40		263.00	125.90
50% Trucks	AADL	1.38		1.52	1.42
	Number of interactions	874.00		1258.00	359.00
	Average speed	67.26		61.34	97.11
	Average travel time	440.97		277.81	162.12
	Speed-right lane	61.34		55.52	90.53
	Speed-middle lane	65.29		65.18	91.07
	Speed-left lane	107.86		61.23	108.19
	Speed-new lane				111.81
	Travel time-car	414.30		260.20	154.00
	Travel time-truck	468.40		296.20	170.20

* Units: speed (kmph); travel time (seconds)

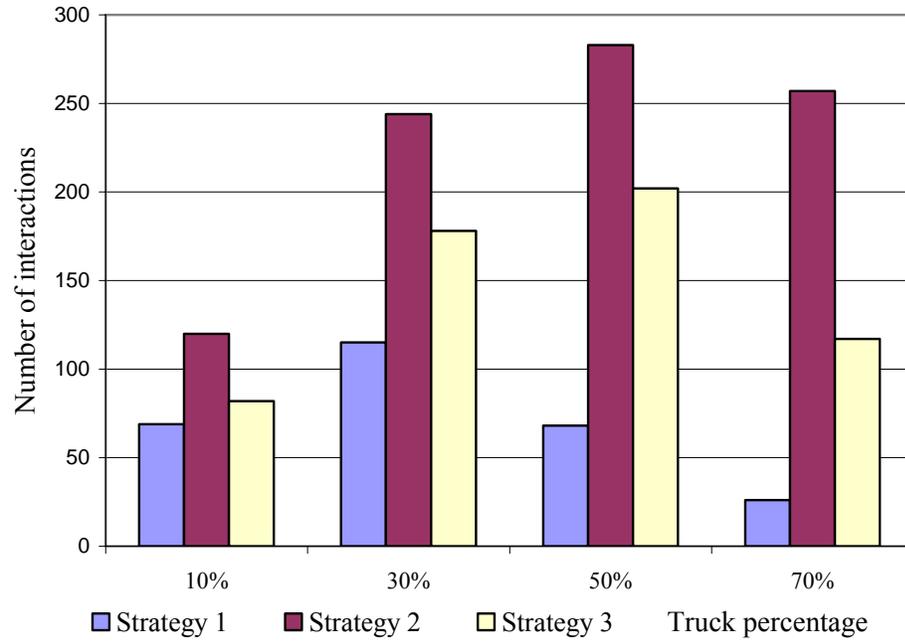


Figure 6.17 Impacts of Truck Percentage on Number of Car-truck Interactions

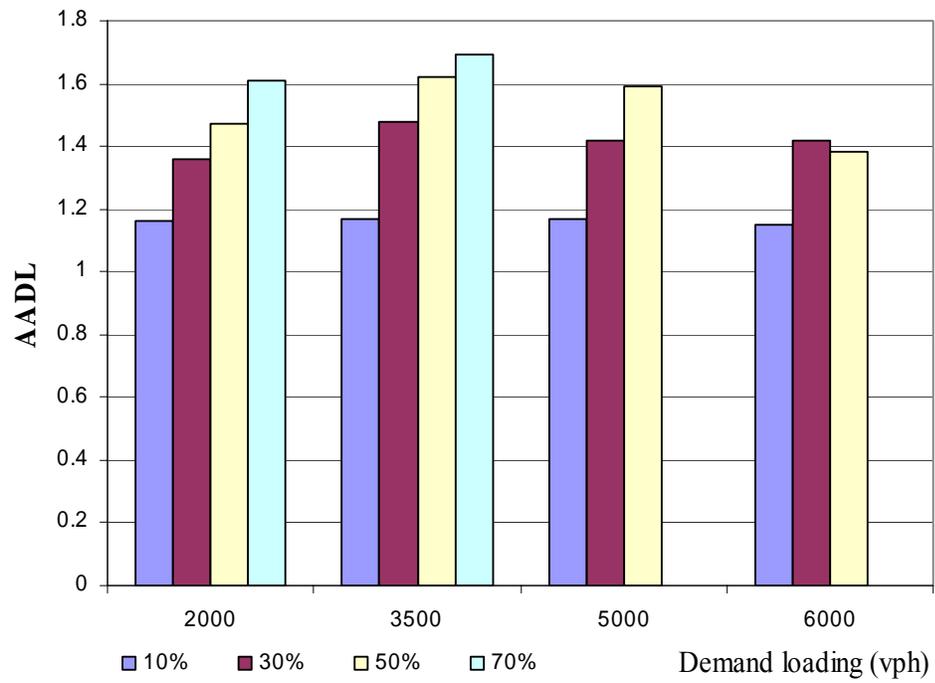


Figure 6.18 Impacts of Truck Percentage on AADL

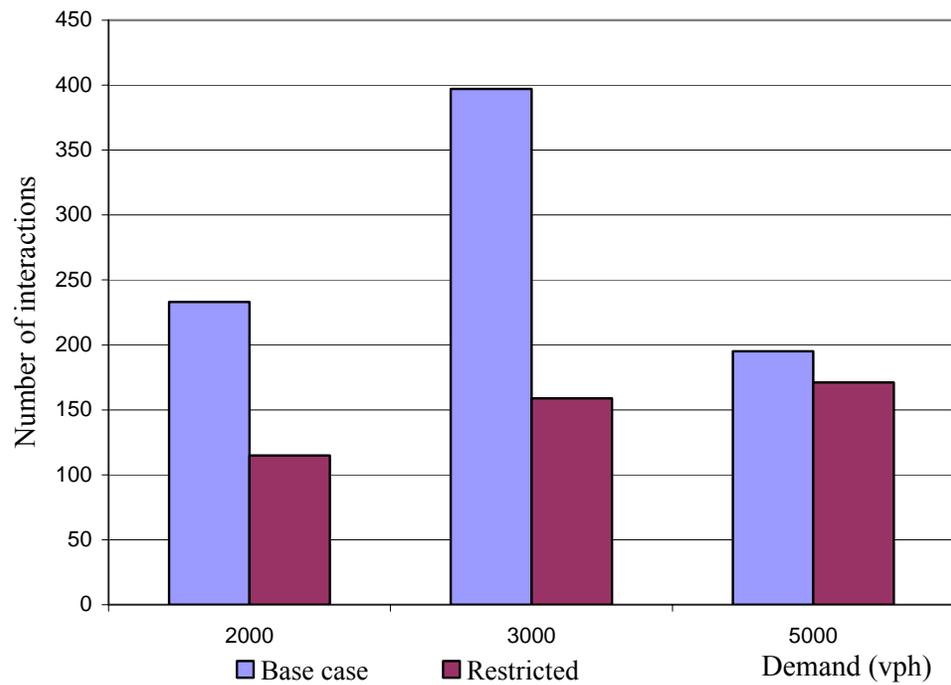
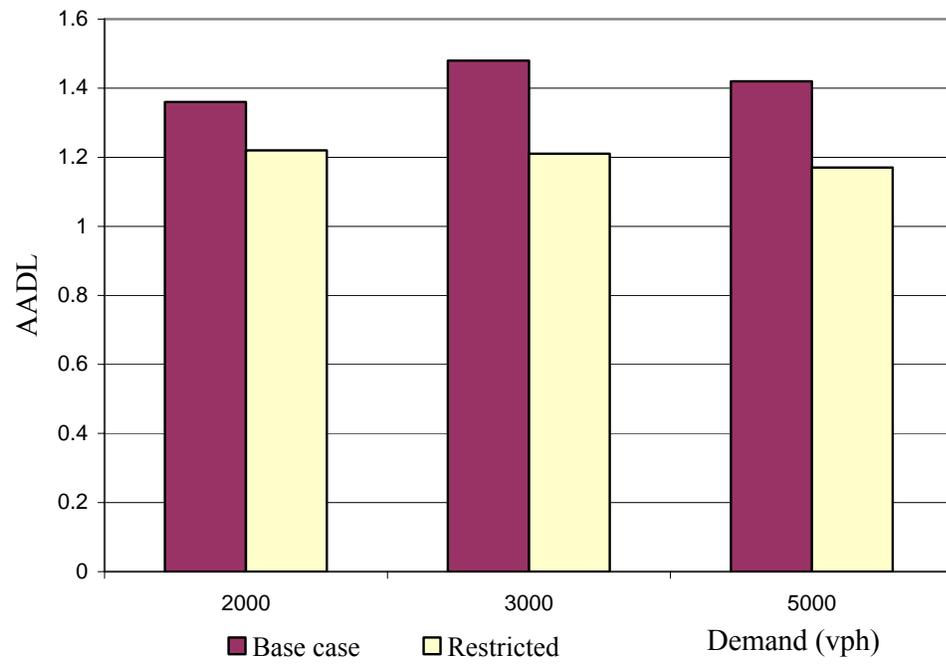


Figure 6.19 Impacts of Strategy 1 (30% Trucks)

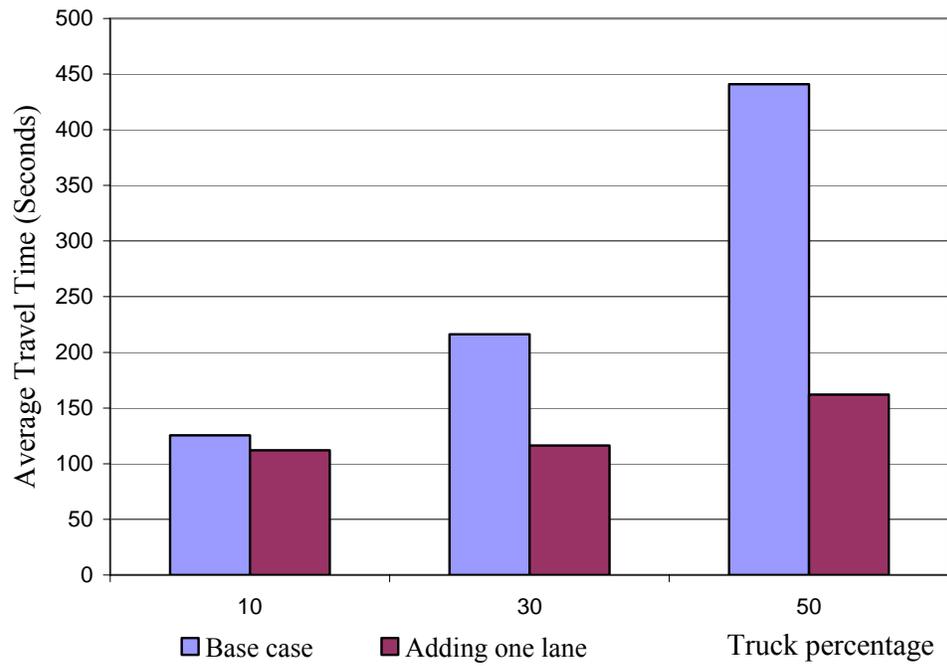
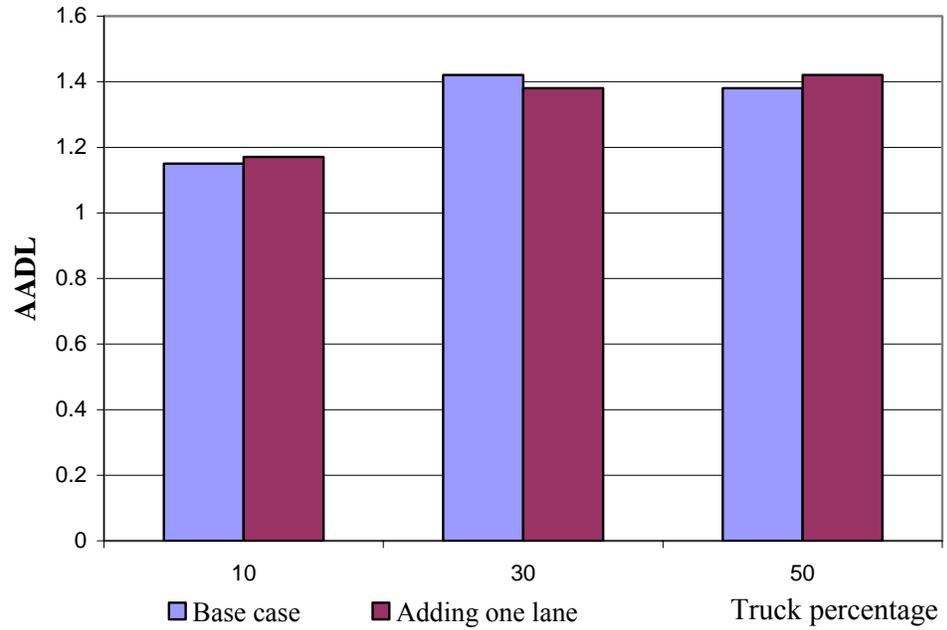


Figure 6.20 Impacts of Adding a Lane (6000 vph)

Table 6.8 Impact of Truck Diversion

	No diversion	50% trucks divert	100% trucks divert
AADL	1.31	1.18	1
Number of Interactions	370	230	0
Average Speed (kmph)	100.5	102.2	105.2
Average Travel Time (seconds)	115.3	113.4	110.1

* Units: speed (kmph); travel time (seconds)

Table 6.9 Comparison of Alternative Mitigation Strategies (3500vph)

Strategies	Truck %	AADL	Average lane speed differential	Average travel time
Base case	10	1.15	4.55	112.2
	50	1.57	7.02	119.3
Restriction of trucks (Strategy 1)	10	1.14	5.71	112.3
	50	1.10	9.11	118.7
Allowing trucks on all lanes (Strategy 2)	10	1.16	1.48	113.5
	50	1.78	0.88	121.0
Adding a lane (Strategy 3)	10	1.13	3.92	110.0
	50	1.48	6.18	117.5

* Units: speed (kmph); travel time (seconds)

CHAPTER 7. CONCLUSIONS

This chapter summarizes the study, identifies its contributions, and provides directions for future research.

7.1. Summary and Insights

This research proposes models to capture car-truck interactions in a traffic stream to more robustly incorporate the impacts of non-truck driver actions in the vicinity of trucks, and to analyze the effectiveness of strategies to reduce car-truck interactions. It bridges a key methodological gap in the traffic flow modeling arena where trucks are not differentiated from other vehicles, especially from a driver behavior perspective.

The study formally introduces the notion of car-truck interactions from the perspective of non-truck drivers while following trucks. It views these interactions from a driver psychology viewpoint and hypothesizes that the driver actions/decisions are due to their “discomfort” in this regard. It seeks to quantify this discomfort on the premise that the associated driver actions depend on the individual socioeconomic characteristics and the situational factors encountered by the driver. Stated preference surveys are conducted for non-truck drivers in the region of interest to characterize socioeconomic patterns, and to elicit their likely responses to several real-world scenarios by explicitly linking these responses to the notion of discomfort. A preliminary analysis of the survey data is performed using discrete choice modeling to identify the significant attributes that contribute to driver discomfort to trucks. The preliminary analysis, survey responses to specific driver actions vis-à-vis discomfort, and insights from past driver behavior studies are used to develop a fuzzy logic based model to quantify driver discomfort. This is done by specifying simple if-then rules, based on the preliminary insights, for the significant causal factors. Some of these factors are inherently subjective, and hence amenable to fuzzy logic based modeling. The fuzzy logic model for driver discomfort level is

calibrated using survey data. The driver discomfort levels are then used to modify the car-following and modified lane-changing logic in the FRESIM microscopic freeway traffic simulator to develop truck-following and modified lane-changing models. These modified models are used to construct an agent-based traffic simulator for freeway segments that is capable of differentiating between trucks and non-truck vehicles vis-à-vis traffic flow and non-truck driver behavior.

A case study, represented by the heavily traveled Borman Expressway (I-80/94) in the Northwest Indiana, is used to analyze the effectiveness of the proposed driver discomfort model and to investigate its sensitivity to the various system parameters. It is then used to analyze the effectiveness of alternative car-truck interactions mitigation strategies.

Based on the case study and survey data, gender, household size, weather conditions, and level of congestion are identified as the factors that significantly influence non-truck driver discomfort to trucks in the Borman corridor region. The discomfort levels increase with the percentage of truck traffic in the traffic stream. Also incidents can magnify discomfort levels due to the increased potential for car-truck interactions, and the congestion induced by them.

Driver discomfort levels are lower under low congestion levels as vehicles are not closely packed in the traffic stream. Also, under low congestion, car-truck interactions tend to be random, that is, the number of car-truck interactions tends to vary under similar low congestion situations. As congestion increases to the medium range, the discomfort levels in the freeway segment increase, as vehicles travel at relatively high speeds but are more closely packed together. As congestion reaches very high levels, vehicles are tightly packed together in the traffic stream and speeds reduce substantially. Under these situations, the discomfort levels decrease because vehicles move slowly enough that drivers are more comfortable driving close to other vehicles.

Alternative car-truck interaction mitigation strategies are analyzed using the agent-based simulator. The analysis suggests that the effectiveness of a strategy

should be viewed more holistically than just focusing on reducing *AADL*. This is because a strategy that is more effective in reducing *AADL* may lead to worse traffic performance and/or increased safety-related concerns. Different strategies are effective under different congestion levels and truck percentages. Under lower congestion levels and lower truck percentages, restricting trucks to the right-most lane can significantly reduce car-truck interactions without negatively impacting traffic performance. Under high congestion levels and truck percentages, allowing trucks on all lanes may represent the best strategy for some traffic scenarios. For other scenarios, adding a new lane may represent the best strategy, though this entails significant monetary investment. A general caveat when seeking to reduce car-truck interactions is that the primary criteria for selection of a strategy should be to improve performance (average travel time) and/or safety (average lane speed differential). This implies that an ideal strategy not only reduces *AADL* but simultaneously improves one or more performance measures.

7.2. Contributions of the Study

This study represents a first step in developing traffic flow modeling components that are sensitive to the differential driver behavior/actions in the vicinity of trucks. Existing traffic flow models, both analytical and simulation-based, acknowledge the differences between trucks and non-truck vehicles in a cursory manner. For example, trucks are represented through passenger car equivalents from a flow perspective in the commonly used Highway Capacity Manual. At best, truck operational characteristics are included in the models. However, the interactions of trucks with other vehicles in a traffic stream are completely ignored. This can have significant ramifications for traffic performance and driver behavior. Even the microscopic traffic flow models do not distinguish between trucks and other vehicles in this context. Hence, car-following models and lane-changing models do not vary by whether the interaction is a car-car interaction or a car-truck interaction. This issue is significant because empirical studies and driving simulators suggest that

driver behavior and actions vary in the vicinity of trucks. This is because truck physical dimensions affect the line of sight of non-truck vehicles following them. In summary, the research addressed in this report:

(i) bridges a significant modeling gap in the current literature by enabling behavior-based traffic flow modeling to capture the impacts of trucks in the traffic stream.

(ii) provides some methodological tools and modeling components for the next-generation of traffic simulation models that need to incorporate increased realism in modeling traffic flow. In this context, the fuzzy logic based approach can be advantageous as it can be calibrated using measurable data. Further, the explicit incorporation of driver behavior is a robust mechanism to address other modeling limitations in the traffic flow arena. For example, the influence of road geometry on driving actions is fundamentally based on driver behavior.

(iii) provides a mechanism to evaluate alternative strategies to reduce car-truck interactions. Currently, there is no methodology that can analyze the advantages and limitations of alternative strategies.

7.3. Future Research Directions

While the research addressed in this study enhances the state-of-the-art in modeling car-truck interactions, there is room for further research in several directions. In the context of this research effort, we address car-truck interactions for freeways. A more general approach entails capturing these interactions for arterial roads and other non-freeway road facilities. Also, while the proposed models can be calibrated using measured data, the associated parameters (for the truck-following and lane-changing logics) were based on past studies. This was primarily due to the lack of resources in terms of adequate video-based sensors or driving simulators. It would be practically insightful to calibrate these parameters using empirical data collected in the region of interest. From a modeling standpoint, truck driver behavior is not addressed explicitly in this study as the focus is on non-truck driver behavior.

Modeling truck driver behavior is useful as truck drivers are constrained by the substantial blind-spot and maneuverability restrictions due to the physical and operational characteristics of trucks.

In the broader context, modeling the effects of road geometry on driver behavior, and the consequent impacts on traffic performance and safety, are key problems that are conceptually similar to the study methodology. This represents another context where truck driver behavior diverges from that of a non-truck driver. It has further ramifications in the context of the use of advanced information systems to route vehicles. Recent studies suggest that truck drivers are not as receptive to suggested unfamiliar routes as there is an inherent uncertainty as to whether the truck can negotiate the prescribed route based on road geometry.

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APPENDIX A

INDOT Survey on Car/Truck Conflicts

INDOT Survey on Car/Truck Conflicts

07/02

Dear Sir/Madam,

We are working on an Indiana Department of Transportation (INDOT) project on minimizing car-truck conflicts on highways. This project seeks to determine alternative strategies to reduce car-truck conflicts, and to enhance safety and mobility on Indiana roadways. Your opinion is highly valuable for us to identify the problematic locations with car-truck conflicts and to explore solution strategies. By car-truck conflicts, we mean: (1) car-truck accidents; (2) traffic congestion caused by car-truck interactions; and (3) discomfort to non-truck drivers. Thank you.

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Weimin Zhou, Graduate Research Assistant
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West Lafayette, IN 47907
E-mail: zhouw@ecn.purdue.edu

1. Personal Information:

◆ Name: _____ ◆ District: _____
◆ Job Title: _____

2. What is your opinion about the severity of car-truck conflicts in Indiana?

◆ Very high _____ ◆ High _____ ◆ Average _____ ◆ Low _____ ◆ Very Low _____

3. Which locations in terms of car-truck conflicts concern you the most? (Please rank-order the various options: 1 for the location with highest concern)

◆ Car-truck conflicts on urban interstate highways _____
◆ Car-truck conflicts on rural interstate highways _____
◆ Car-truck conflicts on urban roads _____
◆ Car-truck conflicts on rural roads _____

4. The primary locations of concern:

1) Freeways:

◆ Freeway name: _____
◆ Specific sections of concern: _____

2) Non-freeways (state roads or rural roads):

- ◆ Non-freeway name: _____
 - ◆ Specific sections of concern: _____
-

**5. If you chose an urban location, what are the primary reasons for that choice?
(Please rank-order the various options: 1 represents the most important reason)**

- ◆ Horizontal and vertical curvature of the roadway _____
- ◆ Number of lanes _____
- ◆ The width of lanes _____
- ◆ The width of the shoulder _____
- ◆ Unsafe driving behavior of passenger vehicle drivers _____
- ◆ Unsafe driving behavior of truck drivers _____
- ◆ The truck scheduling and routing plans of freight companies _____
- ◆ The weight and length of trucks _____
- ◆ Speeding of trucks and cars _____
- ◆ Other: _____

**6. If you chose a rural location, what are the primary reasons for that choice?
(Please rank-order the various options: 1 represents the most important reason)**

- ◆ Horizontal and vertical curvature of the roadway _____
- ◆ Number of lanes _____
- ◆ The width of lanes _____
- ◆ The width of the shoulder _____
- ◆ Unsafe driving behavior of passenger vehicle drivers _____
- ◆ Unsafe driving behavior of truck drivers _____
- ◆ The truck scheduling and routing plans of freight companies _____
- ◆ The weight and length of trucks _____
- ◆ Short of traffic signs and speed limits _____
- ◆ Speeding of trucks and cars _____
- ◆ Other: _____

7. What strategies do you feel would address car-truck conflicts? (Please rank-order the various options; 1 being the most effective option)

1) Freeways:

- ◆ Truck-only lanes at certain locations _____

- ◆ Toll truckways (truck-only lane separated from other traffic on a freeway) _____
- ◆ Restrict trucks to certain lanes _____
- ◆ Allow through trucks to go on the left lanes _____
- ◆ Design special truck routes which will mostly/solely be used by trucks _____
- ◆ Prohibit trucks from entering certain busy roads/sections _____
- ◆ Create local and express lanes _____
- ◆ Provide more traffic information to truck companies/operators/drivers _____
- ◆ Increase truck speed limit _____
- ◆ Reduce truck speed limit _____
- ◆ Improve driver education programs _____
- ◆ Improve geometric features based on truck needs for some highway sections _____
- ◆ Increase/decrease toll fees for trucks _____
- ◆ Truck diversion _____
- ◆ Other options: _____

2) Non-freeways (state roads or rural roads)

- ◆ Restrict trucks to certain lanes _____
- ◆ Allow through trucks to go on the left lanes _____
- ◆ Design special truck routes which will mostly/solely be used by trucks _____
- ◆ Prohibit trucks from entering certain busy roads/sections _____
- ◆ Provide more traffic information to truck companies/operators/drivers _____
- ◆ Increase truck speed limit _____
- ◆ Reduce truck speed limit _____
- ◆ Improve driver education programs _____
- ◆ Improve geometric features based on truck needs for some highway sections _____
- ◆ Truck diversion _____
- ◆ Build by-pass roads _____
- ◆ Other Options: _____

8. Does your agency have strategies to mitigate car-truck conflicts? If so, please list them:

9. Do you have any other comments regarding car-truck conflicts?

Thank You Very Much!!!

APPENDIX B

Nationwide Survey on Car/Truck Conflicts

Survey on Car/Truck Conflicts

07/02

Dear Sir/Madam,

We are working on an Indiana Department of Transportation (INDOT) project on minimizing car-truck conflicts on highways. This project seeks to determine alternative strategies to reduce car-truck conflicts, and to enhance safety and mobility on roadways. Your opinion is highly valuable for us to explore solution strategies. By car-truck conflicts, we mean: (1) car-truck accidents; (2) traffic congestion caused by car-truck interactions; and (3) discomfort to non-truck drivers. Thank you.

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1. Personal Information:

◆ Name: _____ ◆ District: _____
◆ Job Title: _____

2. What is your opinion about the severity of car-truck conflicts in Indiana?

◆ Very high _____ ◆ High _____ ◆ Average _____ ◆ Low _____ ◆ Very Low _____

3. Which locations in terms of car-truck conflicts concern you the most? (Please rank-order the various options: 1 for the location with highest concern)

◆ Car-truck conflicts on urban interstate highways _____
◆ Car-truck conflicts on rural interstate highways _____
◆ Car-truck conflicts on urban roads _____
◆ Car-truck conflicts on rural roads _____

4. If you chose an urban location, what are the primary reasons for that choice? (Please rank-order the various options: 1 represents the most important reason)

◆ Horizontal and vertical curvature of the roadway _____
◆ Number of lanes _____
◆ The width of lanes _____
◆ The width of the shoulder _____
◆ Unsafe driving behavior of passenger vehicle drivers _____

- ◆ Unsafe driving behavior of truck drivers _____
- ◆ The truck scheduling and routing plans of freight companies _____
- ◆ The weight and length of trucks _____
- ◆ Speeding of trucks and cars _____
- ◆ Other: _____

5. If you chose a rural location, what are the primary reasons for that choice? (Please rank-order the various options: 1 represents the most important reason)

- ◆ Horizontal and vertical curvature of the roadway _____
- ◆ Number of lanes _____
- ◆ The width of lanes _____
- ◆ The width of the shoulder _____
- ◆ Unsafe driving behavior of passenger vehicle drivers _____
- ◆ Unsafe driving behavior of truck drivers _____
- ◆ The truck scheduling and routing plans of freight companies _____
- ◆ The weight and length of trucks _____
- ◆ Short of traffic signs and speed limits _____
- ◆ Speeding of trucks and cars _____
- ◆ Other: _____

6. What strategies do you feel would address car-truck conflicts? (Please rank-order the various options; 1 being the most effective option)

3) Freeways:

- ◆ Truck-only lanes at certain locations _____
- ◆ Toll truckways (truck-only lane separated from other traffic on a freeway) _____
- ◆ Restrict trucks to certain lanes _____
- ◆ Allow through trucks to go on the left lanes _____
- ◆ Design special truck routes which will mostly/solely be used by trucks _____
- ◆ Prohibit trucks from entering certain busy roads/sections _____
- ◆ Create local and express lanes _____
- ◆ Provide more traffic information to truck companies/operators/drivers _____
- ◆ Increase truck speed limit _____
- ◆ Reduce truck speed limit _____
- ◆ Improve driver education programs _____
- ◆ Improve geometric features based on truck needs for some highway sections _____

- ◆ Increase/decrease toll fees for trucks _____
- ◆ Truck diversion _____
- ◆ Other options: _____

4) Non-freeways (state roads or rural roads)

- ◆ Restrict trucks to certain lanes _____
- ◆ Allow through trucks to go on the left lanes _____
- ◆ Design special truck routes which will mostly/solely be used by trucks _____
- ◆ Prohibit trucks from entering certain busy roads/sections _____
- ◆ Provide more traffic information to truck companies/operators/drivers _____
- ◆ Increase truck speed limit _____
- ◆ Reduce truck speed limit _____
- ◆ Improve driver education programs _____
- ◆ Improve geometric features based on truck needs for some highway sections _____
- ◆ Truck diversion _____
- ◆ Build by-pass roads _____
- ◆ Other Options: _____

7. Does your agency have strategies to mitigate car-truck conflicts? If so, please list them:

8. Do you have any other comments regarding car-truck conflicts?

Thank You Very Much!!!

APPENDIX C

Non-Truck Driver Behavior Survey

Non-Truck Behavior Survey

06/03

Dear Survey Participant:

We are working on an Indiana Department of Transportation (INDOT) project on minimizing car-truck interactions on highways. As part of it, we seek to understand the effects of driver behavior on car-truck interactions so as to enhance safety and mobility on roadways. **We want to determine the level of discomfort, if any, a non-truck driver feels in the vicinity of trucks.** Your opinions in this regard are very valuable to the study. Thank you.

Srinivas Peeta, Associate Professor, Ph.D.
Weimin Zhou, Graduate Research Assistant
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[Personal Information]

1. Age 1. less than 20 2. 20-29 3. 30-39 4. 40-49 5. 50-64 6. older than 65
2. Gender: 1. male 2. female
3. What is the highest level of education you have completed?
 1. high school or less 2. some college 3. college graduate 4. postgraduate
4. How many persons including yourself live in your household? _____
5. Are you a frequent user of interstate freeways?
 1. very frequent 2. frequent 3. neutral 4. not frequent 5. seldom

[Questions]

1. Do you feel any discomfort when driving in the vicinity of trucks? Please assign scores for your discomfort in relation to the relative position of the truck (**1** represents **no discomfort**; **5** represents **the most discomfort**).

■ Following a truck(s)	1	2	3	4	5
■ Driving parallel to a truck(s) in an adjacent lane	1	2	3	4	5
2. Consider the influence of bad weather (such as rain or snow) on your discomfort. Please assign scores for your discomfort in relation to the relative position of the truck (**1** represents **no discomfort**; **5** represents **the most discomfort**).

■ Following a truck(s)	1	2	3	4	5
■ Driving parallel to a truck(s) in an adjacent lane	1	2	3	4	5
3. Consider the influence of night driving on your discomfort. Please assign scores for your discomfort in relation to the relative position of the truck (**1** represents **no discomfort**; **5** represents **the most discomfort**).

■ Following a truck(s)	1	2	3	4	5
■ Driving parallel to a truck(s) in an adjacent lane	1	2	3	4	5
4. Consider the influence of traffic congestion. Please assign scores for your discomfort in the following situations (**1** represents **no discomfort**; **5** represents **the most discomfort**).
 - a. Congested traffic with smooth flow (crowded, but the speed is still high)

- | | | | | | |
|---|---|---|---|---|---|
| ■ Following a truck(s) | 1 | 2 | 3 | 4 | 5 |
| ■ Driving parallel to a truck(s)
in an adjacent lane | 1 | 2 | 3 | 4 | 5 |
| b. Congestion under slow speeds (implies very congested conditions,
such as stop-and-go traffic) | | | | | |
| ■ Following a truck(s) | 1 | 2 | 3 | 4 | 5 |
| ■ Driving parallel to a truck(s)
in an adjacent lane | 1 | 2 | 3 | 4 | 5 |
| c. No congestion | | | | | |
| ■ Following a truck(s) | 1 | 2 | 3 | 4 | 5 |
| ■ Driving parallel to a truck(s)
in an adjacent lane | 1 | 2 | 3 | 4 | 5 |

5. Consider that the vehicle ahead is a car **or** a truck. Assume that the speeds of the car or the truck ahead are identical. Please assign scores for the following statements (**1** represents **strongly disagree**; **5** represents **strongly agree**).

- | | | | | | |
|--|---|---|---|---|---|
| ■ I prefer to keep a wider gap with a truck ahead than a car ahead when following it | 1 | 2 | 3 | 4 | 5 |
| ■ The speed at which I drive to pass a truck ahead is faster than the speed of passing a car ahead | 1 | 2 | 3 | 4 | 5 |
| ■ I am more likely to pass a truck than a car | 1 | 2 | 3 | 4 | 5 |
| ■ The presence of significant truck traffic influences my decision to choose to avoid driving on a freeway | 1 | 2 | 3 | 4 | 5 |

6. Please rank the reasons for your discomfort with trucks (**1** represents **the most important one**)

- Blocks your sight; you cannot see the traffic in front of the truck
- Speed of trucks is slow
- The truck driver cannot see me
- Feel intimidated by truck size
- Others:

7. Have you heard of “the huge blind spot” for truck drivers? (Also labeled as the “No-Zone”)

1. Yes 2. No

8. What is your discomfort with trucks based on your experience on I-80/94 (the Borman Expressway) in Lake County, Indiana (**1** represents **no discomfort**; **5** represents **the most discomfort**)

- 1 2 3 4 5

9. Consider the speed limits of trucks and non-trucks. Which one would you choose?

1. I feel more comfortable if the posted speed limits are same for trucks and non-trucks.
2. I feel more comfortable if the posted speed limits are lower for trucks.

Thank you!