Modeling and Mitigation of Car-truck Interactions on Freeways

Srinivas Peeta¹*, Weimin Zhou² and Pengcheng Zhang³

¹School of Civil Engineering
Purdue University
West Lafayette, IN 47907-2051
Phone: (765)-494-2209
Fax: (765)-496-7996
E-Mail: peeta@purdue.edu

²School of Civil Engineering
Purdue University
West Lafayette, IN 47907-2051
Phone: (765)-494-2206
Fax: (765)-496-7996
E-Mail: zhouw@purdue.edu

³School of Civil Engineering
Purdue University
West Lafayette, IN 47907-2051
Phone: (765)-494-2206
Fax: (765)-496-7996
E-Mail: zhangp@purdue.edu

*Corresponding Author

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ABSTRACT

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 receiving increased attention. This paper models the behavior of non-truck drivers in terms of their interactions with trucks in the traffic stream, extends existing microscopic freeway traffic flow modeling logic to incorporate these interactions, and evaluates alternative strategies to mitigate them. The car-truck interactions are modeled by associating a “discomfort level” for every non-truck driver in the vicinity of trucks. This discomfort is affected by the driver socioeconomic characteristics and situational factors such as time-of-day, weather, and ambient traffic congestion levels. 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 based model is used to determine the non-truck driver discomfort level. It characterizes non-truck driver behavior near trucks using if-then rules that are constructed using the survey data. The discomfort level is used in conjunction with the car-following and lane-changing logics of a traditional traffic flow model to generate a truck-following model and a corresponding lane-changing model. This redresses a key methodological gap in the literature and provides a capability to analyze alternative strategies to mitigate car-truck interactions. An agent-based freeway segment traffic flow simulator is constructed using these extended microscopic flow models. 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.

Key words: car-truck interactions, fuzzy logic based behavior modeling, truck-following model, mitigation strategies
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 (1). 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 (2, 3).

In this study, the term “truck” is used to denote conventional combination trucks used for freight transportation, typically called “eighteen-wheelers”. Also, the terms “car” and “non-truck” are used interchangeably. 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. 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. As a consequence, the behavior of drivers for car-truck interactions is modeled no differently from that of car-car interactions. However, empirical studies (4) indicate that the headway when following a truck is wider than the headway when following a car. Beyond the flow modeling limitations, other studies (5) suggest that truck and non-truck drivers can react differently when provided routing information as part of an advanced information system, primarily due to the physical/operational characteristics of trucks.

One key factor for car-truck interactions is the distinct difference in the physical characteristics (such as length, acceleration/deceleration limits) of trucks. A common approach in this regard, adopted by the Highway Capacity Manual (HCM) (6), uses “passenger car equivalents” to estimate level of service by converting a truck into a proportional number of passenger cars for analysis. However, the influence of trucks on non-truck driver behavior cannot be captured using such approaches.

Existing studies on driver behavior in the context of truck-related analysis focus primarily on informational campaigns to reduce crashes rather than explicitly addressing interactions that may or may not lead to crashes. One study (7) identifies acts of motorists in the vicinity of large trucks and identifies primary crash factors for which non-truck drivers are responsible. It suggests that while road geometry, truck characteristics, weather, and traffic conditions are key factors, driver actions and behavior are also key causal variables. Kostyniuk et al. (8) use crash data to identify unsafe driving acts and the associated driver-related factors. Yoo and Green (4) explore car-following and truck-following behaviors by conducting experiments using a driving simulator. However, the study is observational only, and does not explore the factors that lead to the differences in behavior in the vicinity of trucks.

Studies are also conducted on identifying truck-related traffic strategies. Garber and Gadiraju (9) use simulation to evaluate the effects of several truck strategies on traffic flow and safety on multilane highways. The strategies used are differential speed limit, truck right lane restriction, and combinations thereof. However, they do not consider the influence of car-truck interactions on traffic performance as existing simulation models do not incorporate them. Such a capability
is essential for robustly evaluating alternative mitigation strategies. Grenzeback et al. (10) investigate the effects of large trucks on peak-period urban freeway congestion. They list strategies to reduce congestion from the supply and demand perspectives, but do not address car-truck interactions.

In summary, past studies do not address the influence of truck characteristics and non-truck driver behavior vis-à-vis car-truck interactions. 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 these 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. This discomfort manifests in terms of the truck-following and lane-changing behaviors of non-truck drivers, and 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. Hence, interactions in the current study are viewed from the perspective of non-truck driver behavior.

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. Specifically, the objectives are to: (i) provide qualitative and quantitative definitions for car-truck interactions so as to analyze the factors that lead to them and enable the development of modeling capabilities; (ii) develop behavioral models for non-truck drivers by seeking to capture their discomfort levels (DLs) in the vicinity of trucks; (iii) develop truck-following and lane-changing components to extend traditional traffic flow models to capture car-truck interactions; and (iv) evaluate alternative strategies to mitigate car-truck interactions.

METHODOLOGY

This section summarizes the study methodology. 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 level towards trucks. Then, the DL is used in conjunction with microscopic flow modeling logic to generate truck-following and modified lane-changing models. These extended simulation modeling components, incorporated into an agent-based freeway segment simulator, are used to infer the degree of car-truck interactions in the ambient traffic stream by using an aggregate time-dependent DL measure. The effectiveness of alternative mitigation strategies is evaluated considering these interactions.

Car-truck Interactions and Non-Truck Driver Discomfort

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, and that the resulting driving actions are influenced significantly by this discomfort.

Based on this definition, the mechanism to identify and quantify car-truck interactions entails the measurement of the DL for a non-truck driver when following a truck. It is reasonable to
expect the non-truck driver behavior to vary across drivers based on their socioeconomic 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. This implies that all non-truck drivers have discomfort to varying degrees in the vicinity of trucks, and that these discomfort levels are dynamic. From a traffic flow modeling standpoint, the car-truck interactions manifest in terms of the truck-following actions and the lane-changing logic when following a truck. 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. This implies the need to define when such an event represents a car-truck interaction and when it does not. In this study, we assume that 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. This 2-second threshold time gap is based on the recommended safe time gap in the Indiana driving manual. It is important to note here that the study methodology is independent of the threshold time gap used.

The DL is a disaggregate parameter specific to individual drivers. However, it is not sufficient to enable 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 aggregated sum of the discomfort levels of all vehicles on a roadway segment for a pre-specified duration averaged over all vehicles and the time duration. 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.

Methodological Framework

Figure 1 illustrates the conceptual framework to infer on car-truck interactions and evaluate alternative mitigation strategies. First, a car-truck interaction mitigation strategy is identified. Let the time duration of interest be discretized into intervals \( t \in [1,2,...,T] \). 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 consisting of trucks and non-truck vehicles is generated 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 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 \( k, k \in [1,2,...,K(t)] \), is set to 1. If vehicle \( k \) is a non-truck vehicle following a truck, the DL is determined. If the associated time gap with the truck is within the 2-second threshold time gap, an interaction is identified and the modified lane-changing model is applied. If an interaction does not occur, then the vehicle stays on the current lane and the lane-changing logic is not triggered. 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 1 is repeated. If \( k > K(t) \), the relevant traffic performance measures and the AADL are computed for interval \( t \). If \( t \leq \tau \), the outer loop in Figure 1 is repeated. Otherwise, the procedure is ended.
Data Collection: Non-Truck Driver Behavior Survey

The factors that contribute to the DL of non-truck drivers can be categorized into socioeconomic characteristics, inherent behavioral tendencies and situational factors. The socioeconomic characteristics include variables such as age, gender, education, and household size. 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 DLs 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. However, revealed preference 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 fully consistent with a driver’s actions in an actual situation (5) as a driver’s stated response is based on virtual scenarios.

Fuzzy Logic Modeling Approach

A fuzzy logic-based modeling approach is adopted to interpret the survey results and model the non-truck driver DL. It is used to combine the contributions of the significant attributes to estimate the DL. It is a robust tool for this problem due to the subjectivity in characterizing driver discomfort and some causal factors. The fuzzy logic modeling approach used here is similar to the approach employed by Peeta and Yu (11).

The structure of the fuzzy logic based DL model can be expressed as:

\[
DL_{k,t} = w_1 \Omega_G(X^G_k) + w_2 \Omega_A(X^A_k) + w_3 \Omega_E(X^E_k) + w_4 \Omega_H(X^H_k) + w_5 \Omega_W(Z^W_t) + w_6 \Omega_T(Z^T_t) + w_7 \Omega_C(Z^C_t)
\]

where:

\(DL_{k,t}\) = discomfort level for non-truck driver \(k\) in interval \(t\);

\(w_j\) = weight associated with attribute \(j\);

\(X^l_k\) = value of socioeconomic variable \(l\) for driver \(k\);

\(Z^m_t\) = value of situational factor \(m\) at time \(t\);

Here, \(\Omega_i(\cdot)\) represents the fuzzy transformation function that generates crisp value for gender (G). Similarly, the other \(\Omega(\cdot)\) operators represent the fuzzy transformation functions to generate the crisp values for age (A), education (E), household size (H), weather (W), time-of-day (T), and congestion level (C). The fuzzy logic procedure to determine these crisp values 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.

If-then Rules A non-truck driver’s DL to trucks is assumed to be based on a set of simple if-then rules that relate it to the driver socioeconomic characteristics and situational factors. 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, then discomfort is high” is one rule related to education 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 (for example, “some college”) may not completely match the associated rule. Then, an implication operation (12, 13) is used to determine to what extent a specific if-then rule matches with this description. An aggregation mechanism is used to combine the implication values for all rules fired for an attribute into one fuzzy set based on the input for the driver. This output fuzzy set is then transformed into a crisp value through a process called defuzzification. This crisp fuzzy value would represent the $\Omega(\cdot)$ term for that attribute for driver $k$ in Equation (1). 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.

**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 (11). Generally, the methods for determining membership functions are heuristic and can be subjective. Here, the membership functions are constructed consistent with the survey data based on the preliminary analysis using the discrete choice model (13), 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.

**Defuzzification Method** Defuzzification is the mechanism to transform the fuzzy output set obtained through the implication operations to a crisp value. The Center of Sums (COS) method is used to defuzzify the fuzzy output as:

$$ y^* = \frac{\int y \cdot \sum_{i=1}^{n} \mu_{B_i}(y) \, dy}{\int \sum_{i=1}^{n} \mu_{B_i}(y) \, dy} $$

(2)

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; for example, $\Omega_k(X^E_k) = y^*_k$.

Based on this approach, crisp values are generated for all explanatory variables in Equation (1). 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.

**Adjustment of the Weights of If-then Rules** The DL of a driver $k$ in interval $t$, $DL_{k,t}$, is computed by obtaining the crisp values for each fuzzy attribute and its importance (weight). 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 (1), the DL for driver $k$ and in interval $t$ can be represented as:

$$DL_{k,t} = \sum_{j=1}^{N_A} w_j y^*_j$$

where:

- $y^*_j$ = the crisp value obtained for attribute $j$ using the fuzzy logic approach;
- $N_A$ = the number of attributes.

The weighted sum approach of Equation (3) 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 $k$. Hence, the unknowns are the weights $w_j$ for the attributes $j \in [1,2,\ldots,N_A]$. 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 $w_j \geq 0$. Once the $w_j$ values are determined, Equation (3) can be used to predict the DL value driver $k$. The DL values are then used to modify the traffic simulation components on car-following and lane-changing, as discussed hereafter.

**Adaptation of Car-truck Interaction Logic to Traffic Flow Modeling**

Existing traffic flow models and simulators do not sufficiently 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 (14) 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. 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. The strategic goal for the models developed in this study is to provide a realistic modeling component for car-truck interactions for the next generation of traffic simulation models (15) that seek greater traffic flow modeling realism. 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 to replicate the traffic flow movement for freeway segments.

**FRESIM Car-following and Lane-changing Modeling Components**
FRESIM is part of the CORSIM corridor simulation model 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 (16) 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. The car-following and lane-changing models embedded in FRESIM are discussed in Halati et al. (14). We extend them to explicitly incorporate the impacts of car-truck interactions.

**Modified Simulation Model to Incorporate Car-Truck Interactions Logic**

The non-truck driver behavior survey suggests that drivers prefer to overtake a truck than a car 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, Yoo and Green (4) conclude that headway when following a car is lower than when following a truck. Based on these insights and other factors, the FRESIM models are extended to develop a truck-following model and a modified lane-changing model.

**Truck-following Model** To reflect the greater spacing when the vehicle ahead is a truck, the FRESIM car-following model is extended by including a term to represent the additional contribution due to the discomfort of the following driver with respect to that truck. This leads to the truck-following model:

\[ H = L + 10 + qv_t + bq(u_t - v_t)^2 + \beta \times (DL - 1) \]  \( (4) \)

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:
  \[ b = \begin{cases} 
  \frac{1}{2}, & u_t < v_t \\ 
  0, & \text{otherwise} 
  \end{cases} \]
- \( \beta \) is coefficient for DL.

The follower vehicle acceleration for any simulation scanning interval \( \delta \) is determined as:

\[ a = \frac{2 \{ x_{t+\delta} - y_t - L - 10 - v(q + \delta) - bq(u_{t+\delta} - v_t)^2 - \beta \times (DL - 1) \}}{\delta^2 + 2q\delta} \]  \( (5) \)

where:
- \( x_{t+\delta} \) = lead vehicle position at time \( t+\delta \);
- \( y_t \) = follower vehicle position at time \( t \).

In Equations (4) and (5), 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 previous subsection, 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) and (5).
The coefficient of the discomfort level term, $\beta$, represents the weight of the contribution of the discomfort to the space headway. A variable value for $\beta$ implies less conservative (smaller $\beta$) or more conservative (larger $\beta$) drivers in terms of the additional space that they would maintain with the truck ahead. We assume that $\beta$ is identical across all non-truck drivers. The value of $\beta$ 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 (4). 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 $\beta_i$ for each driver $i$. An average of these individual $\beta_i$ values generated the $\beta$ value. Based on this procedure, the $\beta$ value of 8.15 was used in our study experiments.

**Modified Lane-changing Model** 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 it is not slow enough to exceed the tolerance level of the follower. Based on this, the FRESI lane-changing logic “desire” component is modified. The desire to perform a discretionary lane change of non-truck drivers when following a truck is then modeled as:

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

where:

- $\omega$ = the desire coefficient associated with $DL$;
- $v_{int}$ = tolerance threshold speed for lane changer;
- $v_{ff}$ = desired free-flow speed (ft/s);
- $D_{truck}$ = desire of non-truck driver to perform a discretionary lane change (percent);
- $v$ = speed of the lane changer.

Akin to the truck-following model, the discomfort level term is subtracted by 1 to ensure consistency with the lane-changing logic. The coefficient $\omega$ has an interpretation similar to that of $\beta$ for the truck-following model. We assume that $\omega$ 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.

The modified simulator logic accounting for non-truck driver discomfort is used to develop the microscopic agent-based simulator for freeway segments.

**Computation of the AADL**

The AADL is a performance measure that can be used to infer on the degree of car-truck interactions on a roadway segment. The individual DL values are obtained from the proposed fuzzy logic approach. The agent-based simulator is used to determine whether a non-truck
vehicle following a truck interacts with it. Based on this data, the AADL for time interval $t$ is computed as:

\[
AADL(t) = \frac{\sum_{k=1}^{N(t)} \xi_{k,t} \cdot DL_k'}{N(t)}
\]

where:

- $N(t)$ = number of non-truck vehicles on the roadway segment of interest during interval $t$;
- $\xi_{k,t} = \begin{cases} 1, & \text{if } k \text{ has interaction with truck ahead in interval } t \\ 0, & \text{if } k \text{ does not have interaction with truck ahead in interval } t \end{cases}$

$AADL(t)$ 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 $AADL(t)$ values over a pre-specified time duration. This $AADL$ averaged over $\tau$ time intervals is denoted by $AADL_\tau$ and is expressed as:

\[
AADL_\tau = \frac{\sum_{t=1}^{\tau} AADL(t)}{\tau}
\]

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

**CASE STUDY**

This section discusses the implementation of the survey and construction of the fuzzy logic based DL model for the Borman expressway case study. 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.

The Borman expressway region in northwest Indiana 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). It represents an ideal testbed to analyze car-truck interactions because while the average daily traffic on it is over 140,000 vehicles, truck traffic represents between 30%–70% of the total volume. This makes it one of the busiest commercial routes in the nation.

**Data Collection and Analysis**

An on-site SP survey of non-truck drivers is used to infer on driver DLs. The first set of questions relate to the socioeconomic characteristics of the respondents. These include age, gender, education level, household size, and frequency of freeway usage. The second set of questions addresses discomfort under various situational factors. 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 a truck. Additional questions seek to identify the reasons for discomfort.

The survey responses were obtained from 159 drivers in the Borman expressway region through driver surveys at rest areas on I-65 and I-94. These two interstates represent the primary demand for the Borman Expressway. The results suggest that under normal conditions, the inherent DL to trucks tends to be relatively low. More than 82% respondents choose a discomfort level less than or equal to 3. The discomfort, however, is significantly 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 where 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.

Next, driver behavior and actions in the vicinity of trucks are solicited. 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 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, which is reflected in our modified lane-changing model.

The survey also seeks reasons for driver discomfort. About 54% of 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.

A preliminary analysis (12) of the survey data is performed using a binary logit model to estimate the significant factors vis-à-vis discomfort level. It identifies gender, household size, weather conditions, and congestion levels as the significant explanatory variables.

**Fuzzy Logic Based DL Model**

A set of simultaneous equations are solved to estimate the weights associated with the crisp values for the fuzzy variables in Equation (1). They 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.

**SIMULATION EXPERIMENTS**

This section 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 are used to derive insights on the characteristics and impacts of car-truck interactions.

**Simulation Experiments Setup**

**Environment**

Simulation experiments are conducted using the agent-based freeway segment simulator, developed in the SWARM (17) programming environment. The simulator is validated by ensuring that the fundamental traffic flow relationships are satisfied (13). Each vehicle, truck or non-truck, is represented as an agent with specific socioeconomic characteristics that are assigned consistent with the survey data. Each vehicle interacts with other vehicles every time step, which is one second in the simulator. The DL towards trucks for each non-truck driver encountering a truck ahead is computed for the relevant time steps using the fuzzy logic approach. The AADL is computed for every simulation interval using the associated procedure.

**Demand Generation and Loading**

The simulator mimics a 2-mile long freeway section. A demand profile and the associated loading factor 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. 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.

**Simulation Parameters**

Several simulation parameters are considered in the experiments. They are classified into two major categories: system parameters (including loading factor, truck percentage, and lane assignment scheme) and agent parameters (including gender, age, household size, education, driver type, and preferred free-flow speed). Loading factor is an indicator to benchmark the demand intensity and to compare alternative demand loads. In this study, the base case entails a uniform demand 2000 vph and is benchmarked as loading factor 1. Truck percentage in the ambient traffic stream can significantly influence car-truck interactions. The experiments consider four truck percentages for analysis (10%, 30%, 50% and 70%). 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.

*Computational Statistics*

The simulation statistics used to analyze different scenarios are the primary performance measures computed for the simulation duration. They include AADL, number of car-truck interactions, average speed, average travel time, and average lane speed differentials. They are briefly defined hereafter. (i) AADL. The AADL is the primary indicator of the degree of car-truck interactions. (ii) Number of car-truck interactions. It is another indicator for the level of 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. (iii) Average speed. The average speed is obtained by averaging the average freeway segment speeds over all time steps for the duration. (iv) Average travel time. The average travel time is obtained by averaging the travel times of all vehicles in the duration. 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. (v) 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. 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.

*Simulation Experiments*

*Situational Factors*

Figure 2(a) illustrates the impacts of truck percentage, night-time driving, and bad weather on the driver discomfort levels represented by AADL for loading factor 2. The AADL increases with truck percentage. This is intuitive because the likelihood of car-truck interactions increases with truck percentage. This is also aided by the fact that the number of non-truck vehicles decrease with increasing truck percentage. 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.

*Congestion (Density)*

The impacts of congestion on AADL are evaluated by tracking its proxy, density, as shown in Figure 2(b). 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 under 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. Therefore, driver discomfort is high for medium congestion levels. 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. 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.

Another clear trend in Figure 2(b) 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 this randomness.

Operational Strategies to Mitigate Car-Truck Interactions

Mitigation strategies identified through a nationwide survey as part of this study (12) are analyzed and compared to the base case. They are evaluated for various congestion levels and truck percentages.

Description of Mitigation Strategies

Alternative operational strategies are proposed to mitigate car-truck interactions. Strategy 1 restricts trucks to the right-most lane. It does not entail monetary investment, but may require legislation. It can reduce the number of car-truck interactions, though the level of service on the right-most lane may deteriorate. Strategy 2 allows trucks on all lanes. It potentially increases the number of car-truck interactions, but the speed differential between lanes is expected to decrease as trucks are present on all lanes. Strategy 3 adds one more lane to the freeway segment, and trucks are then allowed to travel on the two right lanes. It requires significant monetary investment, and the additional capacity may generate additional traffic in the long-term due to system-level interactions. 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 on car-truck interactions only. A key contribution of this paper is that it enables the consideration of car-truck interactions in addition to the other performance measures in making operational decisions.

Results and Insights

Performance statistics are obtained for the three strategies and the base case for different demand loads and truck percentages. Detailed insights are provided in Peeta et al. (13). Here, we focus on the trade-offs and insights from the mitigation strategies for an intermediate demand load of 3500 vph. Table 1 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. In general, AADL values increase with truck percentage. The AADLs for low truck percentages (10%) and low to medium congestion 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 made from a safety perspective rather than from those of car-truck interactions or traffic performance. Under high truck percentages (50%), the strategies that are effective are restricting trucks to the 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, and it is significantly more economical. Since the average lane speed differentials under both strategies are not that different, and average travel times are similar, Strategy 1 is preferred.

Table 1 also shows, in parentheses, average lane speed differentials and average travel times under the no-discomfort scenario, which implies existing models. To obtain these values, DLs are set to 1 for all drivers in the simulator. The results illustrate that the average lane speed differentials for this intermediate demand load are lower (ranging from 3.4% to 15.3%) for most strategies (other than Strategy 2) under the no-discomfort scenario, suggesting that driver DL has an influence on speed differentials. That is, existing models can underestimate the influence of trucks on safety. For Strategy 2, these differentials are higher (19.6% to 34.8%) under the no-discomfort scenario. This is because discomfort to trucks increases the likelihood of non-truck drivers shifting to a faster lane when they encounter a truck ahead. This in turn leads to that lane becoming more congested, reducing its average speed. Thereby, the average speeds across lanes become more uniform when DL is considered. Beyond the safety implications, it should be noted that the proposed models provide the capability to measure driver discomfort unlike existing models. This can provide transportation agencies a basis to identify problematic locations for remedial actions.

Due to space restrictions, the analysis to identify preferred strategies under other combinations of demand loads and truck percentages is not discussed here. We briefly summarize the associated insights. Under low 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 trade-offs exist among the various performance measures. This implies that the effectiveness of a strategy should be viewed more holistically than just focusing on reducing AADL.

CONCLUDING COMMENTS

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.

ACKNOWLEDGEMENTS

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REFERENCES:

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FIGURE 1 Conceptual Framework to Determine Discomfort Levels and Evaluate Car-truck Interaction Mitigation Strategies.
FIGURE 2 Sensitivity Analyses of Simulation Parameters.
### TABLE 1 Comparison of Alternative Mitigation Strategies (3500vph).

<table>
<thead>
<tr>
<th>Strategies</th>
<th>Truck %</th>
<th>AADL</th>
<th>Average Lane Speed Differential</th>
<th>Average Travel Time</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Base Case</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>1.15</td>
<td>4.55</td>
<td>4.20</td>
<td>112.2 (112.7)</td>
</tr>
<tr>
<td>50</td>
<td>1.57</td>
<td>7.02</td>
<td>6.72</td>
<td>119.3 (119.6)</td>
</tr>
<tr>
<td><strong>Restricting Trucks to Right-most Lane (Strategy 1)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>1.14</td>
<td>5.71</td>
<td>5.26</td>
<td>112.3 (112.3)</td>
</tr>
<tr>
<td>50</td>
<td>1.10</td>
<td>9.11</td>
<td>8.37</td>
<td>118.7 (118.7)</td>
</tr>
<tr>
<td><strong>Allowing Trucks on All Lanes (Strategy 2)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>1.16</td>
<td>1.48</td>
<td>1.84</td>
<td>113.5 (113.5)</td>
</tr>
<tr>
<td>50</td>
<td>1.78</td>
<td>0.88</td>
<td>1.35</td>
<td>121.0 (121.1)</td>
</tr>
<tr>
<td><strong>Adding a Lane (Strategy 3)</strong></td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>1.13</td>
<td>3.92</td>
<td>3.79</td>
<td>110.0 (110.6)</td>
</tr>
<tr>
<td>50</td>
<td>1.48</td>
<td>6.18</td>
<td>5.36</td>
<td>117.5 (117.6)</td>
</tr>
</tbody>
</table>

* Units: speed (kmph); travel time (seconds). The numbers in the parentheses represent the no-discomfort scenario.
FIGURE 1 Conceptual Framework to Determine Discomfort Levels and Evaluate Car-truck Interaction Mitigation Strategies.
FIGURE 2(a) Impacts of Situational Factors.

FIGURE 2(b) Impact of Traffic Density (Proxy for Congestion Level).

FIGURE 2 Sensitivity Analyses of Simulation Parameters.