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Behavior-based analysis of freeway car–truck interactions and related mitigation strategies

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Abstract

Freight trucks are an important component of the nation's highway traffic. Due to their physical and operational characteristics, they can significantly impact traffic system performance, safety, and the travel experience of non-truck drivers. Methodological gaps exist in the literature on modeling car–truck interactions that do not result in crashes, especially those resulting from non-truck driver behavior. This paper focuses on the modeling of the behavior of non-truck drivers in the vicinity of trucks to capture these interactions. This is done by quantifying a time-dependent "discomfort level" for every non-truck driver interacting with trucks in the ambient traffic stream. The driver socioeconomic characteristics and situational factors that affect this discomfort are identified through a stated preference survey of non-truck drivers and a preliminary analysis of the survey data using a discrete choice model. A fuzzy logic based approach is proposed to determine the en-route time-dependent non-truck driver discomfort level. This 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 modified lane-changing model in the vicinity of trucks. An agent-based freeway segment traffic flow simulator is constructed using the extended microscopic flow modeling logic. It provides a simulation-based framework to analyze alternative strategies to mitigate car–truck interactions.

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Experiments are conducted to analyze the sensitivity of the discomfort level to the causal variables, and evaluate the effectiveness of alternative mitigation strategies.

Keywords: Car–truck interactions; Driver behavior; Fuzzy logic; Microscopic traffic flow modeling; Agent-based simulation

1. Introduction

Freight trucks represent a key element of the nation's economy. Truck transportation is the most frequently used mode for freight movement in terms of both shipment value and weight. According to the Bureau of Transportation Statistics (2002), commercial truck traffic increased 75% over the past three decades, and this trend is likely to continue over the next 10 years. However, trucks also contribute disproportionately to traffic congestion, infrastructure deterioration, and crashes due to their physical and operational characteristics such as size, weight, braking distance, blind spots, turning radii, and driver fatigue. Quantifiable measures can be used to infer on the influence of trucks on traffic safety and pavement infrastructure deterioration. In addition, the impacts of truck operational characteristics (limits on acceleration, deceleration, and speed) on traffic performance can be robustly identified. However, traffic performance can also be affected by the behavior of truck drivers and non-truck drivers. Truck driver behavior is influenced by the presence of large blind spots (also labeled the no-zone) and the constraints introduced by road geometry. Non-truck driver behavior is affected by the truck physical and operational characteristics, and further, raises quality-of-travel issues for these drivers. These behavior-based influences, which can significantly affect traffic performance, are ignored or cursorily acknowledged in the existing traffic flow modeling literature. They are difficult to model as they involve eliciting latent driver behavioral tendencies which can be dynamically influenced by situational factors such as time-of-day, weather, and ambient traffic congestion. A related factor that contributes substantially to the modeling intractability is the need for difficult-to-measure behavioral data. In this study, we propose a fuzzy logic based modeling framework 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. It provides some generic methodological tools and modeling components for the next-generation of traffic simulation models that need to incorporate increased realism in modeling traffic flow (NGSIM, 2001).

Here, car–truck interactions are viewed as the driving actions of non-truck drivers due to psychological discomfort in the vicinity of trucks. 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. There is a rich body of literature on safety issues involving trucks (FHWA, 2000; Kostyniuk et al., 2002; NHTSA, 1998; Stuster, 1999). These studies mostly focus on the analyses of crash data or on models to understand key causal factors vis-à-vis crashes. However, the existing literature does not address the modeling of traffic flow interactions between trucks and other vehicles arising from a driver behavior perspective, especially those that do not lead to crashes. Such a capability is essential for analyzing strategies to mitigate car–truck interactions, which further influence traffic performance, safety, and the travel experience of non-truck drivers.

From a driver behavior standpoint, existing traffic flow models do not differentiate between trucks and other vehicles on the road. 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. However, a past study (Yoo and Green, 1999) using a driving simulator suggests 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 drivers and non-truck drivers can react differently to the routing information provided through an advanced information system. These behavioral differences highlight the need to address the existing methodological gaps.

In summary, while it may seem that the deterministic tweaking of a parameter in existing traffic flow/simulation models may suffice to capture the differential behavior of non-truck drivers in the vicinity of trucks by modifying the associated headway, it is nonetheless true that such behavior is the net effect of several factors some of which are random and others which are specific to an individual. This is because the behavior of drivers varies across them, and is based on several factors ranging from the socioeconomic characteristics to the situational factors. So, just tweaking an existing model parameter is inadequate from a behavioral perspective. We propose a new parameter called driver discomfort level 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. For example, in Indiana, drivers in some areas have complained about driving discomfort due to the presence of high fractions of trucks. Hence, there is a need to benchmark alternative mitigation strategies from the perspective of driver discomfort in addition to system performance and safety. Finally, we seek to propose a methodological framework that is more general in its scope than just the car–truck interactions problem, and can be used to model other behavioral phenomena in the traffic driver context that have either been ignored or represented inadequately in the existing literature (NGSIM, 2001).

This paper aims to provide a measurable definition of car–truck interactions, identify the causal factors, develop a methodological framework to model these interactions, and enable the evaluation of alternative strategies to mitigate them. The first objective is to provide a qualitative definition for car–truck interactions so as to analyze the causal factors and enable the development of modeling capabilities to derive insights on them. This entails the robust modeling of non-truck driver behavior under the influence of truck physical/operational characteristics. Existing approaches lack mechanisms to capture these behavioral impacts. For example, the Highway Capacity Manual (TRB, 2000) adopts the notion of "passenger car equivalents" to estimate level of service by converting a truck into a proportional number of passenger cars to capture its physical characteristics.

The second objective is to develop behavioral models for non-truck drivers by seeking to capture their psychological discomfort in the vicinity of trucks. Past studies (Stuster, 1999; Kostyniuk et al., 2002) suggest that the presence of trucks can significantly impact the driving actions of non-truck drivers, and that these impacts are key causal factors for car–truck crashes. However, these studies focus primarily on driver actions that lead to crashes rather than explicitly addressing non-crash related interactions. This paper associates "discomfort levels" with non-truck drivers to capture such interactions. A fuzzy logic approach is used to link the non-truck driver characteristics and situational factors with the discomfort drivers feel in vicinity of trucks.

The third objective of this study is to develop truck-related interaction components for microscopic traffic flow models. Existing traffic flow models do not account for car–truck interactions. To the extent that these interactions are manifest at the individual driver level, we extend an existing microscopic flow model to incorporate these interactions by developing truck-following and modified lane-changing models. The extended modeling logic is used to construct an agent-based freeway segment traffic flow simulator.

The fourth study objective is to evaluate alternative strategies to mitigate car–truck interactions using the agent-based simulation (ABS) platform. Some existing studies in the literature analyze truck-related traffic strategies. Garber and Gadiraju (1991) use simulation to evaluate the effects of several truck strategies on traffic flow and safety on multilane highways. Grenzeback et al. (1991) investigate the effects of large trucks on peak-period urban freeway congestion. However, while these studies consider truck operational characteristics, they do not incorporate car–truck interactions due to the limitations of existing simulation models.

A comprehensive review of the literature relevant to the study problem can be found in Zhou (2003). This paper is organized as follows. Section 2 discusses the methodology to quantify car truck interactions through non-truck driver discomfort. Section 3 describes the extensions to an existing microscopic traffic flow model to incorporate these interactions. Section 4 discusses the application of the study methodology to a case study involving the Borman expressway (I-80/94) in northwest Indiana. Section 5 discusses sensitivity analyses for the models developed and evaluates alternative strategies to mitigate car–truck interactions for the case study using simulation experiments. Section 6 provides some concluding comments.

2. Methodology to model non-truck driver discomfort level

2.1. Modeling car–truck interactions using driver discomfort levels

Car–truck interactions are defined in this study as the driving actions of non-truck drivers arising from their discomfort in the vicinity of trucks, primarily due to truck physical/operational characteristics. While interactions can also arise from the truck driver perspective, they tend to be less significant behaviorally as cars are smaller in size and have better operational characteristics. We postulate that the non-truck driver discomfort level (DL) is a quantifiable measure of the associated discomfort, and that it varies across drivers based on their socioeconomic characteristics, past experience, and inherent behavioral tendencies. Also, the DL is time-dependent as it is influenced by situational factors such as weather, time-of-day and ambient traffic conditions. The level of discomfort is revealed through the driving actions in terms of truck-following and associated lane-changing behaviors.

The proposed definition of car–truck interactions suggests that when a non-truck driver follows a truck, there may be varying degrees of discomfort. This implies that different drivers in the same traffic stream may have different DLs due to differences in their behavioral tendencies. By contrast, drivers with similar socioeconomic characteristics may have different DLs if their situational factors are different. Further, 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. Based on the recommended safe time gap in the Indiana Driver License Manual, 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. However, the study methodology is independent of the threshold time gap used.

2.2. Methodological framework to determine driver discomfort level

Fig. 1 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

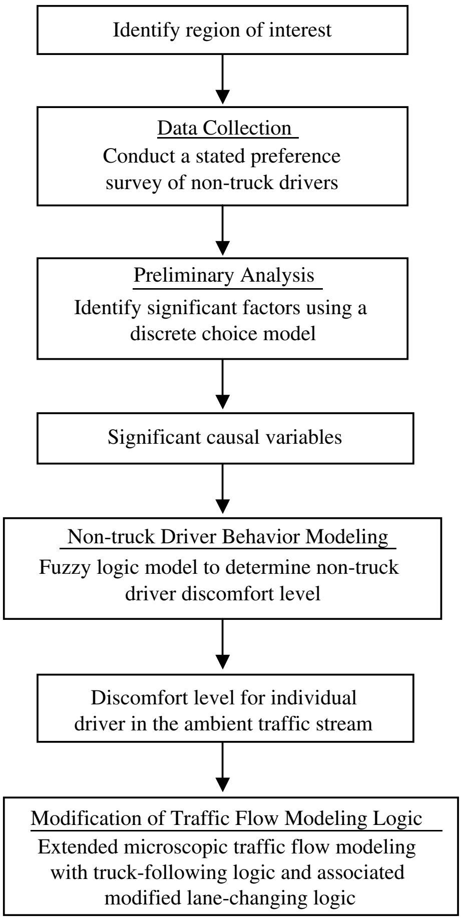


Fig. 1. Conceptual framework to determine driver discomfort level.

that contribute to driver DL. A preliminary analysis of the survey data is performed using discrete choice modeling to identify potential significant factors to generate *if–then* rules for the fuzzy logic modeling approach used. The fuzzy model is used to determine the time-dependent DL for each non-truck driver. The DL is used in conjunction with the car-following logic of a microscopic traffic flow model to obtain a truck-following model. In addition, it is used to modify the associated lane-changing logic. This leads to an extended microscopic traffic flow model that can analyze car–truck interactions. This framework is adopted in Section 5 to evaluate the effectiveness of alternative car–truck interaction mitigation strategies.

2.2.1. Data collection: non-truck driver behavior survey

As stated earlier, a key objective of this study is to interpret driver DL using measurable variables. 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. However, it is difficult to measure the manifestations of driver actions using existing sensor technologies. Further, even if it were possible to do so, it would be highly labor intensive and economically prohibitive. Hence, the non-truck driver discomfort when following a truck cannot be measured trivially.

In this study, the factors that contribute to non-truck driver discomfort are categorized into socioeconomic characteristics, behavioral tendencies and situational factors. The socioeconomic variables consist of age, gender, education, household size, and frequency of freeway usage. The situational factors include bad weather (rain, snow), night driving, and three levels of traffic congestion (low, medium, and high). The socioeconomic variables are primarily static, unlike situational factors which are time-dependent. However, the behavioral tendencies of drivers are latent variables and cannot be measured directly. Hence, the discomfort characteristics of each survey respondent are inferred using a stated preference (SP) survey that seeks potential driver actions in hypothetical scenarios. As is well-known in the literature, the SP data may not be consistent with a driver's revealed actions. However, it provides a consistent basis to build logical *if–then* rules in the proposed fuzzy logic approach.

An on-site SP survey of non-truck drivers is conducted (Zhou, 2003). The first group of questions identifies the socioeconomic characteristics of the respondents. 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 (where 1 represents no discomfort and 5 represents the most discomfort) when following a truck. 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 the difference in driving actions when following trucks.

2.2.2. Fuzzy logic modeling approach

A fuzzy logic based approach is adopted to model the non-truck driver DL by combining the contributions of the significant attributes. It is a robust mechanism for this problem due to the subjectivity in characterizing driver discomfort and some causal factors. A few existing studies use fuzzy logic modeling in related areas: Gonzalez-Rojo et al. (2002) use a fuzzy logic approach to model car-following to estimate the parameters in the associated equations, and Wu et al. (2000) develop a microscopic simulation model using fuzzy logic.

The significant explanatory variables for the driver DL are identified using a preliminary analysis of survey data, as discussed in Section 4.2. Based on this, the structure of the fuzzy logic based DL model in this study can be expressed as:

$$\mathrm{DL}_{k,t} = w_1\Omega_G(X_k^G) + w_2\Omega_A(X_k^A) + w_3\Omega_E(X_k^E) + w_4\Omega_H(X_k^H) + w_5\Omega_W(Z_t^W) + w_6\Omega_T(Z_t^T) + w_7\Omega_C(Z_t^C) \tag{1}$$

where $\mathrm{DL}_{k,t}$ is the discomfort level for non-truck driver k in interval t; X_k^l is the value of socioeconomic variable l for driver k; Z_t^m is the value of situational factor m in interval t; and w_j is the weight associated with attribute j. The $\Omega(\cdot)$ represent the fuzzy logic approach based transformation functions to determine the crisp values corresponding to the specific explanatory variable represented by the subscript. They are: gender (G), age (A), education (E), household size (H), weather (W), time-of-day (T), and congestion level (C).

The fuzzy logic procedure to obtain the crisp values using the transformation functions 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 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 form. Consistent with this approach, the driver DL 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 survey data 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. 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'' based on the survey, it does not directly match the *if–then* rule: ''*if* the driver is well-educated, *then* 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''. 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:

If x is A_i	*then* y is B_i	→ Generic *if–then* rule
x is A_i^*		→ Input value for driver
	y is B_i^*	→ Implication value for driver

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.

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. This crisp fuzzy value would represent the $\Omega_E(X_k^E)$ value for driver k in Eq. (1). The procedure is repeated for the other variables in Eq. (1).

The construction of the *if–then* rules is the most critical step in the fuzzy logic approach. These rules are then 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 maps the fuzzy variable values to the set $[0,1]$, indicating the possibility of each variable value. The possibility is a function that takes values 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). Typically, the shapes of the membership functions are triangular and trapezoidal, and are governed by analytical convenience. In our study, these shapes are used consistent with the survey data.

We use the "education" variable example to illustrate the construction of the membership functions. Fig. 2 illustrates the membership functions for "less-educated" and "well-educated" categories. In the study survey, 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 Fig. 2. 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 Fig. 2. As will be discussed later, 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 Eq. (1) reflect their significance to explaining driver discomfort consistent with the survey data.

Implication operator. As discussed earlier, 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:

$$B_i^* = A_i^* \circ R \tag{2}$$

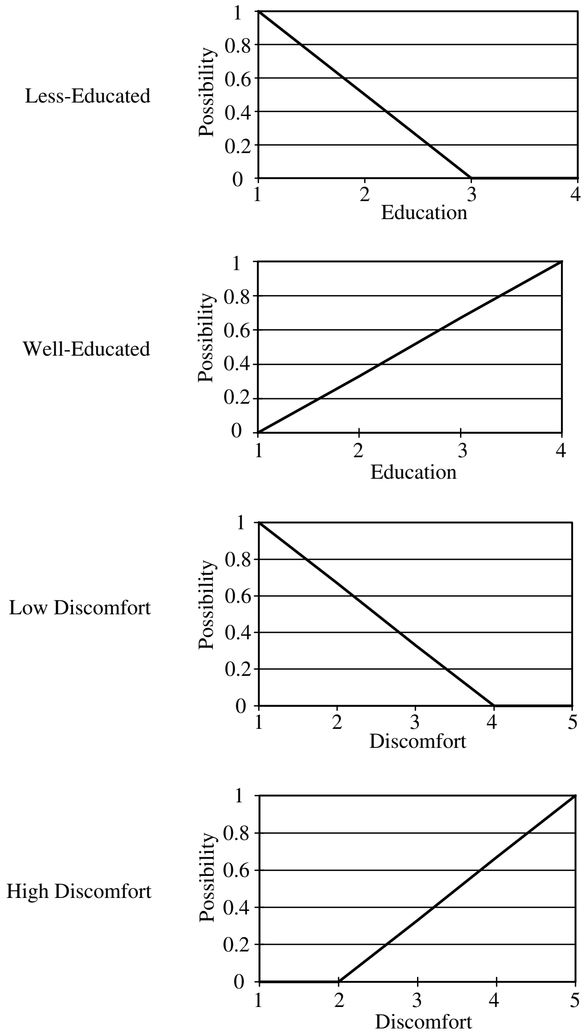


Fig. 2. Determination of membership functions.

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 Larsen Product implication operator (Peeta and Yu, 2002), defined as:

$$\mu_{B_i^*}(y) = \gamma_i \cdot \mu_{B_i}(y) \tag{3}$$

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

$$\gamma_i = \max_{x \in X} \min(\mu_{A_i^*}(x), \mu_{A_i}(x)) \tag{4}$$

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, as shown in Fig. 3. 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

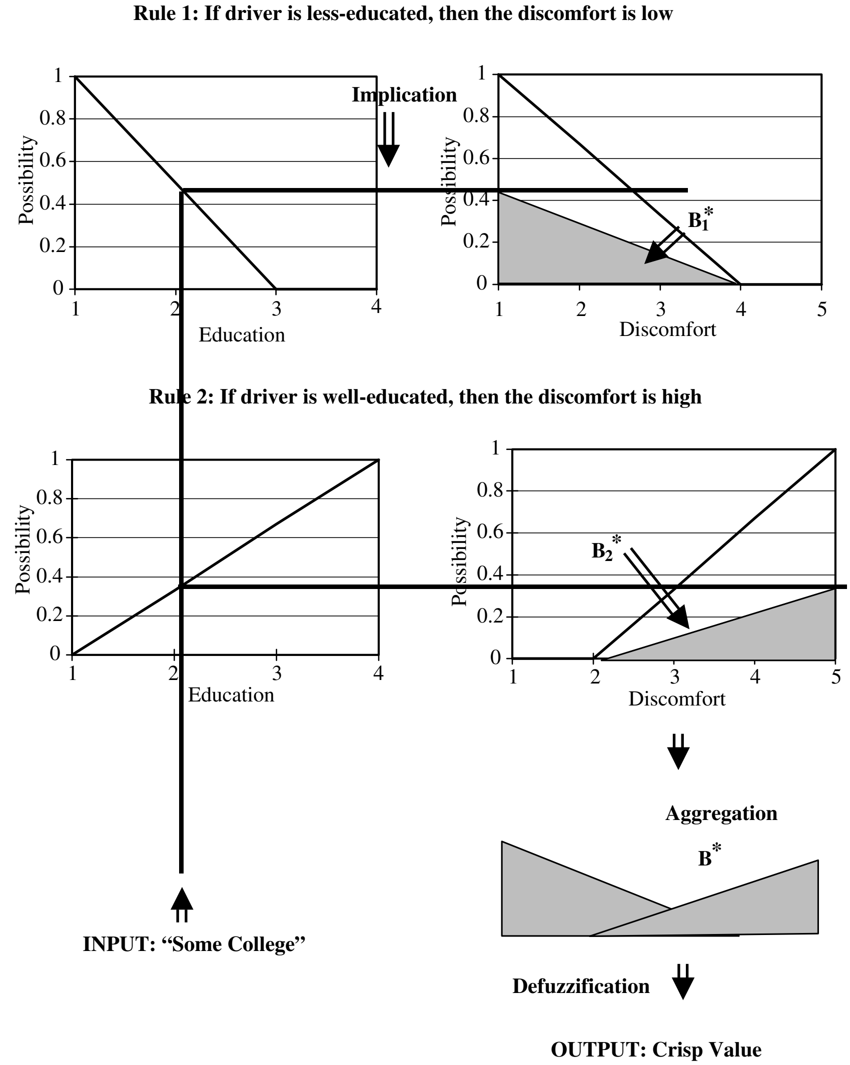


Fig. 3. Computation of crisp values using *if–then* rules.

can be obtained as the highest value of the overlap, as expressed in Eq. (4). Then, Eq. (3) is used to imply the membership function of B_i^* using the known B_i membership function.

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 Fig. 3, for the "education" variable and driver input "some college", both rules in the education category 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 Fig. 3. 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:

$$y^* = \frac{\int_Y y \cdot \sum_{i=1}^{n} \mu_{B_i}(y)\,\mathrm{d}y}{\int_Y \sum_{i=1}^{n} \mu_{B_i}(y)\,\mathrm{d}y} \tag{5}$$

where Y is the range of discomfort levels (1–5), n is the number of rules in the category, $\mu_{B_i}(y)$ is the possibility value of y in fuzzy set B_i, and y^* is the crisp value from defuzzification. Hence, the fuzzy transformation function output in Eq. (1) specifies a crisp value for the corresponding category. For example, for education, we have:

$$\Omega_E(X_k^E) = y_k^{*E} \tag{6}$$

where X_k^E is "some college" for driver k, and y_k^{*E} is the crisp value for driver k. Based on this approach, seven crisp values are generated for the seven explanatory variables for driver k in Eq. (1).

Adjustment of the weights of if–then rules. The final step is to determine the weights of the attribute categories in Eq. (1). These weights reflect the importance of each attribute category (such as education, gender, time-of-day etc.) in contributing to the DL value. The $\mathrm{DL}_{k,t}$ 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 $\mathrm{DL}_{k,t}$, 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 Eq. (1), the DL for driver k and in interval t can be represented as:

$$\mathrm{DL}_{k,t} = \sum_{j=1}^{N_\mathrm{A}} w_j y_k^{*j} \tag{7}$$

where N_A is the number of attributes. The weights of the attributes are determined using the survey data as it provides the stated DL values for different situations for each respondent k. The y_k^{*j} values are computed using the fuzzy logic approach discussed heretofore. To determine the weights w_j, $(N + N_\mathrm{A} + 1)$ simultaneous equations are solved, where N is the number of observations from the SP survey. The additional constraints are due to the normalization requirement $\sum_{j=1}^{N_\mathrm{A}} w_j = 1$, and N_A non-negativity constraints $w_j \geqslant 0$. After the w_j values are determined, Eq. (1) can be used to predict the DL value for a specific driver.

2.3. Computation of the AADL

The DL is a disaggregate parameter specific to an individual driver. However, it is not sufficient to analyze 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 drivers on a roadway segment for a pre-specified duration averaged over all vehicles. 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.

The DL values are obtained from the fuzzy logic approach. The 2-s threshold discussed in Section 2.1 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:

$$\mathrm{AADL}(t) = \frac{\sum_{k=1}^{N(t)} \xi_{k,t} \cdot \mathrm{DL}_{k,t}}{N(t)} \tag{8}$$

where $N(t)$ is the number of non-truck vehicles on the roadway segment of interest during interval t, and:

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

$\mathrm{AADL}(t)$ 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 $\mathrm{AADL}(t)$ values over a pre-specified time duration. This average aggregate discomfort level averaged over τ time intervals is denoted by AADL_τ, and is expressed as:

$$\mathrm{AADL}_\tau = \frac{\sum_{t=1}^{\tau} \mathrm{AADL}(t)}{\tau} \tag{9}$$

The AADL_τ is the primary performance measure used to evaluate the mitigation strategies.

3. Extending traffic flow modeling logic to incorporate car–truck interactions

We extend existing microscopic flow modeling components to incorporate car–truck interactions through the DL variable. The strategic goal is to provide a realistic generic modeling component vis-à-vis car–truck interactions for the next-generation of traffic simulation models. In the interim, the car-following and lane-changing logics in the FRESIM freeway traffic flow simulator (Halati et al., 1991) are extended to obtain truck-following and modified lane-changing logics. FRESIM is part of the CORSIM corridor simulation model (Owen et al., 2000) developed by the FHWA. It is chosen as the base model based on the insights from a previous study (Aycin and Benekohal, 1999) which compares several popular car-following models. It concludes that the FRESIM car-following model more closely replicates the field data compared to other models when the driver sensitivity factors are robustly calibrated. However, FRESIM is not as robust under stop-and-go traffic conditions.

The car–truck interaction modeling in this study is applicable to freeways only, though the proposed methodological framework is not restricted to just the freeway domain. While such models can be developed for the non-freeway context as well, their significance in the context of mitigation strategies is not as apparent. This is because 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. For implementing the proposed framework in Section 5, an agent-based traffic flow simulator for freeway segments is constructed using the modified FRESIM modeling logic.

We now briefly describe the car-following and lane-changing models embedded in FRESIM, and their extensions to incorporate car–truck interactions.

3.1. Truck-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 is used for this purpose (Halati et al., 1991):

$$H = L + 10 + qv_t + bq(u_t - v_t)^2 \tag{10}$$

where H is the space headway (ft) between leader and follower, L is the lead vehicle length (ft), q is the driver sensitivity factor for the follower vehicle, v_t is the speed of the follower vehicle at time t (fps), u_t is the speed of the lead vehicle at time t (fps), and b is a calibration constant defined as:

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

Based on Eq. (10), the follower vehicle acceleration for simulation scanning interval δ is determined as:

$$a = \frac{2\{x_{t+\delta} - y_t - L - 10 - v(q+\delta) - bq(u_{t+\delta} - v_t)^2\}}{\delta^2 + 2q\delta} \tag{11}$$

where $x_{t+\delta}$ is lead vehicle position at time $t + \delta$, y_t is the follower vehicle position at time t, and q is the driver sensitivity factor for the follower vehicle.

As discussed in Section 1, Yoo and Green (1999) conclude that the headway when following a car is lower than when following a truck. To reflect the greater spacing when the vehicle ahead is a truck, Eq. (10) 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:

$$H = L + 10 + qv_t + bq(u_t - v_t)^2 + \beta \times (\mathrm{DL} - 1) \tag{12}$$

and the follower vehicle acceleration:

$$a = \frac{2\{x_{t+\delta} - y_t - L - 10 - v(q+\delta) - bq(u_{t+\delta} - v_t)^2 - \beta \times (\mathrm{DL} - 1)\}}{\delta^2 + 2q\delta} \tag{13}$$

where β is the coefficient for the discomfort level term. In Eqs. (12) and (13), the DL is subtracted by one to ensure consistency between the definition of DL and its computation using the fuzzy logic approach. 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.

β reflects the relative contribution of the discomfort to the space headway. A lesser value for β implies less conservative drivers in terms of the additional space that they would maintain with the truck ahead, and vice versa. In the study experiments, β is assumed identical across all non-truck drivers. Its calibration entails field data or a driving simulator. Due to the lack of either resource, the driving simulator results from Yoo and Green (1999) are used to estimate β. In that study, the

16 subjects followed cars about 10% 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 10% increase in headway and the DL values were used to compute the β_i for each of the 16 drivers. An average of these individual β_i values generated the β value of 8.15 for our study experiments.

3.2. Modified lane-changing model

The other important flow modeling component related to car–truck interactions is the lane-changing behavior. The non-truck driver behavior survey 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 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. Its 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 a discretionary lane change. It 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:

$$v_{\text{int}} = v_{\text{ff}}\left[\frac{50+2c}{100}\right] \tag{14}$$

where v_{int} is the tolerance threshold speed for the lane changer, v_{ff} is the desired free-flow speed (fps), and c is the driver type factor (a randomly assigned number between 1 and 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 determined as:

$$D = \begin{cases} 100, & v \leqslant v_{\text{int}} \\ 100\left[1 - \dfrac{v - v_{\text{int}}}{v_{\text{ff}} - v_{\text{int}}}\right], & v_{\text{int}} < v < v_{\text{ff}} \\ 0, & v \geqslant v_{\text{ff}} \end{cases} \tag{15}$$

where D is the desire to perform a discretionary lane change (%), and v is the speed of the lane changer.

Once a driver has the desire to perform a lane change, the gaps on the adjacent lanes are evaluated (Halati et al., 1991). After confirming that a vehicle desires a lane change and the gaps on other lanes permit it, 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. It 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:

$$F_1 = \begin{cases} 1, & h \leqslant h_{\min} \\ 1 - \dfrac{h - h_{\min}}{h_{\max} - h_{\min}}, & h_{\min} < h < h_{\max} \\ 0, & h \geqslant h_{\max} \end{cases} \tag{16}$$

where $h_{\min}$ is the minimum time headway, $h_{\max}$ is the maximum time headway, and h is the existing time headway in the current lane:

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

where s is the separation distance between the vehicle and its leader in the current lane, F_s is the speed threshold factor, and v_d is the 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.

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 is modified. The desire (in %) to perform a discretionary lane change for non-truck drivers when following a truck is then modeled as:

$$D_{\text{truck}} = \begin{cases} 100, & v \leqslant v_{\text{int}} \\ \min\left(100\left[\left(1 - \dfrac{v - v_{\text{int}}}{v_{\text{ff}} - v_{\text{int}}}\right) + \omega \cdot (\text{DL} - 1)\right], 100\right), & v_{\text{int}} < v < v_{\text{ff}} \\ \omega \cdot (\text{DL} - 1) \cdot 100, & v \geqslant v_{\text{ff}} \end{cases} \tag{17}$$

where ω is the desire coefficient associated with the discomfort level term. The DL is subtracted by 1 to ensure consistency with the lane-changing logic. The interpretation of coefficient ω parallels that of β for the truck-following model. In the study experiments, ω is assumed to be identical for all non-truck drivers. Its value can also be calibrated using field data or a driving simulator. 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.

3.3. Implementation of the extended traffic flow modeling logic in a simulator

Fig. 4 illustrates the implementation of the extended traffic flow modeling logic in a simulation framework to account for driver discomfort when following a truck. In this study, it is enabled by developing an agent-based traffic simulator 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

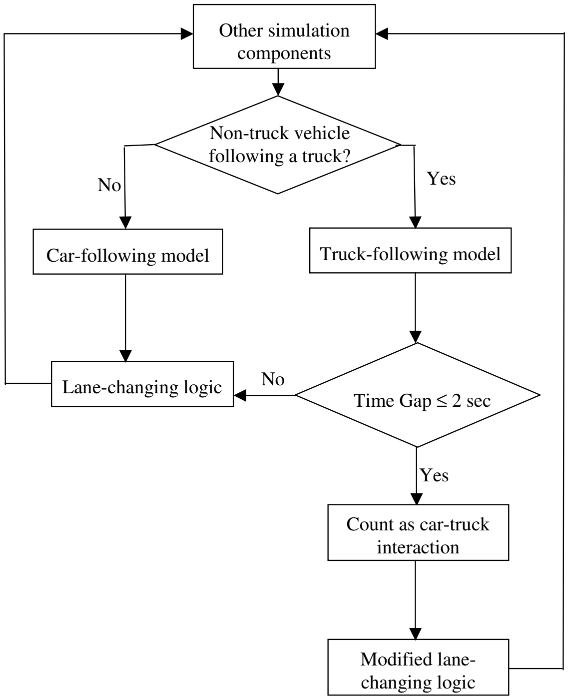


Fig. 4. Implementation of the extended traffic flow modeling logic in a simulator.

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-s time gap, interaction is identified and the modified lane-changing logic is used. If the space gap is greater than the 2-s 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. Case study

The study methodology is analyzed using simulation experiments for a case study involving the Borman expressway in northwest Indiana. It includes the implementation of the non-truck driver SP survey, the preliminary analysis of survey data, and construction of the fuzzy logic based DL model.

The Borman expressway region consists of the Borman expressway which is a 16-mile segment of I-80/94, the surrounding arterials, and nearby interstates, I-65 and I-90. The Borman expressway has heavy truck traffic and represents an ideal testbed to analyze car–truck interactions. The average daily traffic consists of over 140,000 vehicles, and 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.

4.1. Data collection and analysis

The non-truck driver behavior survey discussed in Section 2.2.1 consists of on-site responses from 159 non-truck drivers in the Borman region. The socioeconomic characteristics of the survey respondents are summarized in Table 1. The distribution of the respondents in terms of age groups is not uniform as only about 28% of the respondents are less than 40 years old. 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 the situational factors, the survey results suggest that under normal conditions, the inherent discomfort level to trucks tends to be relatively low, with most drivers choosing a DL

Table 1
Explanatory variables and survey respondent socioeconomic characteristics statistics

Explanatory variable	Mnemonics	Number of survey respondents (%)
Alternative specific constant	ONE	
Gender	GEN	
=1, if male		99 (62.3%)
=2, if female		60 (37.7%)
Age	AGE	
=1, if $\leqslant 20$		3 (1.9%)
=2, if 21–30		19 (11.9%)
=3, if 31–40		23 (14.5%)
=4, if 41–50		34 (21.4%)
=5, if 51–64		49 (30.8%)
=6, if $\geqslant 65$		31 (19.5%)
Education	EDU	
=1, if high school or less		29 (18.2%)
=2, if some college		41 (25.8%)
=3, if college graduate		41 (25.8%)
=4, is postgraduate		48 (30.2%)
Household size	HHS	
=1		22 (13.8%)
=2		65 (40.9%)
=3		24 (15.1%)
$\geqslant 4$		48 (30.2%)
Freeway experience	FRQ	
=1, if very frequent user of freeways		48 (30.2%)
=2, if frequent user of freeways		77 (48.4%)
=3, if neutral user of freeways		21 (13.2%)
=4, if not frequent user of freeways		8 (5.0%)
=5, if seldom user of freeways		5 (3.2%)
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	

value less than or equal to 3. However, the discomfort is pronounced for bad weather. The survey results indicate that time-of-day may not be a significant factor, implying that night driving does not change the relevant behavior. However, this may simply be an artifice of SP surveys. 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 where speeds tend to be higher.

Another set of survey questions seek to elicit driver behavior and actions in the vicinity of trucks. They suggest that most drivers feel that they would keep a wider gap with a truck ahead, and that drivers are more likely to pass a truck than a car. These form the premise for the truck-following and modified lane-changing models in this study. The survey also seeks reasons for driver discomfort in the vicinity of trucks. The primary factors identified relate to the truck physical dimensions: they block the line of sight for non-truck drivers and create blind spots for truck drivers. This suggests that truck size tends to increase the uncertainty in perceiving the traffic ahead by non-truck drivers, making them more cautious. It motivates our hypothesis of using driver discomfort to reflect this cautiousness. A detailed description of the survey data characteristics is provided in Zhou (2003).

4.2. Identification of significant variables

As discussed in Section 2.2, the driver DL is obtained using a fuzzy logic based approach. A key step in this methodology is the construction of the *if–then* rules. This entails the identification of significant explanatory variables for which these rules are constructed. This is done through a preliminary analysis of the survey data using discrete choice modeling. To minimize computational effort, a choice model with only two alternatives (low discomfort or high discomfort), the binary logit model, is analyzed. The structure of the binary logit model estimated using the survey data for driver k is:

$$(V_{ik} - V_{jk}) = \alpha_0 + \sum_{l=1}^{5} \alpha_l W_k^l + \sum_{m=1}^{5} \gamma_m Y_k^m \tag{18}$$

where V_{ik} is systematic component of the utility of choice i (low discomfort), V_{jk} is the systematic component of the utility of choice j (high discomfort), α_0 is the alternative specific constant, α_l is coefficient for socioeconomic variable l, W_k^l is the categorical value (shown in Table 1) of socioeconomic variable l, γ_m is the coefficient for situational variable m, and Y_k^m is the dummy 0–1 explanatory variable for situational variable m. Based on the SP survey, the socioeconomic variables considered are gender, age, education, household size, and frequency of freeway trips. The dummy explanatory variables are considered for bad weather, night driving, low congestion, medium congestion, and high congestion, respectively.

To enable 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. Based on the analysis, the following combination had the best fit:

$$\varepsilon_k = \begin{cases} \text{low discomfort}, & \text{if the stated DL} \leqslant 3 \\ \text{high discomfort}, & \text{if the stated DL} = 4 \text{ or } 5 \end{cases} \tag{19}$$

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.

This model is used to estimate the significant factors vis-à-vis DL using the survey data. Of the 159 responses, 105 are used to estimate the model and the remaining are used for analyzing the model prediction capabilities. The LIMDEP 7.0 software is used to estimate the coefficients in Eq. (18).

Table 1 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. 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 2.

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

Table 2
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
$L(\beta)$	−310.67
ρ^2	0.289

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 substantiated by the survey data, which indicates lower discomfort for high congestion compared to medium congestion when only DL responses 1 and 2 are considered as "low discomfort" in a binary choice framework. Hence, the seemingly greater contribution of the high congestion variable 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, where stated DLs 1, 2, and 3 are grouped as "low discomfort". In that case, the percentage of survey respondents choosing low (or high) discomfort under the MCO and HCO variables is almost identical. We go with this latter viewpoint based on the insights from the survey data which suggest that high congestion implies lesser discomfort compared to medium congestion where 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, we use a single variable for congestion level, labeled CON, and estimated a new model. It indicates that CON is a significant variable. Based on the preliminary analysis, the variables GEN, HHS, WEA, TOD, and CON are found to be significant vis-à-vis discomfort levels.

4.3. Fuzzy logic based discomfort level model

The variables considered for the DL model are highlighted in Eq. (1). They include the socio-economic 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 driv-

Table 3
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 drive 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

ing actions. In general, younger people, whose reaction times are lower, tend to be more aggressive while driving and may 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 though they are not found to be significant in the preliminary analysis. This is because the survey data is skewed towards older drivers.

Table 3 highlights 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. The socioeconomic variables are constant or relatively unchanged. However, the situational factors are time-dependent. Hence, non-truck driver discomfort levels are dynamic variables in the actual driving situation to capture the effects of weather, time-of-day and congestion. The variables represented by the *if–then* rules are fuzzy in nature except for gender input which is precise. Hence, membership functions are constructed for them as shown in Fig. 5 for the case study. The x-axis represents the fuzzy variables and the y-axis denotes the possibility value.

Using the approach discussed in Section 2.2, a set of simultaneous equations are solved to estimate the weights associated with the crisp values for the fuzzy variables in Eq. (1). 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.

5. Simulation experiments

Simulation experiments are conducted for the case study. Sensitivity analyses are performed for the causal variables, and the effectiveness of alternative mitigation strategies are evaluated using the proposed simulation framework.

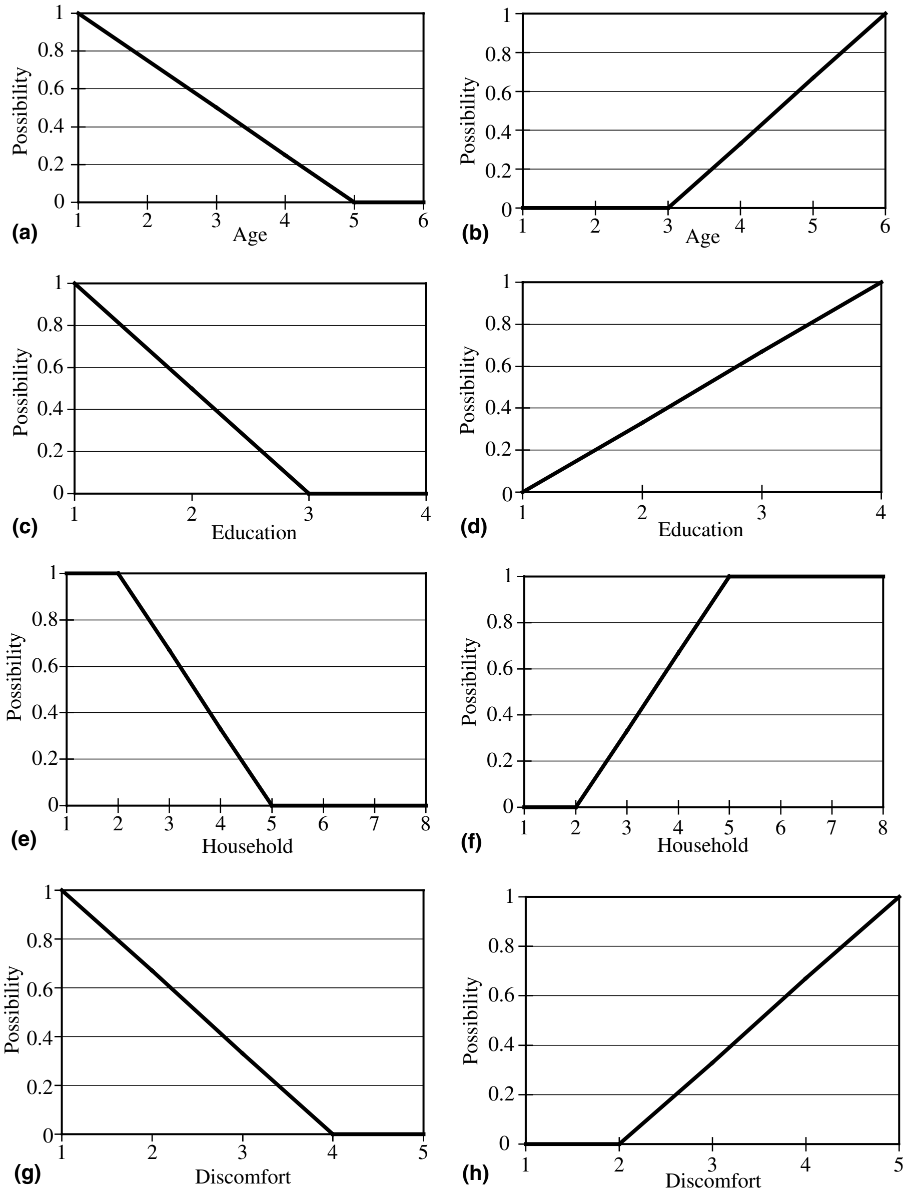


Fig. 5. Membership functions for the fuzzy variables for which *if–then* rules are constructed: (a) driver is young, (b) driver is old, (c) driver is less-educated, (d) driver is well-educated, (e) small household, (f) large household, (g) discomfort is low, and (h) discomfort is high.

5.1. Setup

5.1.1. Programming environment

The simulation experiments are conducted using an agent-based freeway segment traffic flow simulator constructed using the extended microscopic traffic flow modeling logic discussed in Section 3. An ABS approach offers inherent advantages in the traffic modeling context: individual elements in the physical system can be modeled as autonomous agents that are capable of interaction, learning through experience, perception-reaction, and goal-oriented behavior (Franklin and Graesser, 1996). ABS can explicitly incorporate truck-related behavior in the form of simple *if–then* rules for each driver. The simulation model is coded in the SWARM (Minar et al., 1996) programming environment. Each vehicle in the simulator, truck or non-truck, is an agent with specific socioeconomic characteristics that are assigned consistent with the survey data. The simulation time step is one second. 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 every simulation second using the proposed procedure.

5.1.2. Demand generation and loading

Fig. 6 illustrates a 2-mile long freeway segment from the Borman expressway. Vehicles are generated for a 30-min duration for a given demand profile and loading factor. The number of trucks and non-truck vehicles is based on the percentage of trucks in the traffic stream. The vehicles are generated to a single loading stack queue as illustrated in the figure, assigned randomly to a lane subject to lane restrictions, and discharged sequentially using a first-in, first-out discipline. The loading queue can be viewed as a single-lane entrance ramp or the upstream boundary for the segment for which car–truck interactions analysis is desired. The speed of a vehicle as it enters a lane at this boundary is set as the average speed for that lane in that time interval. However, the time of its entrance to the assigned lane depends 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 lane restrictions preclude re-assignment, it is held back till the next interval and the loading logic is repeated. This loading scheme 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 interval. Conversely, long loading queues may exist for heavy demand loads.

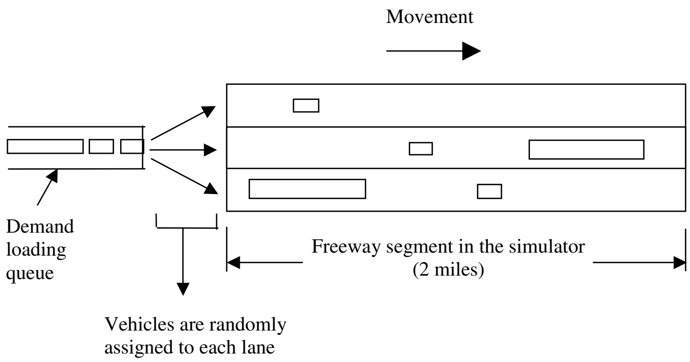


Fig. 6. Freeway segment in the simulator.

5.1.3. Simulation parameters

Loading factor and profile. The loading factor benchmarks the demand intensity and is used to compare alternative demand loads. In this study, the demand 2000 vph is benchmarked as loading factor 1. The loading profile represents the shape of the time-dependent demand generation. We consider the uniform and peaking profiles for the experiments. The peaking profile can be insightful as it can generate a greater intensity of congestion in a time-dependent manner, akin to typical peak periods.

Truck percentage. The truck percentage can vary from 30% to 70% on the Borman expressway. Hence, four truck percentages (10%, 30%, 50% and 70%) are considered for analysis. 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.

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 Borman freeway segment has three lanes, the three strategies considered are: trucks restricted to right lane, trucks 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.

Agent parameters. As stated earlier, the socioeconomic characteristics are generated for individual drivers consistent with the SP survey data. They include: (i) gender: the gender is randomly generated consistent with the survey data; (ii) age: the age ranges from 16 to 80 years; (iii) household size: ranges from 1 to 8; (iv) education: the education level is randomly generated from four possibilities (high school or less, some college, college graduate, and postgraduate); (v) driver type: this is a FRESIM parameter that reflects driver aggressiveness and is a uniform random number between 1 and 10, with 10 representing the most aggressive driver; and (vi) preferred speed: a preferred speed under free-flow conditions is assigned to each driver in the simulator based on the driver type. The preferred speed is uniformly distributed from 60 mph (96.6 kmph) to 70 mph (112.7 kmph) for non-truck drivers and 55 mph (88.5 kmph) to 65 mph (104.6 kmph) for truck drivers. This represents the speed differences among vehicle types along the Borman expressway, which has a speed limit 55 mph. The free-flow speeds for trucks are slightly lower (by 5 mph) based on Indiana speed limits.

5.1.4. Computational statistics

The freeway segment simulator has a 30-min demand generation period. The simulator begins when the first vehicle is generated and ends when the last vehicle leaves the 2-mile segment. Hence, the simulation duration is the time difference between these two events. But, such an 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 it 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. Let T_s denote the total simulation duration. It is the difference between the times at which the last vehicle leaves the freeway segment and the first vehicle enters it. Let T_c denote the intermediate duration for which simulation statistics are computed. Let T_b denote the time duration to populate the freeway section initially; it is the time duration between the simulation start time and 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 s. T_e 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:

$$T_c = T_s - T_b - T_e$$

5.1.5. Performance measures

The performance measures for analyzing alternative scenarios, computed for the duration T_c, are: (i) AADL_{T_c}; this is the primary indicator of the degree of car–truck interactions, and is computed by averaging AADL(t) over the duration T_c. In the study experiments discussed hereafter, we simply use "AADL" to denote this measure. (ii) Number of car–truck interactions: this measure is another indicator for the level of car–truck interactions. It is determined using the logic discussed in Section 2.1 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. (iii) 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. (iv) 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. (v) Average lane speed differential: the average lane speed differential is the average of the differences in the average speeds for adjacent lanes. 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 across lanes. In summary, the performance measures (i) and (ii) are indicators of the level of car–truck interactions; the performance measures (iii) and (iv) relate to traffic network performance; and (v) is a proxy for safety.

5.2. Simulation experiments

One set of simulation experiments analyze the sensitivity of the DL model to various causal variables and model parameters. Another set of experiments evaluate alternative car–truck interaction mitigation strategies.

5.2.1. Validity of the agent-based simulator

Before conducting the experiments, 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 simulator. The base case lane restriction strategy with 20% trucks is used, and demand is varied from 1000 to 8000 vehicles per hour.

The microscopic freeway segment 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

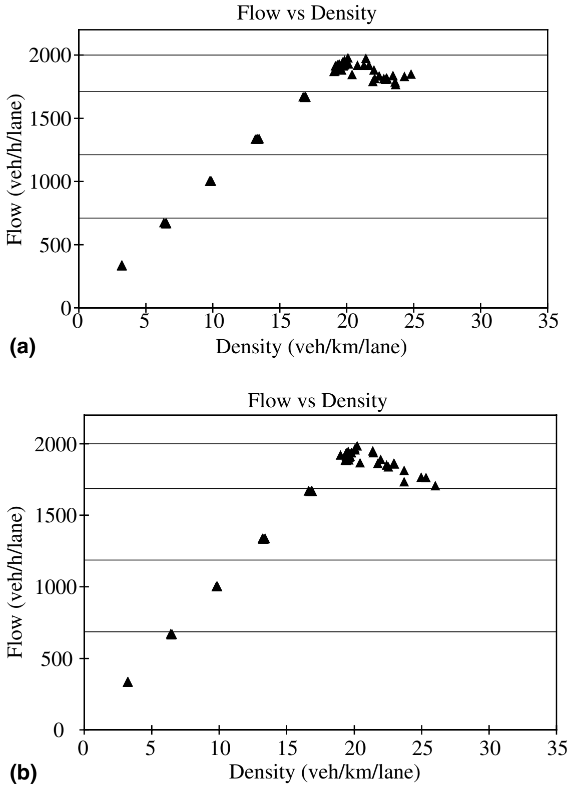


Fig. 7. Fundamental traffic flow relationships generated by agent-based simulator. (a) Traffic flow relationships when car–truck interactions logic is excluded. (b) Traffic flow relationships when car–truck interactions logic is included.

car–truck interaction logic and the modified microscopic agent-based simulator constructed as part of this study. Fig. 7(a) and (b), respectively, show these plots. These data are obtained using 10 simulation runs for the base case with loading factors ranging from 0.5 to 4. In each run, six time snapshots (at 5, 10, 15, 20, 25 min, and the time at which the last vehicle enters the freeway segment) are obtained for the various traffic flow parameters. Hence, 60 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 Fig. 7(b) compared to Fig. 7(a). With this validation, the modified agent-based simulator is used to analyze the study objectives.

5.2.2. Sensitivity analyses

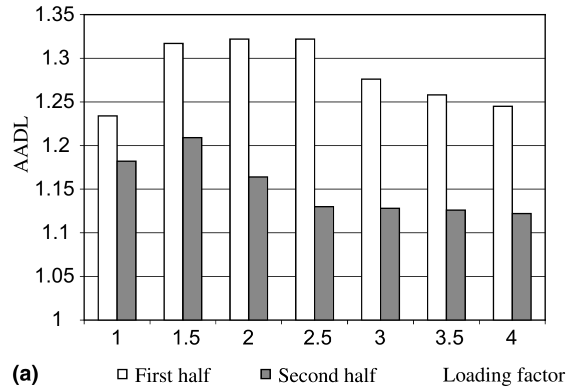
The DL model sensitivity to various causal variables and parameters is conducted using the simulator. With 2000 vph demand and 20% trucks for the base case lane strategy, the DL values range from 1.967 to 4.033 for those non-truck drivers who have interactions with trucks. The impacts of the system parameters (loading factor, demand profile, and truck percentage in the ambient traffic stream) and situational factors (night-time driving, congestion level, and bad weather) on driver discomfort levels are discussed in Peeta et al. (2004). Here, we analyze the influence of other factors and variables.

Congestion. The influence of congestion on AADL can be tracked using its proxy, density. The AADL increases as congestion levels increase from low to medium, but decreases as we move from medium to high levels. This trend is consistent with driver behavior realism. 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 2.1 to identify car–truck interactions. 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 2.1, this reduces the likelihood of car and trucks interacting as the 2-s time gap threshold may not be breached as often as under medium congestion. Detailed insights are provided in Peeta et al. (2004).

Vehicle destination. The vehicle destination 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. We assume that there is an exit ramp at the end of the 2-mile segment, and that there is a sign in the middle of the segment that warns of the impending arrival of the exit. Ten percent of the non-truck 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 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 three runs of the simulator for a loading factor 2. This analysis indicates the significance of vehicle destination to the driver discomfort levels.

Incidents. Incidents 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, the left-most lane is blocked between the 1.0 and 1.5 mile markers for the entire simulation duration. 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 0.5–4) for the first and second halves of the freeway segment, as shown in Fig. 8(a). 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. 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.

Demand loading profile. The shape of the demand loading curve can also impact AADL. The uniform and peaking profiles are considered here. 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 Fig. 8(b). The AADL values for the peaking profile are lower. This is consistent with insights from the sensitivity analysis for congestion levels discussed previously.



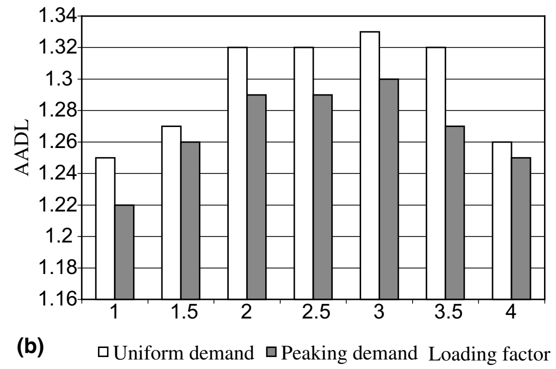


Fig. 8. Sensitivity analyses: (a) impacts of incidents and (b) impact of demand loading profile.

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.

Threshold time gap. As discussed in Section 2.1, we use a 2-s threshold time gap to determine whether an interaction exists between a truck and a car that follows it. However, the study methodology is independent of the threshold time gap used. Fig. 9 shows the impacts of the threshold time gap on the AADL for different congestion levels. It plots the AADL values for threshold gaps 1, 1.5, 2, and 2.5 s. A larger threshold time gap leads to a higher AADL value, and vice versa. 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 interactions problem in a region through the use of 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. Fig. 9 also illustrates the trends for AADL under different congestion levels, which are consistent with the previous discussion.

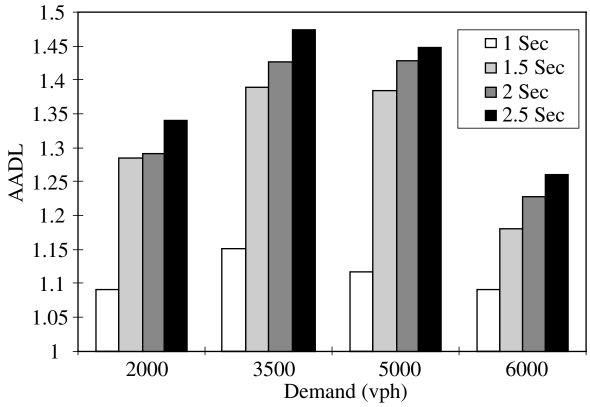


Fig. 9. Impact of threshold time gap.

5.3. Operational strategies to mitigate car–truck interactions

Operational strategies can be used to reduce car–truck interactions. The base case strategy restricts trucks to the two right lanes of the freeway segment. A nationwide survey of traffic engineers was conducted to identify potential strategies in this context (Zhou, 2003). 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 evaluated: (i) *Strategy 1*: This strategy restricts trucks to the right-most lane. Its implementation may require legislation, though no additional monetary investment. It can reduce the number of car–truck interactions, but may also reduce the level of service on the right-most lane; (ii) *Strategy 2*: This strategy allows trucks on all lanes. It can increase the number of car–truck interactions, but the increased homogeneity of traffic across lanes can reduce the lane speed differential; (iii) *Strategy 3*: Here, an additional lane is added to the freeway segment, and trucks are then allowed to travel on the two right lanes. It entails significant monetary costs though it adds more capacity. Also, it may generate additional traffic in the long-term due to system-level interactions of demand and performance. This suggests cost–benefit trade-offs under this strategy; and (iv) *Strategy 4*: In this strategy, trucks are diverted to alternative routes. This can be done using "truck-only routes" "toll truckways" and "express lanes". However, it entails the presence of a viable alternative to route trucks, either through diversion or truck-only routes. Hence, this strategy may involve monetary investment. Also, if a detour route is used, its traffic conditions may deteriorate due to the presence of the diverted trucks.

A key contribution of this paper is the methodology to evaluate car–truck interactions. However, traffic performance, safety and monetary costs are typically the primary factors for decision-making vis-à-vis planning and operations. Hence, it is important to view the effectiveness of a strategy from a more holistic perspective than just focusing on its ability to reduce car–truck interactions. This implies that there are trade-offs involved, and that the mitigation capability may represent a secondary consideration only.

A comprehensive description of the performance measures under the first three mitigation strategies is provided in Zhou (2003) for different demand loads (2000, 3500, 5000, and 6000 vph) and

Table 4
Comparison of alternative mitigation strategies

Traffic load	Strategies	Truck %	AADL	Number of car–truck interactions	Average speed[a]	Average lane speed differential[a]
2000 vph	Base case	10	1.16	124	103.9	4.4
		30	1.36	233	101.3	5.1
		50	1.47	232	99.2	6.7
		70	1.61	176	96.7	7.2
	Strategy 1	10	1.09	69	104.6	5.1
		30	1.22	115	102.0	7.3
		50	1.25	68	98.9	8.3
		70	1.16	26	95.7	8.8
	Strategy 2	10	1.16	120	103.5	1.9
		30	1.38	244	100.5	2.0
		50	1.50	283	98.7	1.4
		70	1.74	257	96.5	1.0
	Strategy 3	10	1.09	82	106.1	3.3
		30	1.26	178	102.8	4.8
		50	1.45	202	99.8	5.5
		70	1.39	117	97.5	5.7
3500 vph	Base case	10	1.17	198	102.8	4.6
		30	1.48	397	99.6	6.2
		50	1.62	400	97.2	7.0
		70	1.69	255	94.5	8.1
	Strategy 1	10	1.15	151	103.4	5.7
		30	1.21	159	100.7	7.8
		50	1.07	34	85.6	9.1
	Strategy 2	10	1.2	219	101.8	1.5
		30	1.48	449	98.0	3.0
		50	1.76	554	96.1	0.9
		70	2.07	461	94.4	0.6
	Strategy 3	10	1.13	178	105.5	3.9
		30	1.34	356	102.3	1.8
		50	1.52	321	98.7	6.2
		70	1.52	174	95.5	6.6
5000 vph	Base case	10	1.17	257	101.3	10.6
		30	1.42	495	98.0	7.0
		50	1.59	467	88.6	8.5
	Strategy 1	10	1.15	208	102.0	6.6
		30	1.17	171	100.0	8.9

Table 4 (*continued*)

Traffic load	Strategies	Truck %	AADL	Number of car–truck interactions	Average speed[a]	Average lane speed differential[a]
	Strategy 2	10	1.17	252	99.2	2.0
		30	1.50	628	95.6	2.0
		50	1.78	831	89.6	3.5
	Strategy 3	10	1.17	259	104.2	4.6
		30	1.40	472	100.6	2.7
		50	1.45	340	97.5	6.8
6000 vph	Base case	10	1.15	272	92.3	5.8
		30	1.42	698	53.6	15.3
		50	1.38	874	26.3	23.3
	Strategy 1	10	1.07	446	42.2	33.5
	Strategy 2	10	1.13	562	57.6	2.9
		30	1.32	1304	44.4	15.1
		50	1.52	1258	41.7	6.9
	Strategy 3	10	1.17	322	103.4	4.7
		30	1.38	505	99.7	6.4
		50	1.42	359	71.5	7.1

[a] Units: speed (kmph).

truck percentages (10%, 30%, 50%, and 70%). Here, we summarize the aggregated values of these performance measures in Table 4. The relevant results are discussed hereafter.

5.3.1. *Effect of truck percentage*

The results indicate that the number of interactions involving trucks and non-truck vehicles increases with truck percentage up to a certain point and reduces beyond that point, especially for the low demand loadings (2000 and 3500 vph). This trend is also valid for the higher demand loading scenarios as well. 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, 6000 vph), the tight packing of vehicles in the traffic stream can reduce this effect at times.

Fig. 10 shows the AADL values for the various demand loads and truck percentages. It illustrates the influence of two effects on AADL: (i) the percentage of lanes that trucks can use, and (ii) the percentage of trucks in the traffic stream. For Strategies 1 and 3, the AADL increases up to a certain point with truck percentage and reduces beyond that point. This is because when trucks are restricted to a lesser percentage of lanes, non-truck vehicles have a greater opportunity to avoid trucks. This effect is further reinforced by the reduced number of non-truck vehicles when the truck percentage increases. The combined effect can lead to reduced AADL for higher truck

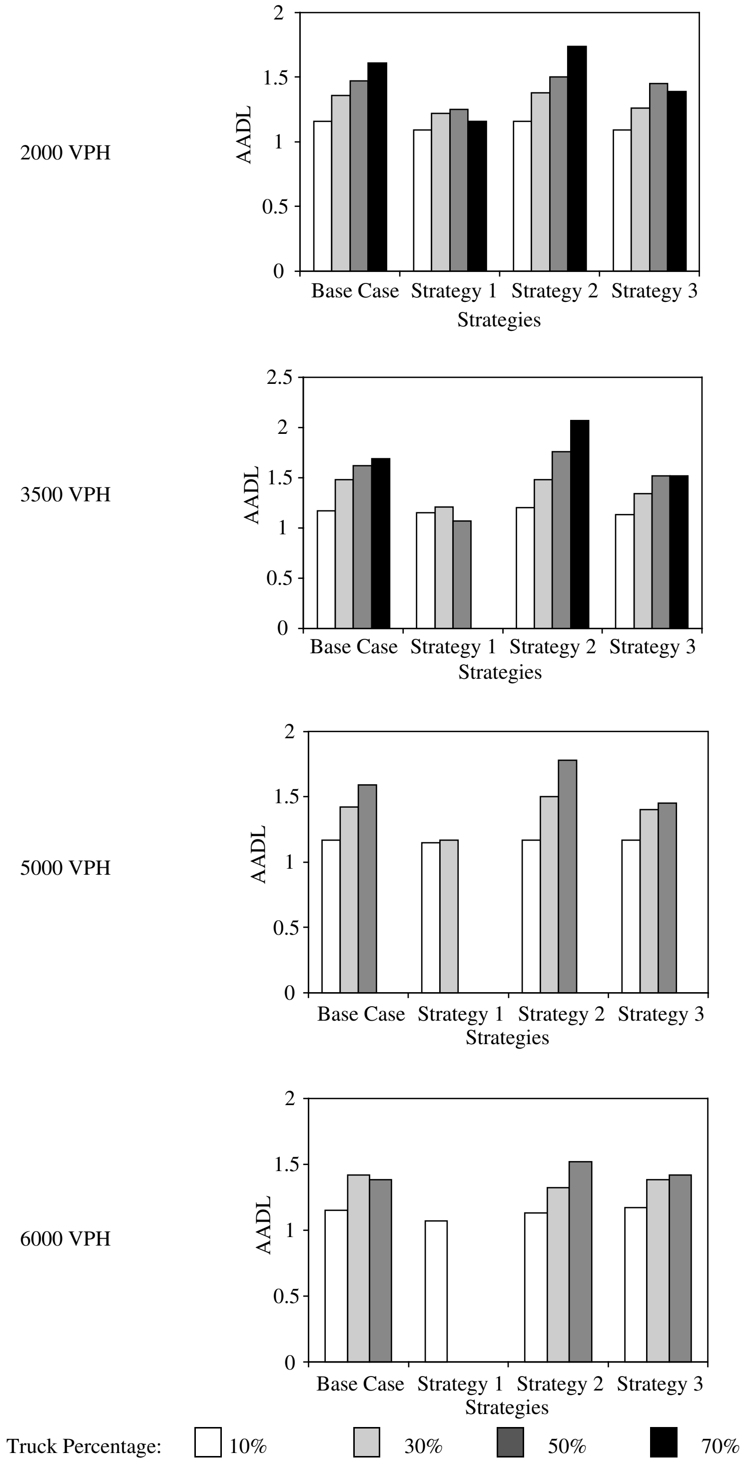


Fig. 10. Comparison of mitigation strategies.

percentages. By contrast, under the base case and Strategy 2, trucks can use a higher percentage of lanes. This leads to a higher probability of interactions with non-truck vehicles, which dominates the effect due to the decreasing number of non-truck vehicles as truck percentage increases.

From the traffic performance viewpoint, since truck free-flow speeds are slightly lower than for non-trucks, the average speeds are lower with increasing truck traffic.

5.3.2. 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). 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. In such situations, 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 Table 4 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 increases 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.

5.3.3. Addition of a lane

The addition of a lane to the existing freeway segment 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. While adding a lane can aid substantially in reducing congestion effects, the influence on AADL may be tangential.

5.3.4. Truck diversion

Strategy 4 is evaluated for different levels of truck diversions. It should be noted here that the impacts on the detour routes due to truck diversion are not considered here. 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. The AADL values are 1.31 and 1.18, respectively, for the 0% and 50% truck diversion cases. Hence, as higher percentages of trucks are diverted, AADL reduces. Truck diversion also improves traffic performance on the freeway segment.

6. Concluding comments

This paper introduces the notion of car–truck interactions from the perspective of non-truck drivers to more robustly incorporate the impacts of their actions in the vicinity of trucks. It views these interactions from a driver psychology aspect 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. Such a capability bridges a key methodological gap in the traffic flow modeling arena where trucks are not differentiated from other vehicles vis-à-vis driver behavior. From a practical standpoint, it provides a mechanism to evaluate alternative strategies to mitigate car–truck interactions, as such interactions can have significant implications for traffic performance, safety, and the non-truck driver travel experience.

The proposed methodology is implemented for freeway segments by extending existing microscopic traffic flow modeling components. Simulation experiments using the Borman expressway case study provide insights on the effectiveness of the methodology to capture the impacts of non-truck driver actions when following trucks. Further, the methodology enables the comparison of alternative mitigations strategies from a holistic perspective that factors performance and safety in addition to the degree of car–truck interactions.

More broadly, the study methodology provides some behavior-based modeling directions and components for the next-generation of traffic flow models that focus on increased realism in replicating traffic conditions. It emphasizes modeling that can be validated and 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 such as the effect of road geometry on traffic conditions.

While the research addressed in this paper enhances the state-of-the-art in modeling car–truck interactions, it motivates further research in several directions. We address car–truck interactions for freeways here. 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 in this paper. It is useful as truck drivers are constrained by the substantial blind spot and maneuverability restrictions due to the physical and operational characteristics of trucks.

Acknowledgments

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References

Aycin, M.F., Benekohal, R.F., 1999. Comparison of car-following models for simulation. Transportation Research Record 1678, 116–127.

Bureau of Transportation Statistics, US Department of Transportation, 2002. National transportation statistics 2002. BTS02-08, Washington, DC, US Government Printing Office.

Federal Highway Administration, US Department of Transportation, 2000. The comprehensive truck size and weight study. Project report, FHWA-PL-00-029, Washington, DC.

Franklin, S., Graesser, A., 1996. Is it an agent, or just a program? A taxonomy for autonomous agents. In: Proceedings of the Third International Workshop on Agent Theories, Architectures, and Languages, pp. 21–36.

Garber, N.J., Gadiraju, R., 1991. Effects of truck strategies on traffic flow and safety on multilane highways. Transportation Research Record 1256, 49–55.

Gonzalez-Rojo, S., Slama, J.G., Pereira, A.L., Mora-Camino, F., 2002. A fuzzy logic approach for car-following modeling. Systems Analysis Modeling Simulation 42 (5), 735–755.

Grenzeback, L.R., Reilly, W.R., Roberts, P.O., Stowers, J.R., 1991. Urban freeway gridlock study: decreasing the effects of large trucks on peak-period urban freeway congestion. Transportation Research Record 1256, 16–29.

Halati, A., Torres, J., Cohen, S.L., 1991. FRESIM-freeway simulation model. Paper presented at the 70th Annual Meeting of Transportation Research Board, Washington, DC.

Kostyniuk, L.P., Streff, F.M., Zakrajsek, J., 2002. Identifying unsafe driver actions that lead to fatal car–truck crashes. Project report prepared for AAA Foundation for Traffic Safety.

Minar, N., Burkhart, R., Langton, C., Askenazi, M., 1996. The swarm simulation system. Working Paper. URL: http://www.swarm.org, Accessed July 30, 2003.

National Highway Traffic Safety Administration (NHTSA), US Department of Transportation, 1998. Trends in large truck crashes. DOT-HS-808-690, Washington, DC.

Next Generation Simulation (NGSIM) Program, 2001. Workshop on Next Generation of Models for Traffic Analysis, Monitoring and Management. J.M Morales & Associates, P.C., Tucson, AZ, 2001.

Owen, L.E., Zhang, Y., Rao, L., McHale, G., 2000. Traffic flow simulation using CORSIM. In: Proceedings of the Winter Simulation Conference, vol. 2. ITT Industries.

Peeta, S., Yu, J.W., 2002. A data-consistent fuzzy approach for on-line driver behavior under information provision. Transportation Research Record 1803, 76–86.

Peeta, S., Ramos, J., Pasupathy, R., 2000. Content of variable message signs and on-line driver behavior. Transportation Research Record 1725, 102–108.

Peeta, S., Zhou, W., Zhang, P., 2004. Modeling and mitigation of car–truck interactions on freeways. Transportation Research Record, in press.

Stuster, J., 1999. The unsafe driving acts of motorists in the vicinity of large trucks. Project report prepared for Office of Motor Carrier Research (OMCR), DTFH61-97-C-00090, Washington, DC.

TRB, 2000. Highway capacity manual. Transportation Research Board, Washington, DC.

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

Yoo, H., Green, P., 1999. Driver behavior while following cars, trucks, and buses. Project report prepared for University of Michigan Transportation Research Institute, UMTRI-99-14, Ann Arbor, MI.

Zhou, W., 2003. Behavior-Based Analysis of Car–Truck Interactions on Freeways. M.S. Thesis, Purdue University.