Core Models for State-of-the-Art Microscopic Traffic Simulation and Key Elements for Applications

Heng Wei, Ph.D., P.E.
Associate Professor, School of Advanced Structures, College of Engineering & Applied Science
792 Rhodes Hall, ML-0071, The University of Cincinnati, Cincinnati, Ohio 45221-0071
Tel: 513-556-3781; Fax: 513-556-2599; Email: heng.wei@uc.edu

ABSTRACT

This chapter summarizes fundamental models for microscopic simulation (such as vehicle generation model and car-following model) and other critical models (such as lane-choice model, lane-changing model, and route-choice model). Most of the critical models introduced in this chapter reflect the latest research results by the author. The primary purpose of this chapter is to provide fundamentals for better understanding of the travel behaviors that are modeled for traffic simulations. To facilitate the applications of traffic simulation models, several key elements for applying state-of-the-art computer traffic simulation tools are summarized. They include the procedure for building models, model calibration and validation. Further more, techniques for collecting vehicle trajectory data, critical elements used for model calibration and validation, are also introduced.

Key Words: model, microscopic traffic simulation, vehicle generation, car-following, lane-choice, lane-changing, route-choice, vehicle trajectory, calibration, validation

INTRODUCTION

Crime preventive measures somehow influence several elements of transport behavior, such as the choice of the number of trips, the destination and the mode of transportation. For example, increased crime offence rates likely lead to decreasing of trips as a consequence of crime-related reputation of an area. The choices of transportation modes, routes and destinations may also be influenced by the crime rates of an area. Quantitative relationships between criminal behaviors, criminal opportunities and transportation environments may provide insight into how to design better crime prevention strategies. Among the factors constituting the transportation environments, travel behaviors over the transportation network play a key role in representing operations of the transportation systems. Microscopic simulation modeling is a significant approach to provide understandings of traffic characteristics and travel behaviors as required by the analysis of on-street crime preventive measures.

Microscopic traffic simulation models are computer models that “mimic” the movements of individual vehicles traveling around a roadway network and effect of traffic control operations. The simulation models are composed of multiple travel behavior models, such as car-following and lane-changing models, gap acceptance rules, signal control operation schemes, and so forth. Those models are coded into computer algorithms which are embedded within a computer software system. The integration of those models enables simulating vehicle-by-vehicle based traffic by updating position, speed, acceleration, lane position, and other state variables on time steps, as the vehicles interact with traffic signals, signs, other vehicles, and roadway geometrics. The time steps are usually designed on a second or smaller time interval basis in order to implement a more accurate behavioral analysis.

Microscopic simulation models aim at providing a representation of actual driver behaviors and network performance. They are therefore viewed as an effective tool for analyzing a wide variety of dynamical problems which are not amenable to study by other means. The purpose of this chapter is to introduce major microscopic simulation models that are viewed as the core of simulation modeling and key elements for simulation application in traffic and safety operations. The chapter is organized as follows: (1) core microscopic traffic simulation models, (2) procedure for building models, (3) techniques
for vehicle trajectory data collection, (4) calibration and validation of applying advanced microscopic simulation software, (5) summary and conclusions, and (6) future research directions.

**CORE MICROSCOPIC TRAFFIC SIMULATION MODELS**

This part presents fundamentals of core models for microscopic traffic simulation modeling, including vehicle generation model, car-following model, lane-choice model, lane-changing model, and route-choice model.

**Vehicle Generation Model**

A vehicle generation model addresses methods for creating vehicles to enter a simulated network which is assumed “empty” at the beginning of a simulation run. While numerous methods in terms of computer programs have been developed to generate random numbers, these numbers only “appear” to be random, sometimes called “pseudo-random” numbers (Lieberman & Rathi, 2000). Departing time models attempt to represent a pattern of how travelers choose a time to hit the road based on their daily travel decisions on the experience gathered from repetitively traveling through the transportation network (Ettema et al, 2003).

Random variants in traffic simulation are used to generate a stream of vehicles. According to some headway distribution based on specified volumes, vehicles are generated at origin points, usually at the periphery of the analysis network. For example, the shifted negative exponential distribution will yield the following expression (Lieberman & Rathi, 2000).

\[
h = (H - h_{\text{min}})(-\ln(1 - R)) + H - h_{\text{min}}
\]  

(1)

Where,
- \( h \) = Headway, seconds;
- \( H \) = Mean headway = \( \frac{3600}{V} \), where \( V \) is the specified traffic volume, vph;
- \( h_{\text{min}} \) = Specified minimum headway; and
- \( R \) = Random number in the range (0 to 1.0), obtained from a pseudo-random number generator.

Ettema et al (2003) proposed a micro-simulation approach in which individuals base their consecutive departure time decisions on a mental model. The mental model is the outcome of a continuous process of perception updating according to reinforcement learning principles, based on a more general theoretical framework proposed by Arentze and Timmermans (2003). In this model system, individual decision makers decide about departure time for a routine trip, such as commuting, on consecutive days. Their decision making is based on a mental model of traffic conditions, specifying the mean and variance of travel time for various departure times. This mental model is updated once new experiences become available.

It is assumed that when choosing a departure time, travelers desire an arrival time to be as closer and prior to the preferred arrival time (PAT). The PAT is associated with the work start time or other scheduled time. Based on Small’s study (Small, 1982), the utility of a trip departing at \( t \), i.e., \( U_t \), can then be specified by the following equation.

\[
U_t = \beta_1 \times T_i + \beta_2 \times SDE + \beta_3 \times SDL + \beta_4 \times L
\]

(2)

Where,
- \( T_i \) = travel time when departing at time \( t \);
- \( SDE \) = early schedule delay;
- \( SDL \) = late schedule delay;
- \( \beta_1, \beta_2, \beta_3, \beta_4 \) = Parameters; and
- \( L \) = Variable indicating late arrival.
The schedule delay is the amount of time one arrives before or after the preferred arrival time

$$PAT, \text{ i.e.,}$$

$$SDE(t, T_t, PAT) = \max((PAT - t - T_t), 0) \quad (3)$$

$$SDL(t, T_t, PAT) = \max((t + T_t - PAT), 0) \quad (4)$$

$L$ is a dichotomous variable indicating late arrival, representing the discomfort of late arrival irrespective of the amount of delay. $L$ is calculated by the following equation.

$$L = \begin{cases} 0 & \text{if } t + T_t < PAT \\ 1 & \text{if } t + T_t < PAT \end{cases} \quad (5)$$

In reality, however, in an individual’s perception of the travel time $T_t$ is not a constant value but a stochastic variable which can be defined by $\mu_t$ and $\sigma_t$, provided following normal distribution. The perceived probability distribution forms an expected utility for a trip departing at $t$, specified as:

$$EU_t = \int_{T_{min}}^{T_{max}} \left[ \beta_1 T_t + \beta_2 SDE(t, T_t, PAT) + \beta_3 (t, T_t, PAT) + \beta_4 L(t, T_t, PAT) \right] f(T_t) d(T_t) \quad (6)$$

Where, $f(T_t) =$ normally distributed with $N(\mu_t, \sigma_t)$

In the expected utility, individuals account for uncertainty in travel time by weighting each outcome by its probability. An error term is associated with each expected utility $EU_t$. The model described by equation (6) was applied using parameter values reported by Small (May, 1990) as follows.

$$\beta_1(T_t) = -0.106 \text{ (1/min)};$$

$$\beta_2(SDE) = -0.065 \text{ (1/min)};$$

$$\beta_3(SDL) = -0.254 \text{ (1/min)};$$

$$\beta_4(L) = -0.58 \text{ (1/min)};$$

Car-Following Model

One of driving tasks concerned in microscopic simulation models is to keep appropriate spacing to the immediate front vehicle for a single vehicle on a single lane. A car-following depicts speed-acceleration-spacing relationships of a vehicle following another where there is no passing, in a given time interval based on the action of the front vehicle at a time step. Car following is a relatively simple task compared to the totality of tasks required for vehicle control (Rothery, 2000). However, it is a task that is commonly practiced on dual or multiple lane roadways when passing becomes difficult or when traffic is restrained to a single lane. Car following is a driving task that has been of direct or indirect interest since the early development of the automobile.

Reuschel and Pipes (May, 1990) firstly developed car-following models in the early 1950s. Pipers’ model followed the rules suggested in the California Motor Vehicle Code, “A good rule for following another vehicle at a safe distance is to allow yourself at least the length of a car between your vehicle and the vehicle ahead for every ten miles per hour of speed at which you are traveling.” The car-following theories developed by researchers associated with the General Motors group were much more extensive. Comprehensive field experiments were conducted and the mathematical bridge between microscopic and macroscopic theories of traffic flow was discovered. The development of car-following models has experienced multiple generations of endeavors by the research team, and all of the models take the following form:

$$\text{Speed response} = \text{function (sensitivity, stimuli)} \quad (7)$$

The speed difference of the two vehicles $\dot{x}_n(t) - \dot{x}_{n+1}(t)$ is termed as the stimuli, which could be positive, negative, or zero. The speed response could then be an acceleration, deceleration, or keep
constant speed. \( \alpha \) is defined as sensitivity term which is associated with spacing between vehicles. The numerical values for the sensitivity term could be measured as an inverse function of the distance headway \( d \), i.e.,

\[
\alpha = \frac{\alpha_0}{d} = \frac{\alpha_0}{x_n(t) - x_{n+1}(t)}
\]  

(8)

Where, \( \alpha_0 \) is constant representing a linear curve sloping between the sensitivity term and inverse of the distance headway. Parameter of distance headway exponent \( l \) and the parameter of speed exponent \( m \) are used to define a general form of the car-following model as shown in the following equation:

\[
\ddot{x}_{n+1}(t + \Delta t) = \frac{\alpha_{l,m} [\dot{x}_{n+1}(t + \Delta t)]^m}{[x_n(t) - x_{n+1}(t)]^l} [\dot{x}_n(t) - \dot{x}_{n+1}(t)]
\]  

(9)

Where,

- \( n \) = Ahead vehicle;
- \( n + 1 \) = Following vehicle;
- \( x_n \) = Position of the ahead vehicle (ft);
- \( x_{n+1} \) = Position of the following vehicle (ft);
- \( \dot{x}_n \) = Speed of the ahead vehicle (ft/sec);
- \( \dot{x}_{n+1} \) = Speed of the following vehicle (ft/sec);
- \( \ddot{x}_{n+1} \) = Acceleration (deceleration) rate of the following vehicle (ft/sec²);
- \( t \) = At time \( t \);
- \( t + \Delta t \) = \( \Delta t \) time after \( t \) time;
- \( l \) = Parameter of distance headway exponent;
- \( m \) = Parameter of speed exponent; and
- \( \alpha_{l,m} \) = Sensitivity parameter at \( l \) and \( m \).

In the above equation various scenarios could be distinguished by \( m \) and \( l \) exponents. When \( l = 0 \) and \( m = 0 \), the \( \alpha = [0.17, 0.74] \) (1/sec) while the reaction time \( \Delta t = [1.0, 2.2] \). When \( l = 1 \) and \( m = 0 \), the parameter values of \( \alpha \) and \( \Delta t \) were resulted from field experiments at three testing sites, namely, General Motors test track, Holland Tunnel, and Lincoln Tunnel. \((\alpha, \Delta t) = (1.5, 40.3)\) at General Motors test track; \((\alpha, \Delta t) = (1.4, 26.8)\) at Holland Tunnel; and \((\alpha, \Delta t) = (1.2, 29.8)\) at Lincoln Tunnel. It should be aware that \( \alpha \) is measured in different units. For example, it is measured with the unit of 1/sec when \( l = 0 \) and \( m = 0 \); ft/sec when \( l = 1 \) and \( m = 0 \).

**Lane-Choice Model**

Lane-choice model addresses a new concept for urban street microscopic simulation. The term “lane-choice” is referred to a driver’s initial lane choice as maneuvering a right or left turning into a multilane urban street segment, as shown in Figure 1. Generally, driving guidance from driving handbook typically stipulates that drivers should choose the closest lane (Wei et al. 2002). For example, if making a right turn in a four-lane highway, it is suggested for drivers to make a tight turn into the right lane of the cross street. For a left turn, enter the cross street to the right of the center line. If a driver follows this guidance, his/her lane-choice behavior is regarded as a regular or normal behavior; otherwise, as an “irregular” or “abnormal” Behavior. As building a model to simulate lane-based routes, the lane choice issue would grow at the rules how to select a lane when a vehicle is turning into an immediate next street segment.
from a left or right turning lane at a signalized intersection. It was used to assume that the driver selects a lane strictly following driving handbook.

Wei (2002) conducted a study based on field observations. In this study, eight urban streets in Kansas City, Missouri, were selected as videotaped observation sites. Figure 1 exhibits an example of statistical analysis of the observations (Wei et al., 2002). Hourly statistical frequencies of choosing the closest lane and the farther lane at Grand Avenue between 22nd and Pershing Road (north bound traffic) are present. The result indicates that such an “irregular” lane-choice is a frequently occurring phenomenon. It was found out that a driver’s initial lane choice is actually related to the driver’s route plan. The choice is most likely beneficial to the driver’s travel maneuvers at downstream intersections. In other words, drivers have common intentions to choose the “target lane” as they are turning into a segment from an intersection. The target lane is defined as the intended destination lane in which the driver needs not to make a lane change before making a turn at the immediate next intersection. In case of entering a segment from a right turn at an intersection, for example, the farther lane (e.g., lane #2 in Figure 1) is the target lane if the driver intends to make a left turn at next intersection. On the other hand, the closest lane (e.g., Lane #1) is the target lane if the driver intends to make a right turn at the next intersection.

![Histogram of Lane-Choice Data over a Two-way Street](image)

**Figure 1** Histogram of Lane-Choice Data over a Two-way Street

Probabilities of various types of lane-choices are derived from statistical analysis of the observed data. Probabilities associated with different lane-choice alternatives are defined as follows:
where,
\[
\xi = \text{Index that represents a vehicle's intended maneuver at the next intersection; } 0 = \text{go straight; } 1 = \text{either right turn or left turn};
\]
\[
V_{RiR} = \text{Number of vehicles entering lane } i \text{ from right-turn entry and turning right at the exit; } i = 1, 2, \ldots, n;
\]
\[
V_{RiL} = \text{Number of vehicles entering lane } i \text{ from right-turn entry and turning left at the exit; } i = 1, 2, \ldots, n;
\]
\[
V_{RS} = \text{Number of vehicles entering lane } i \text{ from right-turn entry and going straight at the exit; } i = 1, 2, \ldots, n;
\]
\[
V_{LR} = \text{Number of vehicles entering lane } i \text{ from left-turn entry and turning right at the exit; } i = 1, 2, \ldots, n;
\]
\[
V_{LrL} = \text{Number of vehicles entering lane } i \text{ from left-turn entry and turning left at the exit; } i = 1, 2, \ldots, n;
\]
\[
V_{LrS} = \text{Number of vehicles entering lane } i \text{ from left-turn entry and going straight at the exit; } i = 1, 2, \ldots, n.
\]

Table 1 summarizes results of statistical analysis of observations conducted in Kansas City, Missouri (Wei et al, 2002). The results indicate that the sampling percentage of choosing the target lane ranges from 97% to 100% while choosing the non-target lane under 3%. It is apparent that the probability of choosing a target lane is very high in reality. Accordingly, it is reasonable to assume that if a driver intends to make a turn at the next intersection, the initially chosen lane is the target lane.

Results also show that the ratio of the percentages of choosing the farther lane over choosing the closest lane ranges from 31%:69% to 85%:15%. The fact that so many drivers chose the farther lane can be reasonably explained by the drivers’ intentions of seeking the correct lane to minimize the number of lane changes that would be needed during the remaining journey. This kind of lane-choice behavior may be regarded a “preemptive” behavior to be in the target lane in advance.

<table>
<thead>
<tr>
<th>Table 1 Summary of Sampling Percentage of Various Lane Choices (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(March 26, 1998, Grand Avenue between 22nd and Pershing Road, Kansas City, Missouri)</td>
</tr>
<tr>
<td>Time</td>
</tr>
<tr>
<td>Target lane Choice</td>
</tr>
<tr>
<td>Non-target Lane Choice</td>
</tr>
<tr>
<td>Closest Lane Choice</td>
</tr>
<tr>
<td>Farther Lane Choice</td>
</tr>
</tbody>
</table>

| (June 3, 1998, North Bound, Grand Avenue between 13th and 14th, Kansas City, Missouri) |
| Time | 2:30 - 4:30 PM | 3:30 - 4:30 PM | 4:30 - 5:30 PM | 5:30 - 6:30 PM |
| Target lane Choice | | | | |
| Non-target Lane Choice | | | | |
| Closest Lane Choice | | | | |
| Farther Lane Choice | | | | |
Lane-Changing Model

The lane-changing behavior is an important component that has a significant impact on the characteristics of traffic flow. With the increasing popularity of microscopic traffic simulation tools, a number of lane-changing models have been proposed and implemented in various simulators in recent years. Most lane-changing models classify lane changes as either mandatory or discretionary. For clarity of the description of concepts used in lane-changing models, Figure 2 illustrates the definitions of various vehicles involved in a lane-changing maneuver.

For freeway users, two types of lane changes are widely acknowledged as mandatory lane change and discretionary lane change. Drivers consider mandatory lane changes when they must move away from their current lanes to follow their paths, avoid a lane blockage, or comply with lane use regulations. In any of these cases, drivers will change to the nearest acceptable lane (Toledo et al, 2005). Drivers pursue discretionary lane changes when they perceive that driving conditions in an adjacent lane are better. The evaluation of the current and adjacent lanes is based on variables such as the traffic speeds and densities in these lanes, the positions and speeds of vehicles that surround the subject vehicle (or called target vehicle), and presence of heavy vehicles. Drivers who decide to change to an adjacent lane evaluate whether the available gap in traffic in this lane can be used to complete the lane change or not.
Toledo et al. (2005) explained the lane-changing model with two choice models: target lane choice model and gap acceptance model. The target lane choice model is defined as the following:

\[
P(TL_{int} = i | \nu_n) = \frac{\exp(V_{int}^TL_i - V_{int}^Tn)\sum_{j \in TL} \exp(V_{int}^TL_j - V_{int}^Tn)}{\sum_{j \in TL} \exp(V_{int}^TL_j - V_{int}^Tn)}
\]

\[\forall i \in TL\{lane 1, lane 2, ..., lane n\}\]

Where,

- \(V_{int}^TL_i\) = Utility of lane i as a target lane (TL) to driver n at time t, i.e.,
- \(V_{int} = \beta_i^TL X_{int}^TL + \alpha_i^TL \nu_n + \epsilon_{int}^TL\), \(\forall i \in TL\{lane 1, lane 2, ..., lane n\}\);
- \(X_{int}^TL\) = Vector of explanatory variables that affect the utility of lane i;
- \(\beta_i^TL\) = Corresponding vector of parameters;
- \(\alpha_i^TL\) = Parameter of \(\nu_n\);
- \(\nu_n\) = Individual-specific latent variable assumed to follow some distribution in the population; and
- \(\epsilon_{int}^TL\) = Random term associated with the target lane utilities.

The choice of the target lane dictates the change direction. If the current lane is also the target lane, no change is needed. Otherwise, the change will be in the direction from the current lane to the target lane. The gap acceptance model determines a driver’s choice whether the available gap in the adjacent lane in the change direction can be used to complete the lane change or not. An available gap is acceptable if it is greater than the critical gap. Critical gaps are assumed to follow lognormal distributions to ensure that they are nonnegative (Toledo et al, 2005):

\[
\ln(G_{nt}^{gd,cr}) = \beta^{st} X_{nt}^{gd} + \alpha^g \nu_n + \epsilon_{nt}^{gd}
\]

\[g \in \{lead, lag\}, d \in \{right, left\}\]

Where,

- \(G_{nt}^{gd,cr}\) = Critical gap g in the direction of change d (m);
- \(X_{nt}^{gd}\) = Vector of explanatory variables;
- \(\beta^{st}\) = Corresponding vector of parameters;
- \(\epsilon_{nt}^{gd}\) = Random term, where \(\epsilon_{nt}^{gd} \sim N(0, \sigma_g^2)\); and
- \(\alpha^g\) = Parameter of the driver specific random term \(\nu_n\).
To date, most available models deal with lane changing behavior on freeways. The lane-changing behavior over the urban street networks has not been studied extensively. Additionally, most available models are based upon either theoretical analysis or limited spot observations. This is likely due to the difficulty of getting simple and clean vehicle trajectory data appropriate for studying lane-changing behavior. Wei (1999) developed a video-capture-based method and a computer software tool, Vehicle Video-Capture Data Collector (VEVID) to help extract traffic related data from a digitized video. Availability of this tool enables the field observations and study of vehicle–based travel behaviors, as well as simulation modeling with use of empirical data.

There are lots of reasons for drivers to change lanes during their travel journeys on urban streets. In addition to mandatory and discretionary lane-changes as conventionally defined (Zhang et al, 1998), Wei’s observations disclosed the third types of lane change, termed as Preemptive Lane Change (PLC). As shown in Figure 3, preemptive lane change refers to the lane change to get in a lane that leads to an easy turning maneuver at a downstream intersection (e.g., turn left or right, get out of the exit lane of intended closed lane), but not the immediate next intersection. In other words, the primary purpose of such a lane change is to get in the correct lane in advance to follow the planned path. Wei’s observations indicate that 461 of total 994 lane changing samples fall into the category of preemptive lane change (Wei, Meyer et al, 2000). The preemptive lane changing samples were analyzed based on different traffic conditions when lane changes occurred, as shown in Figure 3.

Wei characterized lane-changing behaviors on an urban street network with three key components (Wei, Meyer et al, 2000): (1) a lane-changing decision model, (2) a lane-changing condition model, and (3) a lane-changing maneuver model. Drivers’ decisions to change lanes depend on rout plans, the current lane type (i.e., the relationship between the current lane and the driver’s planned route), and traffic conditions in the current and adjacent lanes. A lane-changing condition model is the description of acceptable conditions for different types of lane changes. A lane-changing maneuver model describes the subject vehicle’s speed and duration when a certain type of a lane change is executed. The lane-changing decision model could be established in a heuristic structure, as shown in Figure 4.

Discretionary lane change refers to a lane change executed to pass a slower moving vehicle ahead. A driver expects a lane change whenever he or she thinks the speed of the vehicle ahead in the current lane is intolerable while acceptable gaps in the target lane are available. Gipps (2001) proposed the concept of speed advantage to identify a motivation of a (discretionary) lane change, and Wei (Wei, Meyer et al, 2000) proposed a quantitative definition of the speed advantage (SA) to describe decisional conditions for a discretionary lane change on urban streets. Speed advantage is described by the relative speed difference between the lead vehicle in the target lane and the head vehicle in the current lane. Its mathematical expression is suggested as the following equation.

\[
SA = \frac{V_{LD} - V_{FT}}{V_{LD}} \quad (16)
\]

Where, \( SA \) = Speed advantage compared to an adjacent lane; \( 0 \) if \( V_{LD} \leq V_{FT} \);
\( V_{LD} \) = The lead vehicle’s speed in an adjacent lane, ft/s or mph; and
\( V_{FT} \) = The front vehicle’s speed, ft/s or mph.

Using the SA variable, the probability of motivating a lane change incurring from a speed disturbance by the front vehicle can be estimated by the following equations, which are derived via regression analysis from accumulative curves of observed SA values using the data observed in Kansas City, Missouri (Wei, Meyer et al, 2000):

\[
\text{Probability of lane change} = \begin{cases} 
0.0, & \text{if } SA < 0.5 \\
0.01(10 - SA)^{0.5}, & \text{if } 0.5 \leq SA \leq 10 \\
1, & \text{if } SA > 10 
\end{cases}
\]
For two-way streets:

\[ P(SA) = (0.070 - 0.3175SA + 3.682SA^2 - 2.376SA^3) \times 100\% \]  \hspace{1cm} (17)

For one-way street:

\[ P(SA) = (0.008 + 0.443SA + 0.541SA^2) \times 100\% \]  \hspace{1cm} (18)

Where \( P(SA) \) = probability of generating a motivation to change to the speed-advantaged lane in correspondence to a value of \( SA \). The correlation coefficient \( R^2 \) value for equations (17) and (18) is 0.9915 and 0.9836, respectively. For example, if the front vehicle reduces its speed to 30 mph while the adjacent lane’s speed remains at 50 mph, 31.8% of followers would possibly change to the adjacent lane in a two-way street. Similarly, 27.2% of followers do so in a one-way street.

Both the gap between the lead (in the adjacent lane) vehicle and the subject vehicle (termed as “lead gap”) and the gap between the subject vehicle and the lag vehicle that is in the adjacent lane (termed as “lag gap”) are major factors affecting the driver’s lane-changing decisions. The minimum acceptable...
gaps are greatly dependent upon the speed of the subject vehicle and the lag vehicle. It is hence assumed that the minimum acceptable lead gap for a lane-changing decision could be expressed as a function of the subject vehicle’s speed and the lag gap as a function of the lag vehicle’s speed.

**Figure 4 Lane-Changing Hierarchy**
Figure 5 visualizes the distribution of the observed lead gaps versus the subject vehicle’s speeds and the lag gaps versus the lag vehicle’s speeds. It presents the concerned gap and speed values at the moment as the maneuver of a lane change is started. Comparisons between the observed gap values and the recommended minimum safe gaps (minimum safety braking distances plus reacting distances at varied speeds) recommended in *Kansas Driving Handbook* (1996) are also presented in Figures 6.

![Figure 5: Lead and Lag Gaps versus Lane-Changer's Speed and the Lag Vehicle's Speed. Analysis of Trajectory Data Observed in Kansas City, Missouri (1998)](image)

**Figure 5** Acceptable Gap Conditions in the Adjacent Lane for Lang-Changing Decision-Making

It is seen from Figures 5 that a portion of the sampling drivers, who perform discretionary lane changes as a reaction to a speed disturbance, actually accepts smaller gaps than the handbook-recommended values. Drivers accepting gaps greater than or equal to the handbook-recommended values are viewed as conservative drivers; otherwise as regular drivers. The critical acceptable gaps are modeled using a curve representing the lower boundary of the observed data, as shown by the lowest curve in Figure 5. The minimum acceptable gap conditions to execute a discretionary lane change can be described by the following equation.

$$
\begin{align*}
    \text{Minimum Lead/Lag Gap (m) =} & \\
    & \begin{cases} 
    0.3336(2.2223V_k (m/s))^{1.6398} & \text{(conservative drivers)} \\
    7.979e^{0.1244V_k (m/s)} & \text{(regular drivers)}
    \end{cases}
\end{align*}
$$

$k$ in $V_k$ denotes either the subject vehicle or the lag vehicle. As estimating the minimum lead gap, $V_k$ is the speed of the subject vehicle; $V_k$ is the speed of the lag vehicle as to estimate the minimum lag gap. Tao and Wei’s findings (Wei, Meyer et al, 2000; Tao et al, 2005) from vehicle trajectory data (Wei, 1999) indicate that 90% of observed discretionary lane changes happen before the lane-changers’ speeds are actually affected by the speed disturbance from the front vehicles. A driver who is potentially trapped in the car-following speed disturbance tends to switch onto an adjacent lane before reducing its speed. The 90% probability is on the observation basis. In summary, a driver tends to consider a discretionary lane change only when the following two conditions exist: 1) The driver perceives that the speed of the...
head vehicle is less than his or her desired speed; 2) The driver perceives that he could remain or increase speed by changing to another lane. It is worth being noted that a driver’s motivation for a lane change, including mandatory and discretionary lane changes, is determined by the lane-change decision model (Wei et al, 2000).

Figure 6 Observed Spacing between Pairs of Vehicles at Control Action Times*

Figure 6 shows the distribution of the spacing between pairs of vehicles when a lane change is executed as a reaction to car-following speed disturbance. The equation for estimating minimum spacing is derived from the statistical analysis, as shown in Figure 6. Those minimum spacings are also recommended as thresholds control for car-following scenarios, as summarized in Table 2 and described below.

Table 2 Observed Maximum Accelerations for 10-mph Increments in Urban Streets

<table>
<thead>
<tr>
<th>Type</th>
<th>Typical Maximum Acceleration Rate on Level Road (ft/sec²)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0 - 15 ft/s (0 - 10 mph)</td>
</tr>
<tr>
<td>Starting</td>
<td>0 - 15 ft/s (0 - 10 mph)</td>
</tr>
<tr>
<td>Speed</td>
<td>0 - 15 ft/s (0 - 10 mph)</td>
</tr>
<tr>
<td>Two-way</td>
<td>+11.2</td>
</tr>
<tr>
<td></td>
<td>-8.8</td>
</tr>
<tr>
<td>One-way</td>
<td>+8.9</td>
</tr>
</tbody>
</table>
|            | -6.9                       | -12.7                      | -11.2                      | -12.6                       | -

Data Source: Vehicle trajectory data observed in Kansas City, Missouri, 1998 (Wei, 1999)
Minimum disturbance-effecting spacing vs. speed $V$:

$$S_{\text{min}}(m) = \begin{cases} 
3.5582e^{0.0879V(m/s)} & \text{(Regular Driver)} \\
0.61V(m/s)^{1.4807} & \text{(Conservative Driver)} 
\end{cases}$$  \hspace{1cm} (20)

A lane changing vehicle may accelerate or decelerate when manipulating a lane-changing maneuver so as to keep a safe headway to the lead vehicle and/or to the lag vehicle (in the adjacent lane). Acceleration varies with the individual speeds of the lane changer and the lead vehicle, as well as the differences between them. Table 2 gives observed maximum acceleration or deceleration values for each 10-mpg increment for determining thresholds of acceleration as simulating a lane-changing maneuver.

Wei’s observations also indicate that lane-changing duration has little coherent relationship with speeds of over 10 ft/sec (3 m/s). For discretionary lane change, the average duration of lane changing ranges from 2.33 seconds to 2.51 seconds with standard deviations from 0.56 to 0.93 seconds. Therefore, 2.3 ~ 2.5 seconds may be recommended as an average duration of a lane change.

**Route-Choice Model**

Conventionally a route-choice model is to determine the routes in a concerned transportation network, which is used in traffic assignment models to allocate the traffic onto the simulated roadway network. Rout-choice modeling is typically divided into a two-stage process (Ben-Akiva et al, 2004): the generation of a choice set of alternative routes and the choice of routes among the alternatives in the choice set. A well-known, simplest method for generation of alternative routes is K-shortest path algorithm, which generates the first “k” shortest paths for a given destination pair. Ben-Akiva et al (2004) developed the labeling approach that exploits the availability of multiple link (i.e., roadway segment in a network) attributes, such as travel time, distance and functional class to formulate different “generalized cost” functions that produce alternative routes. The criteria, such as minimum time or distance, or maximum use of expressways, may be used to label the alternative routes.

Several types of route choice models have been recently developed. Most of these models represent modifications or generations of the logit structure, such as C-Logit (Cascetta et al, 1996), Path-Size Logit (PSL) (Ben-Akiva et al, 1999), Cross-Nested Logit (CNL) (Vovsha, 1997), etc. These models are members of the Generalized Extreme Value (GEV) family of models developed by McFadden (Vovsha, 1997). The advent of Intelligent Transportation Systems (ITS) has renewed the interest in modeling the effects of traffic information system on route choice behavior. Advanced Traveler Information Systems (ATIS) are expected to have significant impacts on individual driver behaviors through disseminating routing information onto drivers. Using ATIS, accurate, real-time information about the characteristics of the travel environment can be provided to travelers before their departures and while they are en route. The goal is to alter travel behavior in such a way as to improve the individual driver’s efficiency and the overall characteristics of the travel environment, resulting in accessibility gains for all drivers (Vaugh et al, 1995). For example, the benefits of ATIS in reducing congestion and the potential of large savings in travel time and fuel consumption are based on real-time diversions of traffic from main facilities (e.g., the Interstate system) to lower-class roads (e.g., arterials and the local street system). The effectiveness of ATIS depends on drivers’ reactions to information provided, which is affected greatly by the degree of information’s accuracy. Consequently, the assumptions about real-life route choice behavior in dynamic traffic assignment have received increasing attention recently. One study (Kayisi et al, 1995) indicates that using shortest path guidance is likely to fail if the guidance strategy ignores the impact of drivers’ reactions to information.

Mahmassani and Tong’s investigation (1986) indicates that commuters’ route choices are usually based on perceived delay, the difference between actual arrival time and preferred arrival time, called
tolerable schedule delay. This implies that drivers do not switch to another route that is predicted to have minimum travel cost if the estimated delay falls into the range they can tolerate, called indifference band of route delay (IBRD). This is especially true for urban commuters. Iida, Akiyama and Uchida’s experiment disclosed an interesting attribute of route choice behavior. Drivers may consider other drivers’ behaviors when choosing routes. They believe that when all travelers are given access to the same network information, and if some of them react to it, those staying on the current route may benefit from other drivers’ leaving. These drivers are usually those who are very familiar with the routes based on their driving history. Polydoroulou, Ben-Akiva and Kaysi’s survey (1994) shows that about 75% of the sample drivers are very familiar with at least two different routes to work and around 50% are strongly willing to try new routes to avoid traffic delays. From another survey sample of drivers, they also found that 63% of them rarely or never change their planned route, while 16% often make such a change. 37% of drivers indicated that they often listen to radio traffic reports, and 27% usually follow the recommendations. Only 25% think that radio traffic reports are reliable, whereas 22% consider them irrelevant. Among the drivers who listen to radio traffic reports, 20% often change their routes after listening, whereas 50% completely ignore traffic reports when they are different from their own observations.

In a vehicle-based microscopic simulation system that considers the impact of traveler information on traffic assignment, it is necessary to build a routing choice model that predicts route-change behavior as a function of available information. The IBTD criterion may be used to both objectively evaluate the potential impact of ATIS on route choice, so that vehicle-based microscopic simulation systems may provide higher accuracy of traffic information by better simulating route choice behavior. Wei (2001) presents a structure of a route choice model based on insight from his study of observed travel behaviors (e.g., lane-choice and lane changing behaviors). A fuzzy set is used to reflect different effects of an indifference band of route delay on driver tendency to change routes. Fuzzy sets are also used to model driver response to traveler information with respect to the tendency to change routes.

In this section, the C-Logit Model and the Logit Kernel to route choice situation are briefly presented. A route choice model using indifference band of trip delay is then described.

**Logit Model and the Logit Kernel Formulation**

The C-Logit model is formulated as the following equation (Cascetta et al, 1996):

$$ P(i \mid C_n) = \frac{e^{V_{in} - CF_{in}}}{\sum_{j \in C_n} e^{V_{in} - CF_{in}}} $$  \hfill (21)

Where,

- $V_{in}$ = the utility of path $i$ for person $n$;
- $C_n$ = the path-set for person $n$; and
- $CF_{in}$ = the commonality factor of path $i$ for person $n$.

The commonality factor of path $i$, $CF_{in}$, is used to measure the degree of a person’s similarity of path $i$ between an origin and destination in a network. It can be specified as the following expression (Cascetta et al, 1996; Cascetta et al, 2001):

$$ CF_{in} = \beta_0 \ln \left( \sum_{j \in C_n} \left( \frac{L_{ij}}{\sqrt{L_i L_j}} \right)^\gamma \right) $$  \hfill (22)

or
\[
CF_{in} = \beta_0 \ln \sum_{j \in C_n, j \neq i} \left( \frac{L_{ij}}{L_i L_j} \right) \left( \frac{L_j - L_{ij}}{L_j - L_i} \right)
\]

(23)

Where,
- \(L_{ij}\) = the length of links common to path \(i\) and path \(j\);
- \(L_i, L_j\) = overall lengths of path \(i\) and path \(j\), respectively; and
- \(B_0, \gamma_j\) = parameters to be calibrated.

The general form of the factor analytic Logit Kernel model is proposed by Ben-Akiva et al (2004):
\[
U = \beta^T X + F \xi + \nu
\]

(24)

Where,
- \(U\) = \((J \times 1)\) vector of utility;
- \(\beta\) = \((K \times 1)\) vector of unknown parameters;
- \(X\) = \((J \times K)\) corresponding vector of parameters;
- \(F\) = \((J \times M)\) factor loadings matrix; and
- \(\xi\) = \((M \times 1)\) vector of \(m\) multivariate distributed latent factors.

**Route Choice in a Lane-Vehicle-Based Simulation Process**

A lane-vehicle-based simulation process describes a vehicle's position during its journey in an urban street network (Wei, Lee et al, 2000). To clarify the relationship between route choice and other travel behaviors, primary simulated states are defined as follows and illustrated in Figure 7.

**Origin State:** Defines the original location of a simulated vehicle (where it enters the simulated network), the departure time, and the destination. The vehicle enters the street network at the nearest intersection to the original location.

**Entering State:** Defines the intended route from the origin to the destination at the time of departure. In reality a driver usually chooses his/her route before starting the trip. The driver makes the decision based on updated route information from media such the Internet or previous experience. In the simulation, the pre-trip route is assumed to be the shortest path (by travel time) resulting from the latest available roadway traffic conditions, termed as *current network condition*. This state is simulated only when a vehicle is generated.

**Lane-Choice State:** Defines a specific lane whenever the vehicle enters a street segment from a turning entry at an intersection. Lane-choice decision is simulated depending on the driver’s pre-trip route or en-route plan (Wei & Lee et al, 2000). This state is simulated whenever a vehicle is going to turn in a street segment from an intersection.

**Car-Following State:** Defines vehicle location, speed, spatial and temporal relation with the ahead vehicle (if it exists), as well as its reaction to any change of the ahead vehicle's speed at each simulation time step.

**Lane-Changing State:** Recognizes the vehicle's demand and decision on changing lanes, lane-changing type (mandatory, preemptive, or discretionary), lane-changing conditions to determine whether acceptable gaps are available for changing lanes, and lane-changing maneuvers. Location, acceleration, speed, and duration are estimated at each simulated time step during a lane change. This state is simulated as long as the vehicle is moving within a street segment.
New-Entering State: Determines status of the vehicle as approaching the next intersection, with update of all above states.

En Route Choice State: Updates the vehicle’s remaining route if and only if the current network condition is changed, updated traveler information is available, and the destination has not been reached. This state is simulated when the vehicle is entering a downstream street segment.

Exiting State: Checks the vehicle's current lane and its intention as it approaches the end of the current street segment (next intersection) to go straight, turn, or reach its destination. If the approaching intersection is the destination, the vehicle's trip is ended and is no longer traced. Its recorded locations, clock time, speeds, accelerations, and maneuvers are stored in the database when any action occurs that leads to the change of the vehicle's state. This state is simulated when the vehicle is approaching the downstream intersection.

Each state can be viewed as a travel behavior that can be depicted by a corresponding sub-model. Sub-models for pre-trip and en route choice behaviors are discussed in the following sections.

IBRD-Based Route Choice Model
The *indifference band of route delay* simulates a driver’s tolerable difference in time between the current route and the dynamic best route resulting from the instant network traffic conditions given by the traveler information system (when the former is greater than the latter). According to Mahmassani et al’s studies (Mahmassani & Chang, 1985; Mahmassani & Weimann, 2004), the width of the *indifference band of route delay* is suggested to be 10 minutes; Knippenberg’s study indicates the suggested value of 18 minutes (Knippenberg et al, 1986). However, the trip length should be associated with the values of IBRD. On a 60 minute trip, for example, 10 minutes is not such a big difference. For a 20 minute trip, on the other hand, 10 minute improvement is meaningful to the driver. Fuzzy sets are used to determine the likelihood of a route change if the estimated delay falls into the width of indifference band of route delay.

Figure 8 illustrates the hierarchy of the IBRD-based route choice model with two categories of drivers. In the pre-trip route choice model, the *indifference band of route delay* is the difference in travel time between the driver’s primary route \( \gamma_p \) and the dynamic best route \( \gamma_b \). In en route choice model, it is the difference in travel time between the driver’s current route \( \gamma_c \) and the dynamic best route \( \gamma_b \).

![Figure 8 Hierarchy of IBRD-Based Route Choice Models](image)

Some basic concepts used in the IBRD-based route choice model (as shown in Figure 8) are introduced as follows.

**Classifications of Drivers:** All drivers are generally classified into two categories—aggressive drivers and conservative drivers, denoted by \( Y_1=1 \) and \( Y_1=0 \), respectively. Meanwhile, all drivers are also either information receivers or information neglecters (i.e., drivers who do not receive information),
denoted by $Y_2=1$ and $Y_2=0$, respectively. To clearly describe a driver’s classification as a combination of these two parameters, a driver can be denoted by the following symbols.

\begin{align*}
S_1: Y_1 = 1, \quad Y_2 = 1 &\quad \text{(an aggressive driver who receives information)} \\
S_2: Y_1 = 1, \quad Y_2 = 0 &\quad \text{(an aggressive driver who doesn’t receive information)} \\
S_3: Y_1 = 0, \quad Y_2 = 1 &\quad \text{(a conservative driver who receives information)} \\
S_4: Y_1 = Y_2 = 0 &\quad \text{(conservative driver who does not receive information)}
\end{align*}

Suppose $\varphi_1$ percent of the O-D trips $T_{IJ}$ between zones $I$ and $J$ are assumed to be aggressive drivers, while $(1-\varphi_1)$ percent are conservative drivers. A driver generated during the simulation process can be randomly determined as an aggressive or conservative driver. Assume that a random number $\omega_1$ between $[-\infty, +\infty]$ is assigned to the driver to represent the driver’s aggressiveness. The $\omega_1$ can be converted to a value between 0-100 using the logsig neural function:

$$DA_{1_{n_{-}i{l}}} = \frac{100}{1 + e^{-\omega}}$$

(25)

Then, classification of the drivers is described by $Y_1$ as:

$$Y_{1_{\left(\text{mt}_{-}i{l}\right)}} = \begin{cases} 
1 & \text{if} \quad 0 \leq DA_{1_{n_{-}i{l}}} \leq \varphi_1 \\
0 & \text{if} \quad \varphi_1 < DA_{1_{n_{-}i{l}}} \leq 1
\end{cases}$$

(26)

Similarly, suppose $\varphi_2$ percent of the O-D trips $T_{IJ}$ between zone $I$ and $J$ are assumed to be information receivers, while $(1-\varphi_2)$ percent are information neglecters. A driver generated during the simulation process can be randomly determined as an information receiver or neglector. Assume that a random number $\omega_2$ between $[-\infty, +\infty]$ is assigned to the driver to represent the driver’s attitude toward information (active or not). The $\omega_2$ can be converted to a value between 0-100 using the logsig neural function:

$$DA_{2_{n_{-}i{l}}} = \frac{100}{1 + e^{-\omega}}$$

(27)

Then, the classification of the driver is described by $Y_2$ as:

$$Y_{2_{\left(\text{mt}_{-}i{l}\right)}} = \begin{cases} 
1 & \text{if} \quad 0 \leq DA_{2_{n_{-}i{l}}} \leq \varphi_1 \\
0 & \text{if} \quad \varphi_1 < DA_{2_{n_{-}i{l}}} \leq 1
\end{cases}$$

(28)

**Driver’s Primary Route:** A primary route simulates a driver’s familiar route or route suggested based on average traffic conditions with shortest-distance related algorithm. It is defined as the minimum travel cost route estimated under uncongested conditions, i.e., each link in the network operates at level of service C or better. In this case, the volume to capacity ratio, $\nu/c$, is assumed to be 0.5 or less, and the average speed is assumed to be the posted speed.

**Dynamic/Predicted Best Route:** A dynamic best route simulates the dynamically updated route for a specific vehicle during a given simulation step. In other words, it is the minimum travel cost route from the current vehicle location to the destination, based on the simulated traffic condition at time $t$. If the vehicle is en route at simulation time step $t$, the cost of the predicted best route includes two parts: experienced route—travel cost of the driver experienced from origin to the current position, and dynamic best route—estimated travel cost of rest of route from the current position to the destination based network condition at $t$. In reality, the nearest place where the driver is able to change the current route is the immediate downstream intersection.

**Driver’s Current Route:** A driver’s current route is the route determined based on the last updated route. A driver starts each trip with a primary route that is determined before departure. The primary route is also the driver’s current route when the vehicle is entering the street network. When the vehicle
reaches the immediate downstream intersection, its dynamic best route is determined and provided to the driver. If the predicted best route is different from the primary route, and the driver is disposed to change routes based on the driver’s behavioral characteristics, and then, the driver’s current route will be replaced with the predicted best route. Similarly, the driver’s new route may be replaced by a newer predicted best route at any subsequent intersection, provided the newest predicted best route is preferable to the current route at the time.

The likelihood of changing routes is defined to reflect the driver’s willingness to alter their route (i.e., to the predicted best route). Assume that the value ranges from 0 to 10, representing the degree of the driver’s willingness to change routes. That is, 10 representing the most willingness and 0 representing the least willingness. The control variable is defined as $\Delta C = (Cost \ of \ Current \ Route - Cost \ of \ the \ Predicted \ Best \ Route) \times (30/Primary \ Route \ Length \ in \ minute)$. Figure 9(a) displays a diagram of membership functions (fuzzy sets) of the control variable for the width of IBRD at 0 min, 5 min, and 10 min per 30-minute primary trip, respectively, and the corresponding output curves (probability versus tendency). When a specific $\Delta C$ is obtained (e.g., 7 minutes) and input into the fuzzy system, the output indicates that the driver’s tendency of route switch is valued as 6.1, as shown in Figure 9(b). In other words, the driver’s degree of willingness to switch to the instant best route is measured as 6.1 out of 10. If the criterion for deciding to change routes is 6.0, then the driver decides to change routes.

The heuristic rules of the pre-trip and en route route-choice models are described as follows.

Pre-trip Route-Choice Model: Before a vehicle begins a trip, the following rules are applied:

- If $(Y_1 = 1, Y_2 = 1)$, then the driver chooses the dynamic best route;
- If $(Y_1 = 1, Y_2 = 0)$, then the driver chooses the primary route.
- If $(Y_1 = 0, Y_2 = 1)$, then the driver’s choice of the dynamic best route is dependent on the tendency of the driver to change routes, as illustrated in Figure 9. It is assumed that an aggressive driver is very familiar with the network and can judge the best route instantly by experience.
- If $(Y_1 = 0, Y_2 = 0)$, then the driver chooses the primary route. The conservative drivers without notification of updated route information are assumed to be following their habitual routes all the time and are not willing to try other routes.

En-Route-Choice Model Using Fuzzy Sets: Whenever a simulated vehicle passes through an intersection and is entering a downstream segment, the following rules are applied:

- If $(Y_1 = 1, Y_2 = 1)$, then the driver switches to the dynamic best route;
- If $(Y_1 = 1, Y_2 = 0)$ or $(Y_1 = 0, Y_2 = 1)$, then the driver’s choice of the dynamic best route is dependent on the tendency of the driver to change routes, as illustrated in Figure 9. It is assumed that an aggressive driver is very familiar with the network and can judge the best route instantly by experience. If this is the case, the condition $(Y_1 = 0, Y_2 = 1)$ applies to the rule.
- If $(Y_1 = 0, Y_2 = 0)$, then the driver is in the primary route all the time. The conservative drivers without notification of updated route information are assumed to be following their habitual routes all the time and are not willing to try other routes.
Figure 9 Demonstration of the IBRD-Based Route Choice Model Using the Fuzzy Sets

PROCEDURE FOR BUILDING MODELS
There are generally seven steps considered the procedure for building traffic simulation models through application of advanced microscopic simulation software, as summarized by Lieberman and Rathi (2000). Those seven steps are briefly described as follows.

**Step 1:** Problem statement to
1) Identify the problems that the model is designated to solve;  
2) State the objectives or purposes of the model that is being developed; and  
3) Define the information needed for the problem solving solutions.

**Step 2:** System definition to
1) Identify major components of the system to be studied;  
2) Identify the information as inputs and outputs;  
3) Bound the scope of the system to be modeled; and  
4) Develop the architecture of the system

**Step 3:** Development of the model to
1) Classify the sub-models and define their inputs and outputs;  
2) Define the flow of data among the above sub-models within the system;  
3) Define the functions and processes of the sub-models and other components;  
4) Determine the parameters for calibration;  
5) Determine the mathematical models that will be used for developing algorithms embedded with each of sub-systems;  
6) Create a logical hierarchy for integrating these sub-model and components to support the data flows;  
7) Develop interface requirements;  
8) Select the software development paradigm, programming language(s), user interface, presentation formats of model results;  
9) Design the software: simulation, structured or object-oriented programming language; database, relational/object oriented;  
10) Document the logic and all computational procedures; and  
11) Develop the software code and debug.

**Step 4:** Calibration of the Model to
1) Set up the procedure of the model calibration;  
2) Collect/acquire data to calibrate the model;  
3) Define default values of parameters based on calibration results; and  
4) Introduce this data into the model.

**Step 5:** Model verification to
1) Establish that the software executes in accord with the design specification; and  
2) Perform verification at the model component level.

**Step 6:** Model validation to
1) Set up the procedure of the model validation, including collecting, reducing, organizing data for purposes of validation; and  
2) Establish that the model describes the real system at an acceptable level of accuracy over its entire domain of operation; apply rigorous statistical domain of operation; apply rigorous statistical.

**Step 7:** Documentation to prepare
1) Model documentation including algorithms and software system architecture;
2) Executive summary; and
3) System users manual.

TECHNIQUES FOR VEHICLE TRAJECTORY DATA COLLECTION

A vehicle trajectory describes the vehicle's path over a period of time. Modeling vehicle travel behaviors with interactions and calibration and validation of microscopic simulation models, relies heavily upon multiple vehicle trajectory data. Other parameters that contribute to microscopic simulation modeling, such as velocity, acceleration, and headway, can be derived from vehicle trajectory data. In recent years, video data collection and subsequent transcription of video data to vehicle trajectories are being attempted by many transportation researchers. As part of the Next Generation SIMulation (NGSIM) program, the Federal Highway Administration’s conducted an initial prototype, and three vehicle trajectory data collection efforts (Kovvali et al, 2006).

For example, the cameras were used in a fixed camera platform developed by University of California, Berkeley for the Berkley Highway Laboratory for the I-80 data collection effort (Kovvali et al, 2006). This platform provided a rigid system within which the cameras were mounted, as shown by Figure 10. Original raw AVI files are extracted from the video cameras and output as rectified AVI files through the data processor within the NGSIM. Intel® Xeon™ CPU 3.00GHz or faster processor with 2.0 GB of Ram were used for recording the data. These computers provided the NGSIM team with equipment that can be used both for collecting, and then for transcribing the data. One of the concerns for these types of machines are that they are not made for rugged use, so are capable of failing if proper care is not taken. Other data collection efforts have used Digital Video Recorders (DVR) or tape drives, but these mechanisms do not provide adequate storage for 8 hours of continuous video data at 30 frames per second (Kovvali et al, 2006).

Wei (2005) developed a methodology for extracting vehicular trajectory data using a video-capture technique. To help extract traffic related data from the digitized video, Wei developed a computer package, Vehicle Video-Capture Data Collector (VEVID). VEVID extracts trajectory data from AVI files that have been digitized from videotape using video-capture equipment. Much of the labor traditionally required to extract vehicle trajectory data and to calculate concerned parameters can be eliminated using VEVID. The methodology consists of three basic steps, as shown in Figure 11. First, an urban street is videotaped from an elevated position, and distances between reference points are measured and input into the VEVID parameters file. Second, a segment of video is digitized into a Video for Windows (AVI) file at a user-specified frame rate. Third, the AVI file is registered in VEVID, and then, in each frame, the user simply clicks the mouse over a distinguishable point of targeted vehicles. Trajectories are output into a trajectory data file along with speeds, accelerations and gaps of targeted vehicles.
Figure 11 Structure of Data Collection using Video-Capture Technique

Figure 12 shows an example of the basic form of vehicle trajectory data from VEVID. Given the frame rate of 2 frames per second (that reflects 0.5 second between two consecutive frames), all selected vehicles' positions are calculated by VEVID. Then VEVID automatically calculates the vehicles' speeds and accelerations for each time slice. Figure 13 illustrates trajectory curves corresponding with the data in Figure 12. From Figures 12 and 13, it can be seen that VEVID is not only capable of collecting trajectories of vehicles in the same lane, but also targeting multiple lanes simultaneously. This function is very valuable in the study of lane changing behaviors. Moreover, VEVID outputs calculation results of all traffic feature parameters that are useful to simulation modeling, such as gaps, headway and relative speeds between each two vehicles of interest, type of lane changing, duration of lane changing, and so forth.

Vehicular trajectory data also have great value in calibration and validation of existing traffic models. In addition to simulation modeling, vehicular trajectory data could be applied to other traffic analyses such as analysis of work zone merging behavior (Tao, 2002). In Minderhoud’s study of improved time-to-collision measures for road traffic safety assessment, vehicle trajectories collected over a specific time horizon for a certain roadway segment are critical inputs to calculate the overall safety indicator value (Minderhoud, 2001). Trajectory data that present the tracks of vehicles traveling within the merging area of the studied work zone could provide quantitative description of merging maneuvers.
in terms of gap selecting, merging location selecting, speed changes, duration of merging and so forth. As a result, impact of merging behaviors on upstream traffic could be analyzed. Trajectory data could also be used for before-and-after study of work zone traffic control strategies.

File Name: C:\AVI_Data\Demo1_326KC.tra;
Location: Grand & Pershing, Kansas City, Missouri;
Time: 2:55 pm, 3/26/98

Trajectory of Head Vehicle

<table>
<thead>
<tr>
<th>#</th>
<th>Time(s)</th>
<th>Position(ft)</th>
<th>Mid-position(ft)</th>
<th>Velocity(ft/s)</th>
<th>Velocity(m/h)</th>
<th>Acceleration(ft/s^2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0</td>
<td>172.73</td>
<td>86.36</td>
<td>---</td>
<td>---</td>
<td>---</td>
</tr>
<tr>
<td>1</td>
<td>0.5</td>
<td>190.27</td>
<td>181.50</td>
<td>35.08</td>
<td>23.92</td>
<td>---</td>
</tr>
<tr>
<td>2</td>
<td>1</td>
<td>208.45</td>
<td>199.36</td>
<td>36.35</td>
<td>24.78</td>
<td>2.52</td>
</tr>
<tr>
<td>3</td>
<td>1.5</td>
<td>223.42</td>
<td>215.93</td>
<td>29.93</td>
<td>20.41</td>
<td>-12.82</td>
</tr>
<tr>
<td>4</td>
<td>2</td>
<td>233.93</td>
<td>228.67</td>
<td>21.03</td>
<td>14.34</td>
<td>-17.80</td>
</tr>
<tr>
<td>5</td>
<td>2.5</td>
<td>242.72</td>
<td>238.32</td>
<td>17.56</td>
<td>11.97</td>
<td>-6.94</td>
</tr>
<tr>
<td>6</td>
<td>3</td>
<td>249.80</td>
<td>246.26</td>
<td>14.16</td>
<td>9.66</td>
<td>-6.78</td>
</tr>
<tr>
<td>7</td>
<td>3.5</td>
<td>257.09</td>
<td>253.45</td>
<td>14.58</td>
<td>9.94</td>
<td>0.82</td>
</tr>
<tr>
<td>8</td>
<td>4</td>
<td>264.92</td>
<td>261.01</td>
<td>15.66</td>
<td>10.67</td>
<td>2.15</td>
</tr>
<tr>
<td>9</td>
<td>4.5</td>
<td>273.07</td>
<td>269.00</td>
<td>16.29</td>
<td>11.11</td>
<td>1.27</td>
</tr>
</tbody>
</table>

Trajectory of Target Vehicle

<table>
<thead>
<tr>
<th>#</th>
<th>Time(s)</th>
<th>Position(ft)</th>
<th>Mid-position(ft)</th>
<th>Velocity(ft/s)</th>
<th>Velocity(m/h)</th>
<th>Acceleration(ft/s^2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0</td>
<td>112.67</td>
<td>56.33</td>
<td>---</td>
<td>---</td>
<td>---</td>
</tr>
<tr>
<td>1</td>
<td>0.5</td>
<td>131.15</td>
<td>121.91</td>
<td>36.94</td>
<td>25.19</td>
<td>---</td>
</tr>
<tr>
<td>2</td>
<td>1</td>
<td>147.90</td>
<td>139.52</td>
<td>33.51</td>
<td>22.85</td>
<td>-6.85</td>
</tr>
<tr>
<td>3</td>
<td>1.5</td>
<td>162.99</td>
<td>155.45</td>
<td>30.17</td>
<td>20.97</td>
<td>-6.68</td>
</tr>
<tr>
<td>4</td>
<td>2</td>
<td>177.41</td>
<td>170.20</td>
<td>28.83</td>
<td>19.66</td>
<td>-2.67</td>
</tr>
<tr>
<td>5</td>
<td>2.5</td>
<td>194.60</td>
<td>186.01</td>
<td>34.38</td>
<td>23.44</td>
<td>11.09</td>
</tr>
<tr>
<td>6</td>
<td>3</td>
<td>214.02</td>
<td>204.31</td>
<td>38.83</td>
<td>26.48</td>
<td>8.90</td>
</tr>
<tr>
<td>7</td>
<td>3.5</td>
<td>231.66</td>
<td>222.84</td>
<td>35.26</td>
<td>24.04</td>
<td>-7.14</td>
</tr>
<tr>
<td>8</td>
<td>4</td>
<td>249.80</td>
<td>240.73</td>
<td>36.28</td>
<td>24.73</td>
<td>2.02</td>
</tr>
<tr>
<td>9</td>
<td>4.5</td>
<td>269.26</td>
<td>259.53</td>
<td>38.92</td>
<td>26.53</td>
<td>5.27</td>
</tr>
</tbody>
</table>

Trajectory of Lead Vehicle

<table>
<thead>
<tr>
<th>#</th>
<th>Time(s)</th>
<th>Position(ft)</th>
<th>Mid-position(ft)</th>
<th>Velocity(ft/s)</th>
<th>Velocity(m/h)</th>
<th>Acceleration(ft/s^2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0</td>
<td>223.42</td>
<td>111.71</td>
<td>---</td>
<td>---</td>
<td>---</td>
</tr>
<tr>
<td>1</td>
<td>0.5</td>
<td>246.78</td>
<td>235.10</td>
<td>46.72</td>
<td>31.85</td>
<td>-10.15</td>
</tr>
<tr>
<td>2</td>
<td>1</td>
<td>267.60</td>
<td>257.19</td>
<td>41.64</td>
<td>28.39</td>
<td>-6.79</td>
</tr>
<tr>
<td>3</td>
<td>1.5</td>
<td>287.22</td>
<td>277.41</td>
<td>39.24</td>
<td>26.76</td>
<td>-6.65</td>
</tr>
<tr>
<td>4</td>
<td>2</td>
<td>308.62</td>
<td>297.92</td>
<td>42.80</td>
<td>29.18</td>
<td>7.10</td>
</tr>
<tr>
<td>5</td>
<td>2.5</td>
<td>328.36</td>
<td>318.49</td>
<td>39.47</td>
<td>26.91</td>
<td>-6.65</td>
</tr>
<tr>
<td>6</td>
<td>3</td>
<td>346.37</td>
<td>337.37</td>
<td>36.02</td>
<td>24.56</td>
<td>-6.88</td>
</tr>
<tr>
<td>7</td>
<td>3.5</td>
<td>363.61</td>
<td>354.99</td>
<td>34.46</td>
<td>23.49</td>
<td>-3.12</td>
</tr>
<tr>
<td>8</td>
<td>4</td>
<td>379.81</td>
<td>371.71</td>
<td>32.41</td>
<td>22.09</td>
<td>-4.10</td>
</tr>
<tr>
<td>9</td>
<td>4.5</td>
<td>394.62</td>
<td>387.22</td>
<td>29.61</td>
<td>20.19</td>
<td>-5.58</td>
</tr>
</tbody>
</table>

Trajectory of Lag Vehicle

<table>
<thead>
<tr>
<th>#</th>
<th>Time(s)</th>
<th>Position(ft)</th>
<th>Mid-position(ft)</th>
<th>Velocity(ft/s)</th>
<th>Velocity(m/h)</th>
<th>Acceleration(ft/s^2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0</td>
<td>0.40</td>
<td>0</td>
<td>---</td>
<td>---</td>
<td>---</td>
</tr>
<tr>
<td>1</td>
<td>0.5</td>
<td>23.0</td>
<td>11.73</td>
<td>45.30</td>
<td>30.88</td>
<td>---</td>
</tr>
<tr>
<td>2</td>
<td>1</td>
<td>45.87</td>
<td>34.46</td>
<td>45.61</td>
<td>31.10</td>
<td>0.62</td>
</tr>
<tr>
<td>3</td>
<td>1.5</td>
<td>69.65</td>
<td>57.76</td>
<td>47.56</td>
<td>32.45</td>
<td>3.90</td>
</tr>
<tr>
<td>4</td>
<td>2</td>
<td>93.92</td>
<td>81.79</td>
<td>48.54</td>
<td>33.09</td>
<td>1.94</td>
</tr>
<tr>
<td>5</td>
<td>2.5</td>
<td>120.30</td>
<td>107.11</td>
<td>52.75</td>
<td>35.96</td>
<td>8.41</td>
</tr>
<tr>
<td>6</td>
<td>3</td>
<td>144.19</td>
<td>132.24</td>
<td>47.79</td>
<td>32.58</td>
<td>-9.91</td>
</tr>
<tr>
<td>7</td>
<td>3.5</td>
<td>166.24</td>
<td>155.22</td>
<td>44.09</td>
<td>30.06</td>
<td>-7.40</td>
</tr>
<tr>
<td>8</td>
<td>4</td>
<td>186.50</td>
<td>176.37</td>
<td>40.51</td>
<td>27.62</td>
<td>-7.14</td>
</tr>
<tr>
<td>9</td>
<td>4.5</td>
<td>205.51</td>
<td>196.00</td>
<td>38.02</td>
<td>25.92</td>
<td>-4.98</td>
</tr>
</tbody>
</table>
Introducing video-capture to traffic data collection, especially multiple vehicle trajectory data for microscopic simulation modeling, is a significant advancement. The methodology proposed provides an effective and economic approach to studying microscopic traffic characteristics. With the help of VEVID, better quality data can be collected more efficiently. This advancement will result in better models of traffic in the urban environment.

The limitation of the video-capture-based approach lies in the extracting trajectory data of the vehicles located over 460 m or 1500 ft away from the observation site, if a regular (family-use) camcorder is used. The far is the vehicle from the observation location, the longer distance does a pixel present in the image of an AVI frame. Thus, capability to produce high resolution of an AVI frame is one of major factors in selecting camcorder and accuracy testing is needed using sample data. In choosing place to install the camera, the site at which a very oblique camera angle is needed should be avoided at all possible.

CALIBRATION AND VALIDATION OF APPLYING ADVANCED MICROSCOPIC SIMULATION SOFTWARE

Advanced Microscopic Simulation Software

Many simulation models have been developed to evaluate the benefits of transportation operations. Traffic simulation has been in use since the early 1950s, but the recent advancement in computer technology and programming tools has helped to develop more sophisticated software for use in simulation modeling (Narasimha, 2005). As the computing power increases so will the simulation
capability to illustrate precise description of roadway and facility conditions on-screen for analysis. To
date, typically popular microscopic software for the present includes VISSIM (German for Traffic in
Towns - Simulation) models, Paramics (Quadstone) (PARAllel MICroscopic Simulation), and AIMSUN2
(Advanced Interactive Microscopic Simulator for Urban and Non-urban Networks). The major features
and functions can be obtained at the web sites of the software developers (Institute for Transport Studies,
2006). The following sections discussing the experienced procedures for application of above advanced
microscopic simulation models.

The general reasons for applying microscopic traffic simulation software to traffic operations and
system evaluations include, but are not limited to, the following aspects:

• For its ability to capture the full dynamics of time dependent traffic phenomena;
• As a complementary tool for the detailed evaluation of alternative designs beyond the
classical ones;
• For the detailed assessment of traffic management schemes;
• For assessment of advanced traffic management and information systems applications;
• For evaluation of new traffic control methods;
• For accurate emission and fuel consumption modeling; and
• For needs of animation (Seeing is believing!).

Calibration and Validation of Simulation Models

Any microscopic simulation model must be calibrated and validated before its application for real
problem-solving practice. The calibration involves checking the model results against observed data and
adjusting parameters until the model results fall within an acceptable range of error (Chu et al, 2004). The
collected data included roadway traffic volume and travel time data. Chu et al (2004) summarized an
overall calibration procedure based on their experience in study of simulating the I-45 freeway and its
surrounding roadway network in California using PARAMICS simulation model. The following four
steps of calibration efforts are included in the procedure:

• Calibration of driving behavior models;
• Calibration of route choice model;
• Origin-Destination estimation; and
• Model fine-tuning.

It also should be noted that the network coding errors are major source of abnormal vehicular
movements (Chu et al, 2004). Such errors can be found at any time during the process of the calibration
from some. Accordingly, fixing network coding errors is an important task throughout the whole
calibration process. The number of simulation runs is one of contributing factors influencing the
calibration accuracy. Before determining the number of simulation runs, the variance of a number of
performance measures from simulation results should be estimated. The number of simulation runs could
be estimated by the following equation (Chu et al, 2004).

\[ N = \left( \frac{t_{a/2}}{\mu \varepsilon} \right)^2 \]  

(29)

where \( \mu \) and \( \delta \) are the mean and standard deviation of the performance measure based on the already
conducted simulation runs; \( \varepsilon \) is the allowable error specified as a fraction of the mean \( \mu \); \( t_{a/2} \) is the critical
value of the t-distribution at the confidence interval of 1-\( \alpha \).

Two objectives of calibration are required to meet: 1) to minimize the deviation between the
observed traffic counts (\( VOL_{ob} \)) and corresponding simulated traffic counts (\( VOL_{sim} \)) at selected
measurement locations for the peak hour of the simulation period \( (t = 1, T) \); and 2) to minimize the
deviation between the observed travel time (\( TT_{ob} \)) and corresponding simulated travel time \( TT_{sim} \) along
selected measurement routes (number of sample \( n = 1, N \)). Those two objective functions are expressed by the following equations.

\[
\min \sum_{i=1}^{T} \sum_{n=1}^{N} (VOL_{obs}(n,t) - VOL_{sim}(n,t))^2
\]

(30)

\[
\min \sum_{i=1}^{T} \sum_{n=1}^{N} (TT_{obs}(n,t) - TT_{sim}(n,t))^2
\]

(31)

The major driving behavior models include car-following and lane-changing models, which govern vehicular traffic movement and need to be calibrated for the specific region. The car-following model in a microscopic simulation software such (e.g., AIMSUN2) could be tested and calibrated in various with measured and simulated travel distance within a certain period of time. The error metric used to measure the accuracy of the fitting between measured and simulated values can be expressed by the following equation (Barceló1, 2000).

\[
Em = \left[ \sum_{i=1}^{N} \left( \log \left( \frac{d_{sim}(i)}{d_{obs}(i)} \right) \right)^2 \right]^{1/2}
\]

(32)

Where, \( d_{sim}(i) \) is the distance of the simulated vehicle at \( i \)th simulation run, and \( d_{obs}(i) \) is the distance measured with the test vehicle, and \( \log \) denotes the logarithm base 10.

Model validation is typically an iterative process linked to each model calibration (Chu et al, 2004). The model validation is generally conducted with a different data set of larger area within the modeling network in order to check if the calibrated model parameters are suitable. Model validation is regarded as a final stage to investigate if each component adequately reproduces observed travel characteristics and the overall performance of the model is reasonable. The measure of goodness of fit could be for validating the calibrated simulation model. Mean Absolute Percentage Error (MAPE) is measure of accuracy in a fitted time series value in statistics, specifically trending. It usually expresses accuracy as a percentage. MAPE is expressed by the following equation (Chu et al, 2004):

\[
MAPE = \frac{1}{T} \sum_{t=1}^{T} \frac{M_{abs}(t) - M_{sm}(t)}{M_{abs}(t)}
\]

(33)

Where, \( M_{abs}(t) \) and \( M_{sm}(t) \) are field measured and simulated time-series values during a period of time \( t \).

**SUMMARY AND CONCLUSIONS**

This chapter summarizes research results by the author on the core models of microscopic traffic simulations, including lane-choice, lane-changing, and route-choice models, as well as techniques on vehicle trajectory data extraction. Multiple vehicle trajectories provide the basis for the microscopic modeling of traffic on an urban street network. In the past, however, the difficulty of collecting vehicle trajectory data has been an obstacle to deriving verifiable models from empirical data. Introducing video-capture to traffic data collection, especially multiple vehicle trajectory data for microscopic simulation modeling, is a significant advancement. With the help of VEVID, better quality data can be collected more efficiently. In the end, this advancement will result in better models of traffic in the urban environment. Many models as of introduced in this chapter would not be developed without the above methodology.

Using video-capture techniques and the VEVID software, the author conducted a lengthy observation of lane-changing behaviors on urban streets and analyses of observed vehicle trajectory data. This study presents new findings from real-world observations. New findings inspired the authors, from the systematic standpoint of view, to explore the hierarchy in recognizing and understanding lane-choice
and lane-changing behaviors on urban streets. Based on new findings from observations conducted on four-lane urban streets, the author developed the heuristic structures of a lane-based vehicle assignment procedure along with a lane-choice model and a lane-changing model. The models presented in this research are a significant advancement in lane-specific vehicle-based microscopic simulation modeling, and provides a good basis for conducting further research on six or more lanes streets, as well as improving a microscopic simulation models.

In this chapter, the route choice problem is explored for a lane-vehicle-based microscopic simulation system. Since different categories of drivers have different reactions to the traveler routing information, traditional models assuming that every driver is very familiar with the network and always chooses the shortest path are not applicable to the study of the impact of traveler information on drivers’ route choice behaviors. The methodology introduced in this chapter attempts to more realistically simulate route choice behavior. For instance, it is assumed that all drivers must have their primary routes before the trips, based on route information (e.g., from the Internet) or from experience. When they receive updated routing information while en route, aggressive drivers are more likely than conservative drivers to follow the advice. Aggressive drivers who are not exposed to the updated information may still adjust their primary route based on differences between expected and experienced traffic characteristics. But route changes also depend on familiarity with the road network. In general, if a driver on the route decides to change routes, the change cannot occur until the next downstream intersection is reached.

More importantly, drivers do not switch to another route that is predicted to have minimum travel cost if the estimated delay falls into indifference band of route delay. Different categories of drivers have varied criteria of the width of indifference band of route delay. Thus, fuzzy sets may be an appropriate theoretical method to be use for estimation of a specific driver’s tendency to change routes. Further investigation and study on threshold values of the width of the indifference band of route delay may be needed for the areas of interest.

This chapter is written through systematically integrating above models into a simulation modeling system while merging some supplementary models and concepts resulted from literature reviews, including vehicle generation model and car-following models. In additionally, to facilitate the applications of the simulation models, procedure for building models and calibration and validation of simulation models are also summarized.

**FUTURE RESEARCH DIRECTIONS**

Traffic is the result of human behaviors and it is therefore mutual important to find out how traffic decisions are motivated and what results from the complex interactions of various participants (Schreckenberg & Selten, 2004). As a consequence it was not sufficient to model mobility in an entire mechanistic way. The human behavioral parameters need to be better underpinned (Ettema et al, 2003). For example, experiments to test how travelers learn and adjust in a controlled laboratory setting may be one of ways to conduct. Taken into account the fact that traffic decisions are made by individuals on the basis of interactions with other individuals makes the problem highly interdisciplinary and very complex. It will be also important to represent different types of decision makers (Ettema et al, 2003), such as early adaptors, risk takers and risk avoiders, optimizing and satisfying travelers, etc. There are different ways to approach the problem. For example, the widely used approaches include empirical (experimental) and theoretical methods. Regardless of the approaches for building the models, all models must be calibrated and validated prior to their applications.

The speed and capacity of desktop computers is steadily increasing. Tasks that were once the province of mainframe computers can be easily handled by the latest generation of personal computers. Increases in hardware speed generally result in greater capabilities of the models that run on them. Therefore it should soon be possible to see much more advanced micro-simulation models to deal with aspects that today’s models consider too computationally expensive. Conventionally, large amount of data required for simulating larger networks is always a question. With increasing functionality of the
intelligent transportation systems that automatically collects traffic data through field detection systems, the data collection task is being made easier. Simulation-based analysis of a larger network is expected to become more practical with ease in the future.

As indicated earlier, multi-lane vehicle trajectories are a key in advancing the identification and modeling of traffic characteristics under varied conditions. It’s high time to update VEVID to accommodate more requirements for modeling. Most notably, how to relate traffic crime and offenses into the traffic simulation system as a tool to support the analysis of crime prevention strategies is a challenge to traffic simulation modeling. However, this research will apparently need an interdisciplinary research on the similar topics.

REFERENCES


ADDITIONAL READING


**INDEX**

Calibration, 22, 26, 27  
Car-following  
- car-following, 1, 2, 3, 4, 12, 13, 28, 29  
- driving task, 3  
Lane-changing  
- discretionary lane change, 7, 9, 12, 14  
- head vehicle, 9, 13  
- lag vehicle, 10, 11, 12, 14  
- lane change, 5, 6, 7, 8, 9, 12, 13, 14, 16  
- lane-changing behavior, 7, 9  
- lane-changing decision, 9, 11  
- lane-changing maneuver, 7, 9, 14  
- lane-changing model, 2, 8, 29  
- lane-changing models, 1, 7, 28  
- lead vehicle, 9, 14  
- mandatory lane change, 7  
- speed advantage, 9  
- target vehicle, 7  
Lane-choice  
- lane-choice behavior, 4, 6  
- lane-choice model, 4  
- target lane, 5, 6, 8, 9  
Route-choice  
- aggressive drivers, 18, 19, 29  
- conservative drivers, 12, 18, 19, 20, 29  
- IBRD, 15, 17, 18, 20  
- indifference band of route delay, 15, 18, 29  
- indifference band of route delay (IBRD), 15  
- route-choice modeling, 14  
- tolerable schedule delay, 15
Route-Choice
   route-choice model, 2, 14
Simulation
   lane-vehicle-based simulation, 16
   microscopic traffic simulation modeling, 2
   Microscopic traffic simulation models, 1
   micro-simulation approach, 2
   traffic simulation, 1, 2, 7, 22, 27, 30
   vehicle-based microscopic simulation, 15, 29
Validation, 26
   validation, 2, 22, 23, 24, 28, 29
Vehicle Generation
   pseudo-random, 2
   random numbers, 2
   Random variants, 2
   vehicle generation model, 2, 29
Vehicle Trajectory
   AVI, 23, 25, 26
   trajectories, 24
   vehicle trajectory, 2, 9, 12, 23, 24, 26, 28, 29
   Vehicle Video-Capture Data Collector (VEVID), 23
   VEVID, 9, 23, 24, 25, 26, 28, 29, 30
   video-capture technique, 23