6. Traffic Simulation with MITSIMLab

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Abstract

MITSIMLab (MIcroscopic Traffic SIMulation Laboratory) is a microscopic traffic simulation model that evaluates the impacts of alternative traffic management system designs at the operational level and assists in their subsequent refinement. MITSIM models the travel and driving behavior of individual cars, the detailed movement of buses, and the various control and information provision strategies through a generic controller. A calibration methodology for important parameters and inputs was also developed. The model has also been extended to address the special driving behavior in urban networks.

6.1 Introduction

MITSIMLab (MIcroscopic Traffic SIMulation Laboratory) is a microscopic traffic simulation model that evaluates the impacts of alternative traffic management system designs, traveler information systems, public transport operations, and various ITS strategies, at the operational level and assists in their subsequent refinement. MITSIMLab can evaluate systems such as advanced traffic management systems (ATMS) and route guidance systems.

MITSIMLab was developed by MIT's Intelligent Transportation Systems (ITS) Program (Yang, 1997, Yang and Koutsopoulos, 1996, Yang et. al.,

2000). The model was used to evaluate several aspects of the traffic management system for the Central Artery/Tunnel (CA/T), by simulating its operations. The CA/T network consists of approximately 110 lane-miles equipped with 1600 sensors and is used by 300,000 vehicles per day. It features an extensive traffic control system, including Lane Control Signals (LCS), incident detection, tunnel closing, electronic toll collection (ETC), and Variable Message Signs (VMS) for route guidance. MITSIMLab was used to evaluate various operating strategies associated with these traffic management functions, and make recommendations for improvements, including ITS design, ramp configuration, and construction staging. For the CA/T application, MITSIMLab was calibrated with behavior data of Boston drivers.

MITSIMLab serves as a laboratory for the evaluation of ITS and other traffic and transit strategies and systems. The model's application framework for these evaluations is outlined in Figure 6.1. Based on the objectives of the evaluated system, scenarios are generated to test the design. Appropriate measures of performance are generated from the simulations, used to evaluate the system performance, and may lead to subsequent design refinements.

MITSIMLab supports:

- Objective and independent evaluations.
- Thorough representations of all relevant interactions in the transportation system, including vehicles, traffic control devices, algorithms and other elements of the traffic management center (e.g. surveillance system).
- Assessment of the technical aspects of the algorithms, the performance and impact of interfaces and communication channels, sensitivity to errors, robustness, and ability to recover from malfunctions.

MITSIMLab represents the related functions of the traffic management system at a fine level of detail, including the important aspects of the traffic management center, the surveillance system, the guidance and control

logic, and algorithms, in order to evaluate a wide range of design aspects of ATIS/ATMS. Researchers have used MITSIMLab for practical applications in the USA, UK, Sweden, Italy, Switzerland, Japan, Korea, Malaysia and elsewhere. It was the main tool used to test and demonstrate the various driving behavior models developed within the NGSIM (Next Generation SIMulation) project, which facilitated the advancement of traffic simulation models by improving realism in the driving behavior models they incorporate. In 2004, an open-source version of MITSIMLab was released. It is available at the MIT ITS Program website (http://mit.edu/its/mitsimlab.html). The structure and models in MITSIMLab also formed the basis for the development of the traffic simulation software TransModeler (*www.caliper.com/transmodeler/default.htm*).

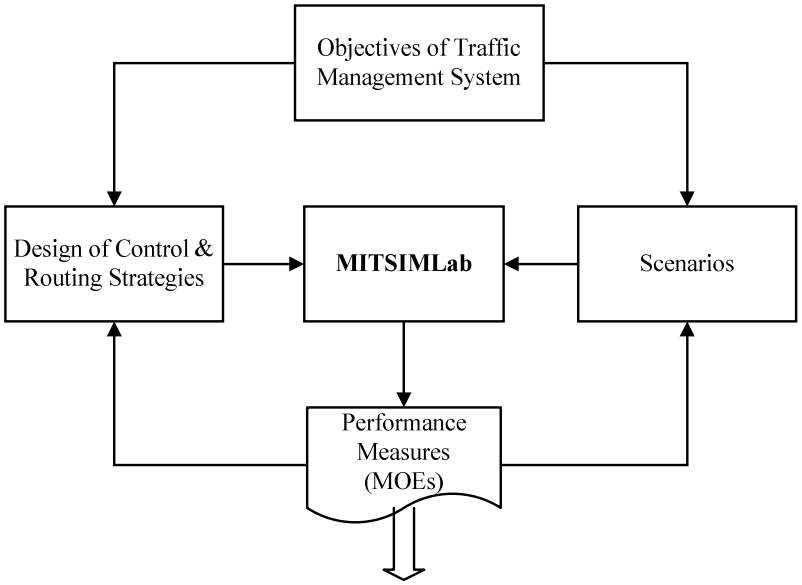


Fig. 6.1. Evaluation framework

This chapter describes the structure and main characteristics of MITSIMLab, the methodology used for model calibration and validation, followed by several application examples.

6.2 Model Building Principles in MITSIMLab

In order to allow maximum flexibility in defining the evaluated systems, travelers' behavior in the presence of these systems, and the dynamic interactions between the management system and travelers, MITSIMLab is implemented as three separate modules, which exchange information as shown in Figure 6.2.

Within the traffic simulator module (TS), the movements of individual vehicles (cars and transit vehicles) are represented by detailed travel and driving behavior models. Traffic flow characteristics emerge from these individual behaviors. Vehicles traveling in the network activate surveillance devices (e.g. loop detectors, communication beacons, video sensors). The data gathered by the surveillance system are transferred to the traffic management simulator (TMS), which mimics the traffic control and routing strategy or transit strategy under evaluation. The control and routing strategies generated by the TMS determine the states of traffic control and route guidance devices. These settings are transferred to the TS. The simulated drivers respond to the various traffic controls and guidance, while interacting with each other. The TMS is a virtual transportation system operations control center, processing performance data from the sensor network and generating a strategy. The TMS also simulates a wide range of transit operations control strategies (e.g. transit signal priority, holding for service restoration, etc) defined by the user. The simulation output can be obtained as numerical data tables and via the graphical user interface (GUI), which visualizes traffic impacts through vehicle animation. MITSIMLab generates various output reports with measures of effectiveness that may be used to evaluate the performance of potential ITS strategies.

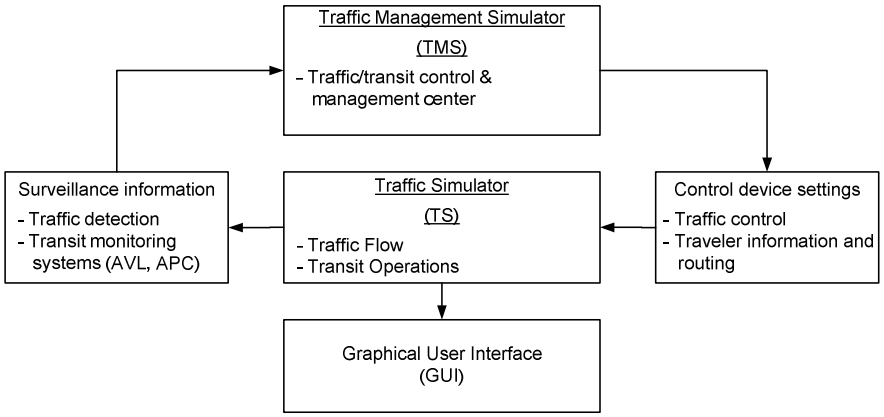


Fig. 6.2. MITSIMLab structure

Travel demand is represented by time-dependent origin to destination (OD) trip tables, which show expected conditions or are defined as part of a scenario for evaluation. Based on these tables, individual vehicles are generated. The generated vehicles are assigned driver characteristics (e.g. aggressiveness, planning capability, look-ahead distance, level of compliance with various signs and regulations) and vehicle attributes (e.g. acceleration and speed capabilities and the impact of grade on these capabilities) based on pre-determined distributions. Route choices are based on a probabilistic model that captures the impact of travel times and biases towards routes that use freeways over urban streets. The impact of real-time information on routing decisions is captured by a route switching model in which informed drivers re-evaluate their pre-trip route choices based on the traffic conditions observed en-route. MITSIMLab is a time-based simulation model with time steps that may differ for various functions from 0.1 to 1.0 seconds. It also incorporates event-based approaches for situations such as crash avoidance and responses to changes in traffic controls and information settings.

6.3 Fundamental Core Models

The core of MITSIMLab consists of travel and driving behavior models. The travel behavior models capture the driver's pre-trip and en-route route choices. The driving behavior models deal with tactical and opera-

tional driving decisions, mainly acceleration and lane changing. The models that capture these choices in MITSIMLab are probabilistic, based on the theories of random utility maximization.

6.3.1 Driving Behavior

Driving behavior decisions are modeled as a series of interdependent choices that are based on a specific plan/tactic. For example, drivers select a target lane and adapt their acceleration and lane changing actions to facilitate arriving at the chosen lane. The evolving circumstances (i.e. behavior of other drivers, traffic control) can cause changes to the plan. For example, drivers may initially plan to merge into mainline traffic through normal gap acceptance. But as they approach the end of the merging lane and are unable to find acceptable gaps, they may force merge. Drivers' plans are generally unobservable in the real-world (only drivers' actions are observed). Therefore, MITSIMLab captures this behavior using an integrated modeling framework based on latent plans.

The general framework of these models is shown in Figure 6.3. At any instant, drivers choose a plan based on the state they are faced with. Their actions depend on the chosen plan. These actions, the actions of the other drivers and changes in the state of the control system (e.g. traffic light indications) may lead drivers to change their plans.

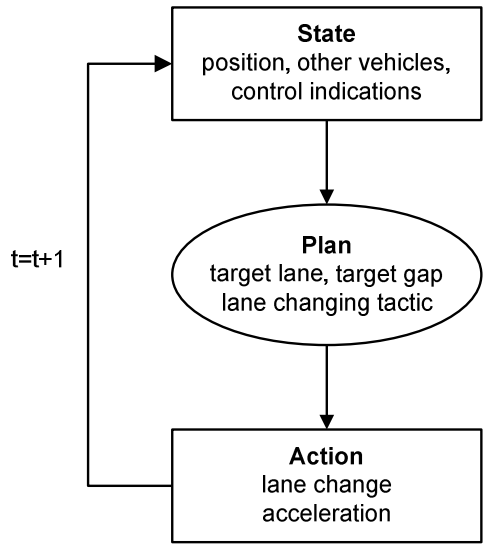


Fig. 6.3. General decision structure

The plan drivers choose may depend on their previous plan choices and be affected by anticipated future conditions. The models that capture the plan choice and the action choice, conditional on this plan, are based on the utility maximization theory. The interdependencies and causal relationships between various decisions over time and across choice dimensions result in serial correlation and state-dependence among the observations. Driver specific random terms are incorporated in the models in order to capture heterogeneity in drivers' behavior that stems from differences in aggressiveness, planning capabilities, etc. A Hidden Markov Model is used to capture the effect of previously chosen plans on the choice of the current one. Effects of anticipated future circumstances are captured using predicted conditions based on current information in the decision-making. For a complete description of the latent plan model structure see Choudhury (2007).

The main driving behavior models in the latent plan structure are lane changing and acceleration. In MITSIMLab, they are modeled using an integrated framework as shown in Figure 6.4. The figure shows the decision

process for a driver currently in lane 3 of a 4-lane road. Chosen (latent) plans are shown as ovals and the resulting actions as rectangles.

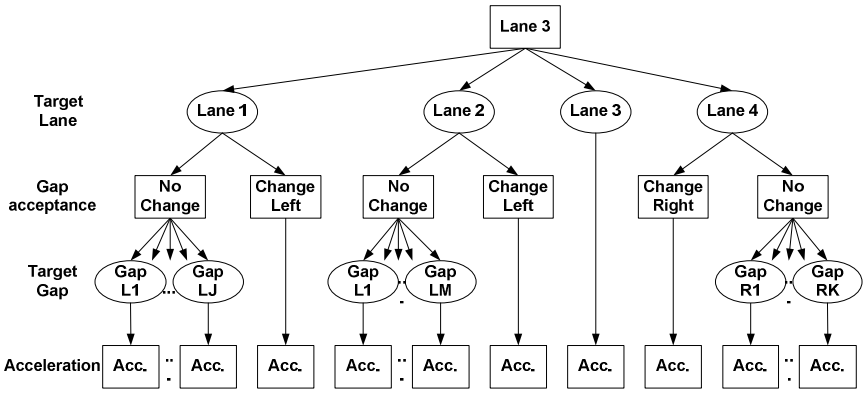


Fig. 6.4. Structure of the driving behavior model

Drivers select the target lane as the lane they perceive to be the best among all available lanes (lanes 1, 2, 3, and 4 in this case).

The target lane model uses a multinomial logit (MNL) structure. Important variables that affect lane choices include the distance to the point where the driver must be in specific lanes in order to follow the path, the number of lane changes required to be in these lanes, the attributes of the various lanes (e.g. average speed and density of the lane, lane cost/toll), and variables that capture the conditions in the immediate vicinity of the vehicle such as the relative speeds and spacing from lead vehicles, the presence of heavy vehicles and characteristics of the driver (e.g. aggressiveness, network familiarity). If the target lane is different from the current lane, a lane change is required. Drivers then search for an acceptable gap to complete the lane change.

The gap acceptance model in MITSIMLab is probabilistic, where the available gaps are compared against the critical gaps. The model defines the lead and lag gaps as the clear spacing between the subject vehicle and the lead and lag vehicles in the adjacent lane, respectively. A gap is accepta-

ble only if the lead and lag gaps are acceptable (i.e. available gap ≥ critical gap). Critical gaps are assumed to be log-normally distributed, where the mean is a function of explanatory variables, which include the relative speeds of the lead and lag vehicles.

The drivers that cannot change lanes immediately select a short-term plan to perform the desired lane change. Short-term plans are defined by the various traffic gaps in the target lane. The target gap choice probabilities are modeled with an MNL structure where the trade-offs among different attributes of the gap (e.g. gap size, distance to the gap etc.) are accounted for.

Drivers adapt their acceleration behavior to facilitate their short term plans (i.e. target lane and gap). Different accelerations are applied depending on the current plan the driver implements: stay-in-the-lane, lane changing or target various gaps for lane changing. The stimulus-sensitivity framework proposed within the GM model (Gazis et al. 1961) is adapted for these acceleration models. The response (acceleration or deceleration) the driver applies to a stimulus is lagged to account for reaction time as follows:

$$response_n(t) = sensitivity_n(t) \times stimulus_n(t - \tau_n) \tag{6.1}$$

where, *t* is the time of observation and τ_n is the reaction time for driver *n*.

The driver reacts to different stimuli depending on the chosen plan and constraints imposed. Within each one of the acceleration behaviors, the driver is assumed to be either in a constrained or unconstrained regime. A constrained regime applies when the driver is close to the lead vehicle (the headway is smaller than the threshold) and affected by its behavior. For stay-in-lane and target gap accelerations, the lead vehicle is the front vehicle in the current lane. For lane-changing acceleration, the lead vehicle is the front vehicle in the lane the driver is changing to. In the constrained regime, the stimulus is the relative speed of the lead vehicle and has different parameters for acceleration and deceleration. In the unconstrained regime, for the stay-in-the-lane and lane-changing cases, free-

flow acceleration is applied. For target gap cases, the stimulus is determined by a desired position that would facilitate completion of the lane change. The reaction time and time headway threshold distributions account for the heterogeneity among drivers and are common to all components of the acceleration model. See Ahmed (1999) and Toledo (2008) for details of the target gap choice and acceleration models.

One of the main factors affecting lane choices is the need to follow the travel path. The implementation of path awareness (i.e., when do drivers become aware and begin to respond to path-following constraints) impacts the simulation results. The path awareness model in MITSIMLab assumes that drivers are aware of the path-plan up to a certain distance downstream of their current position. They will react to any path-following constraints that arise within this “look-ahead” distance and ignore those that are further downstream. The look-ahead distances are characteristics of the driver and are assumed to be randomly distributed in the driver population. This approach overcomes the excess weaving and merging maneuvers arising from late lane changes that occur when the awareness is based on the network structure (i.e. drivers are only aware of the next link(s) on their path), particularly in urban networks that are characterized by short links and paths that may require frequent turning movements.

6.3.2 Travel Behavior

The travel behavior models include both pre-trip and en-route path choices. Drivers in MITSIMLab may have either predefined paths or compute them dynamically. Depending on whether alternative paths were predefined, a path-based route choice model or a link-based route generation model may be used.

In the path-based route choice model, a list of predefined paths is used as input. Each path is defined by the list of links it consists of. The choice among these lanes is modeled with the path-size model (Ben-Akiva and Bierlaire, 2003), which accounts for the similarity among paths that over-

lap in parts. With this model, the probability that a driver will choose route *i* from the path choice set *C* is given by:

$$P(i) = \frac{\exp\left(V_i + \ln PS_i\right)}{\sum_{j \in C} \exp\left(V_i + \ln PS_i\right)} \tag{6.2}$$

where, V_i and V_j are the systematic utilities of routes *i* and *j*, respectively. The systematic utilities in the route choice model are functions of path attributes such as path travel times and freeway bias. Travel times may be habitual or predicted. PS_i and PS_j are the corresponding path sizes. These terms capture the effect of overlapping routes on drivers' perceptions.

The link-based route generation model does not require path enumeration, which may be expensive in large urban networks. Instead, it represents a myopic behavior. This model is also useful in generating an initial set of paths between origins and destinations. With this model, drivers choose only the next link at each intersection. An MNL model is used for this choice:

$$P\left(k \mid s, d\right) = \frac{\exp\left(V_{kd}\right)}{\sum_{j \in L_s} \exp\left(V_{jd}\right)} \tag{6.3}$$

where, $P\left(k \mid s, d\right)$ is the probability of choosing link *k* as the next link on the path to destination *d* at node *s*. L_s is the set of links emanating from node s. V_{kd} is the systematic utility associated with link *k* for getting to destination *d.*

Since link travel times are time-dependent, path travel times account for the time that drivers are expected to arrive at each link on their path. The travel time in the utility for each alternative link is the travel time from node *s* through the specific link to the destination, as illustrated in Figure 6.5:

$$TT_{skd}(t) = tt_{sk}(t) + TT_{kd}(t + tt_{sk}(t)) \tag{6.4}$$

where, $TT_{skd}(t)$ is the travel time to *d* using link *k* for vehicles arriving at *s* at time *t*. $tt_{sk}(t)$ is the travel time on the link s*k* for vehicles entering the link at time *t*. $TT_{kd}(t + tt_{sk}(t))$ is the travel time from *k* to the destination on the shortest path at the time the vehicle arrives to *k*.

To avoid using very long or circular paths, the link-based model uses additional parameters to screen out the choices leading to paths that are considered unrealistic. The first screening criterion removes alternatives with travel times that are too long compared to the alternative with the shortest travel time. A second screening criterion prevents vehicles from moving to nodes that are farther away from the destination compared to their current position.

The effects of traveler guidance and information on route choices are captured in the path-based and the link-based route choice models. Drivers in MITSIMLab are classified as informed or uninformed. In the presence of traffic information, informed drivers base route choices on updated travel times that incorporate real-time traffic conditions. If en-route traveler information is available (e.g. through in-vehicle units or VMS) route choices are reevaluated whenever new information is received. In the path-based model, drivers' preferences to keep their previously chosen paths are captured by a diversion dummy variable, which penalizes switching from the previously chosen route. Uninformed drivers use the habitual travel times, which represent prevailing traffic conditions on these paths. For networks with prescriptive VMS and route guidance systems, a compliance factor is defined to account for the fact that not all drivers adhere to the prescribed route.

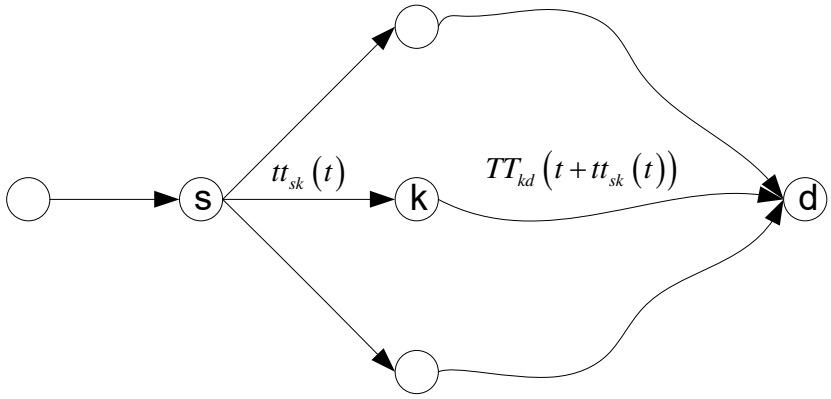


Fig. 6.5. Travel times in the link-based model

6.3.3 Traffic Control

MITSIMLab, through the traffic management simulator (TMS), mimics the traffic control system in the evaluated network. A wide range of traffic control and route guidance systems can be simulated:

1. Ramp control
2. Freeway mainline control
   - Lane Control Signs (LCS)
   - Variable Speed Limit Signs (VSLS)
   - Portal Signals at tunnel entrances (PS)
3. Intersection control
4. Variable Message Signs (VMS)
5. In-vehicle route guidance

The TMS's general structure can represent different logical designs of such systems at varying levels of sophistication: from isolated pre-timed signals to real-time predictive systems. For example, a generic traffic con-

troller is at the heart of the TMS. The generic controller breaks down control strategies into basic logic elements and implements them within a modular framework. Specific control logic can then be recreated from these basic components. The modular structure allows any specialized features to be implemented easily. The logic behind the generic controller is specified in terms of signal groups (not phases). Each group is defined by the intersection movements that it controls and by the logic that governs its operation. A signal group holds data about its current status and its relationship to other groups, including its current indication (e.g. green arrow), its current action (e.g. holding the current period), the next indication to show (e.g. yellow arrow), its conflicting groups, and stored sensor data. In MITSIMLab, the status and position of every vehicle is updated at a specified step size (i.e. 0.1 seconds). A similar approach is used for the generic controller, which evaluates each signal group at every time step and determines if the state of any group needs updating. An overview of the logic of the generic controller is shown in Figure 6.6.

Upon initialization, the controller obtains information about the signals that it will direct, the movements controlled by each signal group, the initial state of each signal group, and the conditions that specify the control logic for each signal group. During a simulation run, the controller iterates through all the signal groups, evaluating the logic conditions, and determines whether the group's state should be updated. This evaluation step is iterative because the group states may be interdependent with the state of one group being an input to the logic of another group. There are four types of conditions that correspond to different actions: *general* conditions that perform miscellaneous functions, *change* conditions that advance the signal group to the next period, *hold* conditions that keep the group in the current period, and *skip* conditions that indicate if the next specified number of conditions should be skipped. By combining the conditions in a specific order, a full controller logic can be specified. The types of control strategies that can be simulated include isolated controller operations (both fixed-time and demand-responsive) and coordinated oper-

ations (also both fixed-time and demand-responsive). A framework to incorporate fully adaptive control strategies has also been developed.

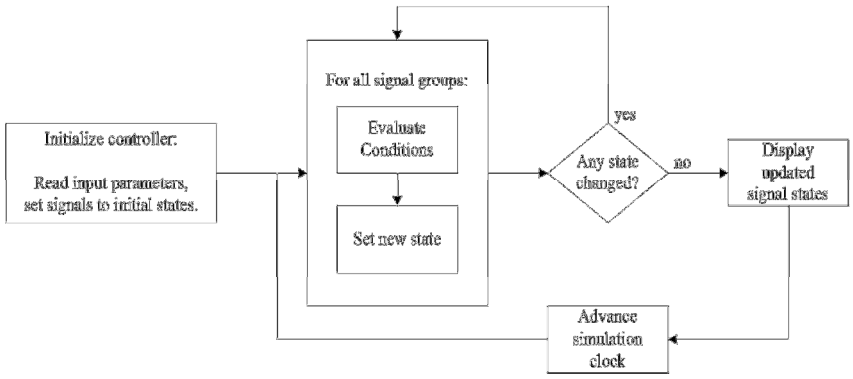


Fig. 6.6. Overall logic of generic controller

6.3.4 Transit Representation

The framework adopted to model bus operations benefits from MITSIM-Lab's modular organization. The main elements include the representation of the transit network, the movement of buses, the passenger demand, the transit surveillance system and the operations of the transit control center.

The components of the transit system (transit network, schedule design and fleet assignment) are considered as static information that is provided as input. A detailed representation of routes and schedules allows transit and traffic operations in the simulated network to be sensitive to the variations in the route and schedule inputs. MITSIMLab represents detailed trip chaining to explicitly capture the propagation of uncertainty in the network.

The driving behavior models control the transit vehicle movements. Specific transit operator models are applied in the sections between stops (considering downstream stops in the lane choice), when approaching stops (including undertaking lane changes to get to the stop lane), depart-

ing from stops (merging to the general traffic lanes) and dwell times at stops. The behavioral models also incorporate the impact of the transit vehicle presence on the lane choices of other vehicles.

The representation of passenger demand determines the detail in passenger arrival and departure patterns on the transit network. A minimum representation of demand involves passenger impacts on dwell times at stops. This simplified representation ignores the impact of passenger interactions during boarding and alighting on bus progression, which affects dwell times downstream (since dwell times at a stop are independent of dwell times at stops upstream). The second level of demand representation uses arrival and alighting rates (defined as a percentage of the bus load) at stops to determine the numbers of boarding and alighting passengers. The model assumes that passengers arrive according to a probabilistic distribution (e.g. time-dependent Poisson) and randomly generates the number of passengers waiting to board based on the actual bus headway.

Transit surveillance and monitoring systems including onboard detection and sensing technologies, such as automated vehicle location (AVL) and automatic passenger counters (APC) are explicitly modeled.

Transit operations control center activities and decentralized field-deployed strategies, are simulated in the TMS (see Figure 6.2 above). The TMS mimics the logic of the strategy under evaluation, and may use real-time traffic and transit data from the surveillance system as input for that logic. Device-based control strategies, such as signal priority, are simulated using sensors to detect approaching buses and to deliver bus data to the signal controller. Other strategies, such as stop-based control (e.g. holding) are simulated by placing conditions on the bus departure from a stop.

6.3.5 Measures of Performance

A number of measures of performance (MOP) may be collected to characterize and evaluate the system. These measures may be defined at any

level of detail for the general and transit systems. Traffic-related outputs include flows, speeds, densities, travel time, delays and queue lengths. They are available at the system, link, segment (a part of a link with uniform geometry), lane, sensor, and vehicle levels. The sensor level data is particularly useful for calibration and validation of the simulation model against real-world data. The high level of detail of the collected individual vehicle data (positions at every 0.1 seconds of all vehicles) provides all the information necessary to develop statistics such as emissions and fuel consumption, which may be used for evaluation,.

With respect to the transit system, a number of MOPs may be generated that are useful to assess the performance of the system both from a productivity point of view and the passenger level of service perspective. As with general traffic, these MOPs may be in different levels of detail: system-wide (e.g. total passenger travel times, number of late trips, driver overtime), route segments (e.g. average running speed, travel time distribution), stop (e.g. average dwell times), vehicle and passenger (e.g. waiting times and travel times).

6.4 Dynamic Traffic Assignment

MITSIMLab is not designed as a dynamic traffic assignment model and does not seek equilibrium travel time and traffic flow solutions automatically. It simulates drivers' route choice behavior based on input travel times and other path attributes. However, in the absence of habitual travel times, it requires an alternative method to assign vehicle trips to alternative paths from their origins to their destination. This method would consist of two related components: (1) determining the values of path attributes including the perceived link travel times, and (2) computing the choice probabilities of the alternative paths. The models used to compute the path choice probabilities are described in Section 6.3.2.

A day-to-day learning process was used with MITSIMLab to estimate the congested link travel times. Multiple simulation runs were made. Each run represented a day. Travel times were updated as the weighted sum of the

expected and experienced travel times from the current day (simulation run):

$$c_{it}^{(k+1)} = \lambda^{(k)}\, \hat{c}_{it}^{(k)} + \left(1 - \lambda^{(k)}\right) c_{it}^{(k)} \qquad k = 0, 1, \ldots \tag{6.5}$$

where the indices *i*, *t*, and *k* are for the link, time interval and simulation iteration (day), respectively. $\hat{c}_{it}^{(k)}$ and $c_{it}^{(k)}$ are the input (expected) and output (experienced) link travel times respectively. $\lambda^{(k)}$ is a weighting parameter for iteration *k*, which may be determined for example, according to the method of successive averages (Sheffi and Powell, 1982).

To support this functionality and to model response to real-time information, MITSIMLab maintains two time-variant travel time tables. The first represents the historical travel time associated with habitual route choices (input from another model or study, or generated through the process outlined above). The second consists of the updated link travel times based on the real-time information system (if one is available).

6.5 Calibration and Validation

This section outlines the methodology that has been developed and applied for the calibration and validation of MITSIMLab, and the implemented behavioral models.

6.5.1 Overall Framework

Figure 6.7 illustrates the framework used for the model calibration and validation. The process uses both disaggregate and aggregate data. In the disaggregate calibration (or model estimation) phase, the behavioral model components (e.g. acceleration, lane changing and route choice models) are estimated using detailed data at the individual user level. For driving behavior models, the required data are vehicle trajectories at a high time resolution. For route choice models, the necessary data are the routes individual travelers have chosen. This estimation approach does not use traffic simulators, making the estimated models simulator independent.

In the aggregate calibration phase, the estimated models are calibrated jointly with other model components within MITSIMLab. This phase is also crucial if MITSIMLab is applied in a network where detailed trajectory data is not available, but aggregate data such as sensor counts and speeds are available. Part of the aggregate dataset is used to adjust key parameters in the behavior models and to estimate the travel demand on the case study network. This aggregate calibration problem is formulated as an optimization problem, which seeks to minimize a function of the deviation of the simulated traffic measurements from the observed measurements and of the deviation of calibrated values from their *a priori* estimates, if available (Toledo et al. 2004, Balakrishna et al. 2007b)**.** The rest of the data (to the extent possible, collected under different conditions) are used for the validation, which is based on comparisons of MOPs, calculated from the available data (e.g. sensor speeds and flows, the distribution of vehicles among the lanes, amount and locations of lane changes) with the corresponding values generated from the simulation runs.

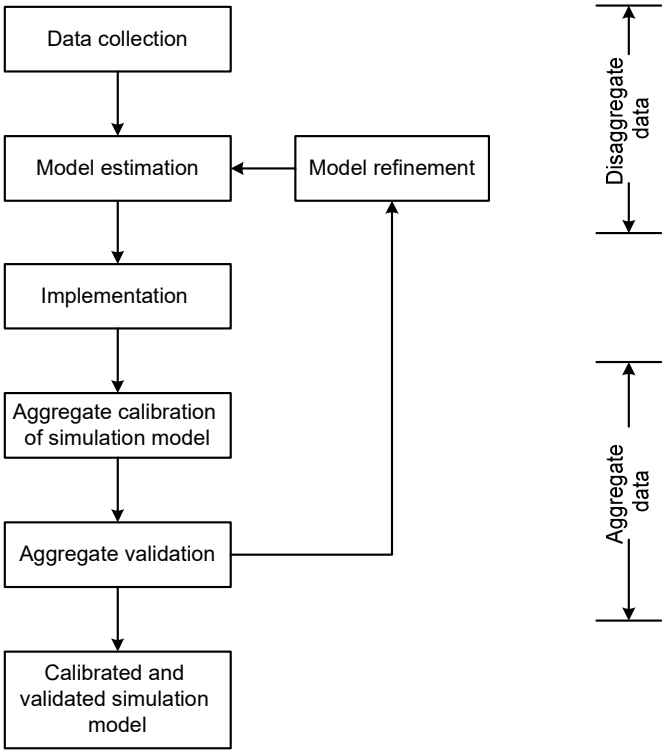


Fig. 6.7. Calibration and validation framework

6.5.2 Disaggregate Model Estimation

The disaggregate model estimation methodology is demonstrated through the estimation of a lane changing model, which consists of drivers' lane selection and gap acceptance decisions (a simplified version of the model presented in Figure 6.4). The specifications of the various components of this model are presented next, along with the resulting likelihood function to be maximized in the estimation.

The lane-changing maneuver is modeled as a two-stage process: (1) a choice of target lane (plan), and (2) a decision to accept available gaps (execution of plan). The target lane is the lane the driver perceives as the best while accounting for a wide range of factors and goals. A lane-change is executed when the available lead and lag gaps are perceived as ac-

ceptable. An example of the structure of this lane-changing model is shown in Figure 6.8. The decision maker is a driver currently in lane 3 of a four-lane road. The latent plan is captured by the choice of target lane. This latent choice dictates the immediate decisions of the driver: if the target lane is the same as the current lane (Lane 3 in this case), no change is required. The direction of change is to the right if the target lane is Lane 4, and to the left if the target lane is either Lane 1 or Lane 2. If the target lane choice dictates a lane change, the driver evaluates the gaps in the adjacent lane corresponding to the direction of change and either accepts the available gap and moves to the adjacent lane or rejects the available gap and stays in the current lane. In the trajectory data, the target lane choice is not observed. Only completed lane changes (or no changes) are observed. In Figure 6.8, latent choices are shown as ovals and observed choices are represented as rectangles.

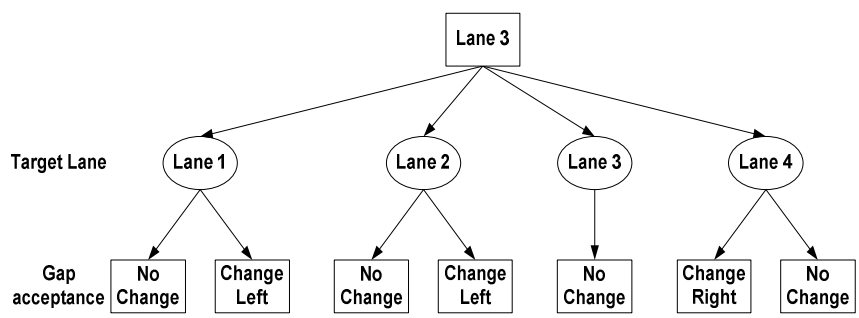


Fig. 6.8. Structure of the simplified lane-changing model

The latent plan choice is captured by the target lane. The target lane choice set constitutes of all the available lanes the driver may travel in. The driver chooses the lane with the highest utility as the target. However, utilities are unobserved and modeled as random variables:

$$U_{int} = X_{int}\beta_i + \alpha_i \upsilon_n + \varepsilon_{int} \tag{6.6}$$

where U_{int} is the utility of lane *i* to individual *n* at time *t*. X_{int} and β_i are a vector of explanatory variables affecting the lane utility and the corresponding vector of parameters, respectively. υ_n and α_i are an individual-specific error term and the corresponding parameter. ε_{int} is a random error.

Different choice models are obtained depending on the assumptions for the distribution of ε_{int} :

$$P\left(TL_{int} \middle| \upsilon_n\right) = g_i\left(X_{int}, \beta_i, \alpha_i, \upsilon_n\right) \tag{6.7}$$

where $g_i(.)$ is the function denoting the target lane choice.

The choice of target lane *i* dictates the change direction, d_i if one is required. If the current lane is also the target lane, no change is needed. Otherwise, the change will be in the direction of the target lane.

The gap acceptance model captures drivers' decisions in executing the chosen plan. That is, whether or not the available gap in an adjacent lane can be used to complete the desired lane change. To make this decision, the driver evaluates the available lead and lag gaps, which are defined by the free spacing between the subject and the lead and lag vehicles in the adjacent lane, respectively. The gap acceptance model assumes that the driver must accept both the lead and lag gap to change lanes. The probability of changing lanes, conditional on the individual-specific term and the direction of change is given by:

$$\begin{aligned} &P\left(l_{nt} = d \middle| d_{nt}, \upsilon_n\right) = \\ &P\left(\text{accept lead gap} \middle| d_{nt}, \upsilon_n\right) P\left(\text{accept lag gap} \middle| d_{nt}, \upsilon_n\right) = \end{aligned} \tag{6.8}$$

where, $d_{nt} \in \{Right, Current, Left\}$ is the direction of change as determined by the target lane choice. l_{nt} is the lane-changing action.

The joint probability density of a combination of target lane (*TL*) and lane action (*l*) observed for driver *n* at time *t*, and the individual-specific characteristic, υ_n is given by:

$$P\left(TL_{int}, l_{nt} \middle| \upsilon_n\right) = P\left(TL_{int} \middle| \upsilon_n\right).P\left(l_{nt} \middle| TL_{int}, \upsilon_n\right) \tag{6.9}$$

where, $P\left(TL_{int} \mid \cdot\right)$ and $P\left(l_{nt} \mid \cdot\right)$ are given by Equations (6.7) and (6.8), respectively.

Only the driver's lane-changing actions are observed over the sequence of observations. Assuming that, conditional on υ_n, these observations are independent, the joint probability of the sequence of observation for a given driver, $\boldsymbol{l_n}$, is given by:

$$P\left(\boldsymbol{l_n} \middle| \upsilon_n\right) = \prod_{t=1}^{T_n} \sum_{j \in TL} P\left(TL_{jnt}, l_{nt} \middle| \upsilon_n\right) \tag{6.10}$$

The unconditional probability of observing the sequence of lane changes by an individual *n* is obtained by integrating over the distributions of the unobserved individual-specific variables:

$$L_n = P\left(\boldsymbol{l_n}\right) = \int_{\upsilon} P\left(\boldsymbol{l_n} \middle| \upsilon_n\right) f\left(\upsilon\right) d\upsilon \tag{6.11}$$

Assuming that the observations from different drivers are independent, the log-likelihood function for all *N* individuals observed is given by the formula below. The model parameters are estimated by maximizing this function.

$$L = \sum_{n=1}^{N} \ln(L_n) \tag{6.12}$$

The results from applying the methodology are presented through the gap acceptance parameters. The assumption is that the driver evaluates the available adjacent gap in the target lane and decides whether the lane change is possible through the gap acceptance functions. The available lead and lag gaps must be larger than the corresponding critical gaps to

be acceptable. The critical gaps (i.e. the smallest gaps a driver is willing to accept) are assumed to follow the lognormal distribution. The mean of the distribution is a function of explanatory variables:

$$\ln(G_{lnt}^{lead\,cr}) = X_{lnt}^{lead}\beta^{lead} + \alpha^{lead}\upsilon_n + \varepsilon_{lnt}^{lead} \tag{6.13}$$

$$\ln(G_{lnt}^{lag\,cr}) = X_{lnt}^{lag}\beta^{lag} + \alpha^{lag}\upsilon_n + \varepsilon_{lnt}^{lag} \tag{6.14}$$

where, $G_{lnt}^{lead\,cr}$ and $G_{lnt}^{lag\,cr}$ are the lead and lag critical gaps in target lane *l*, respectively. X_{lnt}^{lead} and X_{lnt}^{lag} are explanatory variables that affect the critical gaps. β^{lead} and β^{lag} are the corresponding parameters. υ_n is an individual-specific latent variable that captures the correlations among decisions made by the same driver over time and choice dimensions. α^{lead} and α^{lag} are the coefficients of this latent variable. ε_{lnt}^{lead} and ε_{lnt}^{lag} are random terms: $\varepsilon_{lnt}^{lead} \sim N\left(0,\sigma_{lead}^2\right)$, $\varepsilon_{lnt}^{lag} \sim N\left(0,\sigma_{lag}^2\right)$

The variables that have a significant impact on the critical gaps are the relative speeds with respect to the lead and lag vehicles. The estimated lead and lag gaps were:

$$G_{lnt}^{lead\ cr} = \exp\begin{pmatrix} 1.541 - 6.210Max\left(0,\Delta V_{lnt}^{lead}\right) - \\ -0.130Min\left(0,\Delta V_{lnt}^{lead}\right) - 0.008\upsilon_n + \varepsilon_{lnt}^{lead} \end{pmatrix} \tag{6.15}$$

$$G_{lnt}^{lag\ cr} = \exp\left(1.426 + 0.640Max\left(0,\Delta V_{lnt}^{lag}\right) - 0.240\upsilon_n + \varepsilon_{lnt}^{lag}\right) \tag{6.16}$$

where, ΔV_{lnt}^{lead} and ΔV_{lnt}^{lag} are the relative speeds with respect to the lead and lag vehicles, respectively.

The lead critical gap decreases with the relative lead speed (i.e. it is larger when the subject vehicle is faster relative to the lead vehicle). The effect of the relative speed is strongest when the lead vehicle is faster than the subject. In this case, the lead critical gap quickly diminishes as a function of the speed difference. This shows that drivers perceive very little risk from the lead vehicle when it is getting away from them.

In the gap acceptance model, the lag critical gap increases with the relative lag speed: the faster the lag vehicle is relative to the subject, the larger the lag critical gap. In contrast to the lead critical gap, the lag gap does not diminish when the subject is faster. A possible explanation is that drivers maintain a minimum critical lag gap as a safety buffer since their perception of the lag gap, through mirrors, is not as reliable as their perception of the lead gap. Estimated coefficients of the unobserved driver characteristics variable, υ_n , are negative for lead and lag critical gaps. This is consistent with the interpretation of υ_n as being negatively correlated with aggressive drivers who require smaller gaps for lane changing (for detailed results see Toledo et al., 2005).

6.5.3 Aggregate Calibration

This section presents a mathematical formulation and solution approaches to the aggregate calibration problem. The methodology is appropriate for the simultaneous calibration of supply and demand parameters and inputs to microscopic traffic simulation models.

Let the time period of interest be divided into intervals $h = 1, 2, \ldots H$. Let X_h denote the vector of OD flows departing their respective origins during time interval *h*. Let β be the vector of simulation model parameters (possibly also time-varying) that need to be calibrated together with the OD flows. The calibration problem may then be formulated mathematically in the following optimization framework:

$$Minimize \quad z(\mathbf{x}_1, \ldots, \mathbf{x}_H, \boldsymbol{\beta}) = \sum_{h=1}^{H} \left[z_1\left(\mathbf{M}_h, \mathcal{M}_h\right) + z_2\left(\mathbf{x}_h, \mathbf{x}_h^a\right) + z_3\left(\boldsymbol{\beta}, \boldsymbol{\beta}^a\right) \right] \tag{6.17}$$

subject to

$$\left.\begin{array}{l} \mathcal{M}_h = f\left(\mathbf{x}_1, \ldots, \mathbf{x}_h, \boldsymbol{\beta}, G_1, \ldots, G_h\right) \\ l_h^x \le \mathbf{x}_h \le u_h^x \\ l^\beta \le \boldsymbol{\beta} \le u^\beta \end{array}\right\} \qquad \forall \quad h \in \{1, 2, \ldots, H\} \tag{6.18}$$

where $\mathbf{M}_h$ and $\mathcal{M}_h$ are the observed and simulated sensor measurements for interval *h*; $\mathbf{x}_h^a$ and $\boldsymbol{\beta}^a$ are *a priori* values corresponding to $\mathbf{x}_h$ and $\boldsymbol{\beta}$; z_1, z_2 and z_3 are goodness-of-fit functions. *F*( ), the simulation model, is a function of the unknown OD flows and model parameters $\boldsymbol{\beta}$, and network G_h. The network may vary from time period to time period due to accidents, etc, and hence is presented as time-dependent G_h. l_h^x, l^β, u_h^x and u^β represent lower and upper bounds on the OD flows and model parameters.

The *a priori* values can ensure reasonable calibrated estimates. They may be based on the modeler's experience and judgment from past studies, or transferred appropriately from similar studies. This problem formulation introduces the flexibility to incorporate other traffic measurements beyond the standard link counts. For example, speeds, occupancies or travel times may be used. All model inputs and parameters of interest may be calibrated simultaneously, using all information from the available measurements, without iterating between various parameter subsets.

To solve the resulting large-scale optimization problem, the simultaneous perturbation stochastic approximation (SPSA) algorithm developed by Spall (1998, 1999) has been used. The method performs well computationally and in terms of the solution quality. Further details on the aggregate calibration problem and the solution approaches are presented in Balakrishna et al., 2007a.

The methodology outlined above is illustrated through a case study, based on a network in Lower Westchester County, NY (Figure 6.9). This network is heavily congested, especially during commute periods. Truck traffic is prohibited from parkways. Given the significant truck percentage in the network traffic, passenger cars and truck demand were treated independently by calibrating multi-class demand matrices.

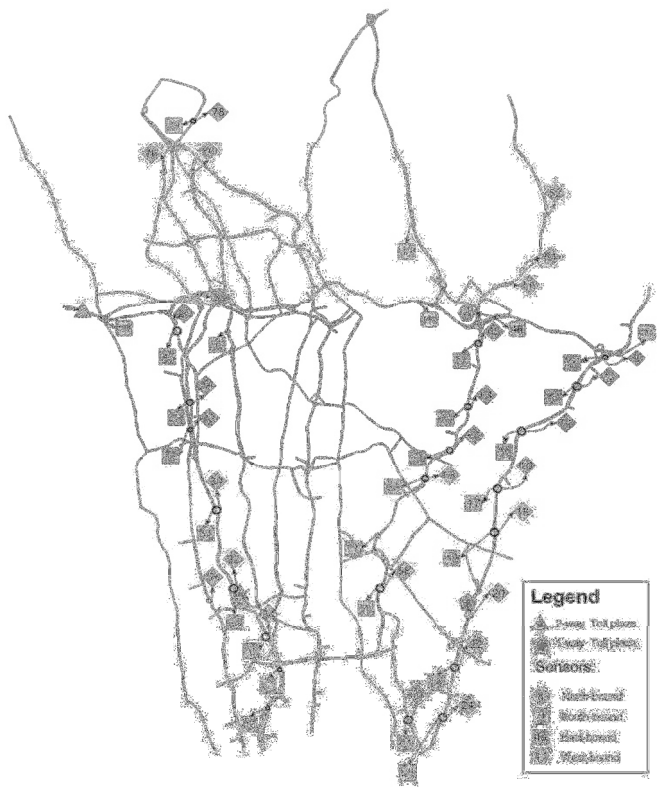


Fig. 6.9. The case study network showing sensor locations used for calibration

The network representation of the study area comprises of 1767 directed links and 482 OD pairs. The data for the calibration process included count data from 33 sensors shown in Figure 6.9, and an all-day static OD matrix. Disaggregate data on individual vehicles passing through toll plazas were also available. These observations also contained vehicle class information. A time-dependent OD matrix was estimated for all vehicles using the SPSA algorithm. This demand was further decomposed into two components (passenger cars and trucks) prior to being input into MITSIM-Lab using the time-dependent observed vehicle mix from the toll-plaza data. The normalized root mean squared error, root mean squared percent error (RMSPE), mean percent error (MPE), and Theil's coefficient were used as goodness of fit statistics to evaluate the calibrated model.

The normalized root mean square error (RMSN) and root mean square percent error (RMSPE) quantify the overall error of the simulator. These measures penalize large errors at a higher rate than small errors. The mean percent error (MPE) statistic indicates the existence of systematic under- or over-prediction in the simulated measurements.

$$RMSNE = \frac{\sqrt{N\sum_{n=1}^{N}\left(Y_n^s - Y_n^o\right)^2}}{\sum_{n=1}^{N} Y_n^o} \tag{6.19}$$

$$RMSPE = \sqrt{\frac{1}{N}\sum_{n=1}^{N}\left[\frac{Y_n^s - Y_n^o}{Y_n^o}\right]^2} \tag{6.20}$$

$$MPE = \frac{1}{N}\sum_{n=1}^{N}\left[\frac{Y_n^s - Y_n^o}{Y_n^o}\right] \tag{6.21}$$

Where, *N* is the number of observations, Y_n^o and Y_n^s are an observation and the corresponding simulated value, respectively.

Theil's inequality coefficient is a measure of relative error given by:

$$U = \frac{\sqrt{\frac{1}{N}\sum_{n=1}^{N}\left(Y_n^s - Y_n^o\right)^2}}{\sqrt{\frac{1}{N}\sum_{n=1}^{N}\left(Y_n^s\right)^2} + \sqrt{\frac{1}{N}\sum_{n=1}^{N}\left(Y_n^o\right)^2}} \tag{6.22}$$

U is bounded between zero and one (where *U* = 0 implies perfect fit between observed and simulated measurements). Theil's inequality coefficient may be decomposed into three proportions of inequality, the bias (U^M), the variance (U^S), and the covariance (U^C) proportions (their sum is equal to 1):

$$U^M = \frac{\left(\bar{Y}^s - \bar{Y}^o\right)^2}{\frac{1}{N}\sum_{n=1}^{N}\left(Y_n^s - Y_n^o\right)^2} \tag{6.23}$$

$$U^S = \frac{\left(s^s - s^o\right)^2}{\frac{1}{N}\sum_{n=1}^{N}\left(Y_n^s - Y_n^o\right)^2} \tag{6.24}$$

$$U^C = \frac{2\left(1-\rho\right)s^s s^o}{\frac{1}{N}\sum_{n=1}^{N}\left(Y_n^s - Y_n^o\right)^2} \tag{6.25}$$

where, ρ is the correlation between the two sets of measurements; s^s and s^o are the standard deviations of the average simulated and observed measurements, respectively and $\overline{Y^s}$ and $\overline{Y^o}$ are their expected values.

The bias proportion reflects the systematic error. The variance proportion indicates how well the model replicates the variability in the observed data. These two proportions should be kept as close to zero as possible. The covariance proportion measures the remaining error and therefore should be close to 1.

Table 6.1 compares the values of the above statistics for the calibrated model and to the values from the initial demand case. All measures improved over the initial values, especially the bias measures.

Table 6.1. Goodness of fit statistics for the case study network

Statistic	Calibrated model	Model with a-priori demand
RMSPE (%)	22.1	41.6
RMSNE (%)	23.1	47.6
MPE (%)	-5.3	-28.9
Theil's coefficient U	0.113	0.264
Bias proportion	0.116	0.461
Variance proportion	0.015	0.020

6.5.4 Validation

MITSIMLab has been validated in a number of studies. This section discusses the results from a validation study in Stockholm, Sweden. The study used a mixed urban-freeway network in the Brunnsviken area, north of the CBD, shown in Figure 6.10. It contains the E4 motorway connecting the northern suburbs to the CBD. A parallel arterial is also included. These routes experience heavy congestion during the AM peak period. Sensor data from May 1999 were used to calibrate MITSIMLab. Similar data was collected a year later for validation. Measurements of point-to-point travel times and queue lengths by probe vehicles and from aerial photography were also available for validation. Sensor and other measurement locations are shown in Figure 6.10. A static AM peak OD flows matrix, previously developed for planning studies, was used in the OD estimation.

The model validation used the comparison of measured and simulated traffic flows, travel times, and queue lengths during two hours of the AM peak data from May 2000 at 15 min. intervals. The traffic flows were also used in the estimation of OD matrices for this period. Figure 6.11 compares average simulated travel times and individual probe vehicle observations for the inbound section CD, which was the most congested during this period. The section also includes a bus lane for buses and other commercial vehicles. In general, simulated travel times match observed travel times well.

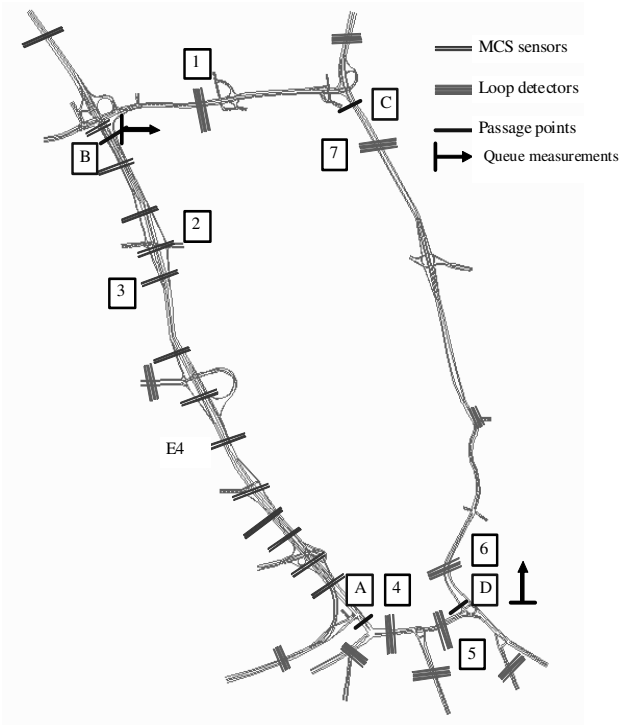


Fig. 6.10. The Brunnsviken network

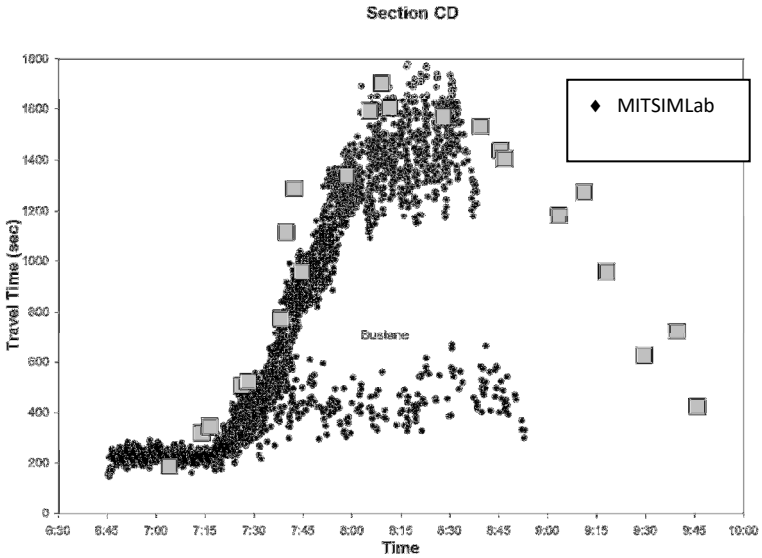


Fig. 6.11. Point-to-point travel time validation results (section CD)

Similarly, Figure 6.12 presents the validation results for the queue lengths measured by the probe vehicles and from aerial photographs. Queues are represented in the simulation both by magnitude and time of occurrence.

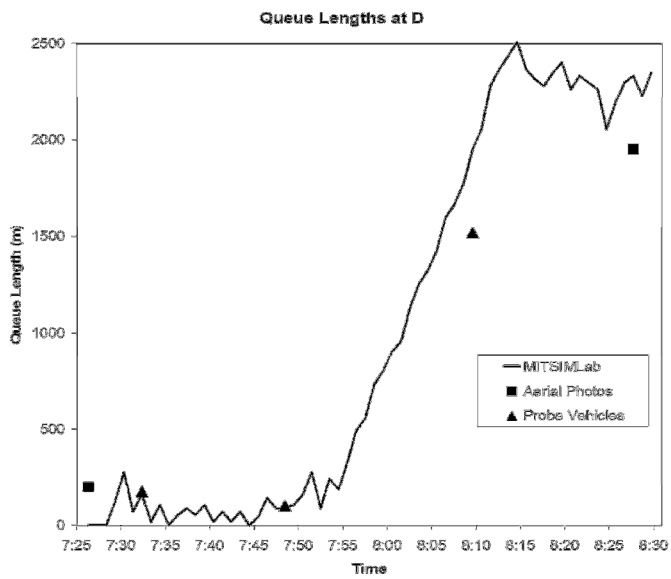


Fig. 6.12. Queue length validation results (location D)

6.6 Extended Modeling Capabilities: Working with External Applications

MITSIMLab has been integrated with a number of external applications. This section presents two cases: the use of MITSIMLab to evaluate the performance of DynaMIT, a dynamic traffic assignment (DTA) and traffic predictions generation tool; and the integration of MITSIMLab with a mesoscopic traffic simulation model to create a hybrid model.

6.6.1 Closed Loop with DynaMIT

MITSIMLab provides a controlled environment to conduct objective evaluations of advanced ITS concepts, such as DTA-based traffic prediction and information generation. MITSIMLab was integrated with DynaMIT (Dynamic Network Assignment for the Management of Information to Travelers) in a closed loop system (Balakrishna et al. 2005). DynaMIT is a model system for (real time) traffic estimation and prediction. A detailed description of DynaMIT is provided in Chapter 10 of this book.

The closed-loop system provides a framework for off-line evaluation of dynamic traffic management systems such as DynaMIT. In the closed loop evaluation MITSIMLab replaces the real world. Figure 6.13 illustrates this evaluation framework and the interactions between the two applications.

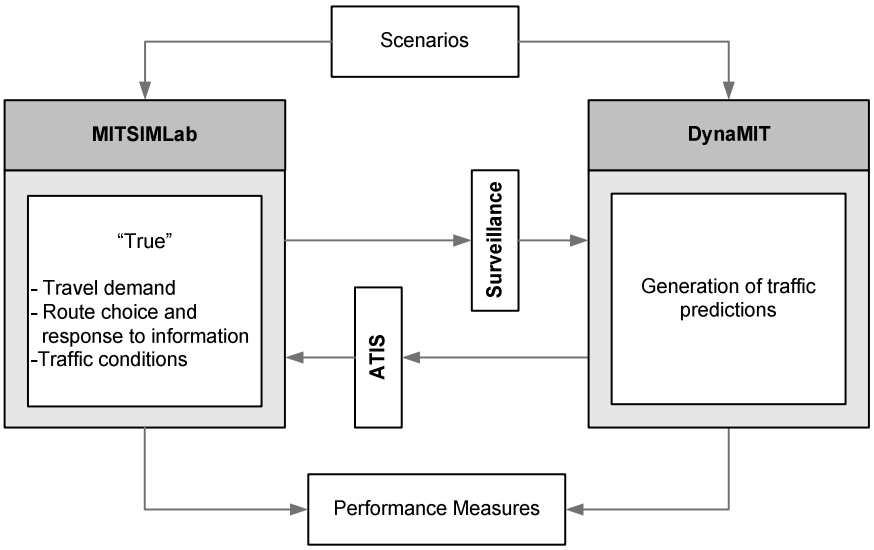


Fig. 6.13. MITSIMLab-DynaMIT closed loop evaluation framework

The two models are run in parallel using the same network and scenario database. Traffic data from the simulated surveillance system in MITSIMLab are transmitted in real-time to DynaMIT. Prediction-based guidance is

passed back to the control and routing devices simulated in the TMS, and then to equipped drivers in MITSIMLab. The drivers' reactions to the disseminated information and changes in the control system are reflected in subsequent traffic flows, which are measured by the simulated surveillance system and transferred to DynaMIT for the next prediction generation step. Network performance measures are computed to assess the effectiveness of the guidance and dissemination system. The integration of DynaMIT within TMS is similar to the interface between DynaMIT and a real traffic control center.

The advantage of the closed loop laboratory is that it allows great flexibility in performance evaluations. The testing of advanced traveler information systems, in response to various parameters and design characteristics is an example:

- *Modeling errors.* DynaMIT uses a number of models to simulate the demand aspects of the transportation system (e.g. route choice, departure times) and network performance (e.g. queue formation and dissipation). MITSIMLab also uses OD flows and travel behavior models (i.e. route choice). The error associated with the models used by DynaMIT (compared to the “true” behavior in MITSIMLab) can be controlled, and its impact on the effectiveness of the system assessed.
- *Design parameters*. A number of design parameters influence the effectiveness of the system. Examples of such parameters of interest include the prediction horizon, the frequency of updating the traffic information, and the time resolution of the provided guidance.
- *Computational delay*. Many strategies are computationally demanding. The time to generate a new strategy for implementation depends on the size of the network and the available computational resources. The laboratory tests the effectiveness of the system as a function of the computational delay.
- *Design of the surveillance system*. The impact of the location, type, and number of sensors can be assessed. In addition, sensors are assigned an (measurement) error attribute, allowing for the evaluation of the surveillance system characteristics. The impact of the accuracy of in-

formation with respect to incidents and their severity on the effectiveness of the system can also be evaluated. Typically, incident information may be delayed, and duration uncertain.

- *Communication system and interfaces.* Important aspects of the communications between the various elements of the system can be modeled, and their significance assessed. Such parameters include latency in information transmission, and errors and noise in the information, etc.

6.6.2 Hybrid Simulation

Microscopic simulation models provide a detailed representation of the traffic process. Other types of traffic simulation models, namely macroscopic and mesoscopic, capture traffic dynamics in less detail. But they require less input data preparation, and can simulate large scale networks efficiently (from a computational point of view). Hybrid simulations combine mesoscopic or macroscopic models for most of the network; and microscopic models in the areas of interest. Hybrid models have the advantages of both types of simulation since they combine high fidelity micro-simulation in areas of particular interest, with meso-simulation of the surrounding areas (in order to represent routing decisions more accurately). Another advantage of the integration is that it reduces the computational requirements and the data collection and calibration effort of the overall model.

An important aspect in developing a hybrid meso-micro traffic simulation model is the identification and implementation of conditions for consistent interfaces between the two components. These conditions range from structural compatibility issues in terms of modeling traffic flows in the two models, to consistency of traffic dynamics at the meso-micro boundaries, to compatibility of route choice (see Burghout et al. 2005).

Burghout (2006) integrated MITSIMLab with Mezzo, a mesoscopic model, to illustrate the principles of integration and its advantages. The hybrid simulation model was demonstrated through its application to the Brunnsviken network in Stockholm. The network was divided into a

mesoscopic part in the north, which consists mainly of freeways, and a microscopic part in the south, which consists of complex intersections with coordinated signal control and a large roundabout as shown in Figure 6.14.

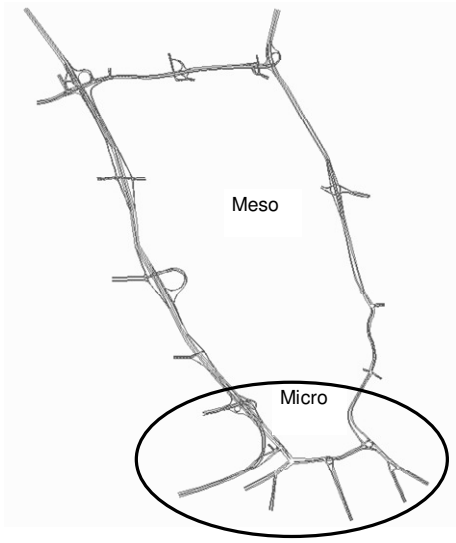


Fig. 6.14. Hybrid model for the Brunnsviken network

Table 6.2 summarizes the fit of the simulated flows in the hybrid model to field observations and compares it against standalone applications of MITSIMLab and Mezzo. The RMSPE and Theil's coefficient statistics indicate that MITSIMLab provides the best fit. But, the hybrid simulation outperforms the mesoscopic model and only suffers a slight reduction in fit. Using the hybrid model improves the fit compared to the mesoscopic one, in the microscopic part of the network and in the mesoscopic part. Using Theil's proportions to break down the error shows that the mesoscopic model has a larger systematic error compared to the hybrid model. The computational time for the hybrid model is also superior. This difference is expected to increase as the network grows.

Table 6.2. Results of various models

Statistic	MITSIMLab	Mezzo	Hybrid

RMSPE (%)			
Entire network	12	16	15
Meso part	10	13	11
Micro part	14	18	17
Theil's coefficient U	0.051	0.055	0.054
Bias proportion	0.001	0.147	0.075
Variance proportion	0.010	0.002	0.017

6.7 Advanced Case Studies and Applications

6.7.1 ATIS evaluation and design

The closed-loop system from section 6.6.1 was used to evaluate several design aspects of information generation systems. The case study detailed in Balakrishna et al. (2005) explores the impacts of several factors including the guidance penetration rate (i.e. fraction of drivers with access to the information), the frequency of information update, and errors in the quality and effectiveness of travel time guidance generated by the demand prediction and route choice model. The case study uses the Central Artery/Tunnel network in Boston, shown in Figure 6.15. This network consists of 182 nodes and 211 links.

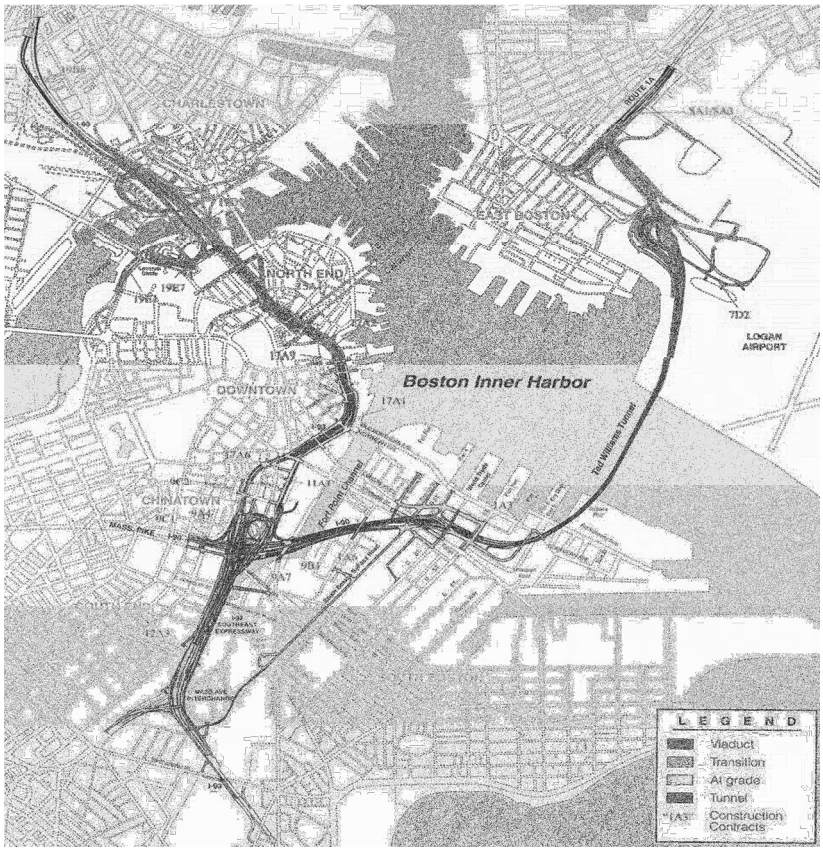


Fig. 6.15. The Central Artery/Tunnel network (source: http://www.masspike.com/bigdig/multimedia/plans.html

The case study included the AM peak period starting at 7:00 AM. At 7:10 AM, an incident occurred in the Ted Williams Tunnel, blocking one lane and reducing the speed on the other lane. The incident lasted 20 minutes. Approximately 3500 vehicles per hour flow through the Ted Williams Tunnel. The simulated incident created substantial delays to travelers. The simulation lasted until 8:45 AM to ensure that traffic conditions were returned to normal after the end of the incident.

Guided drivers are assumed to have access to descriptive information in their vehicles. Various values of the percentage of guided vehicles (0%, 20%, 30%, 50%, 70% and 100%) were tested. The results are summarized in Figure 6.16. The results indicate decreasing average travel times as the

percentage of guided drivers increases. Some over-reaction was indicated by the slight increase in travel times as the guided fraction increased beyond 70%. Predictive guidance does not eliminate over-reaction due to the discrete nature of the representation of the problem, as well as modeling and algorithmic approximations. For example, the results indicate that when the update frequency decreases, the shorter update intervals allow the system to quickly adjust to changing network conditions, and the impact of over-reaction is almost eliminated. This result highlights the need for better, more accurate anticipatory traveler information that accounts for future demands and driver behavior.

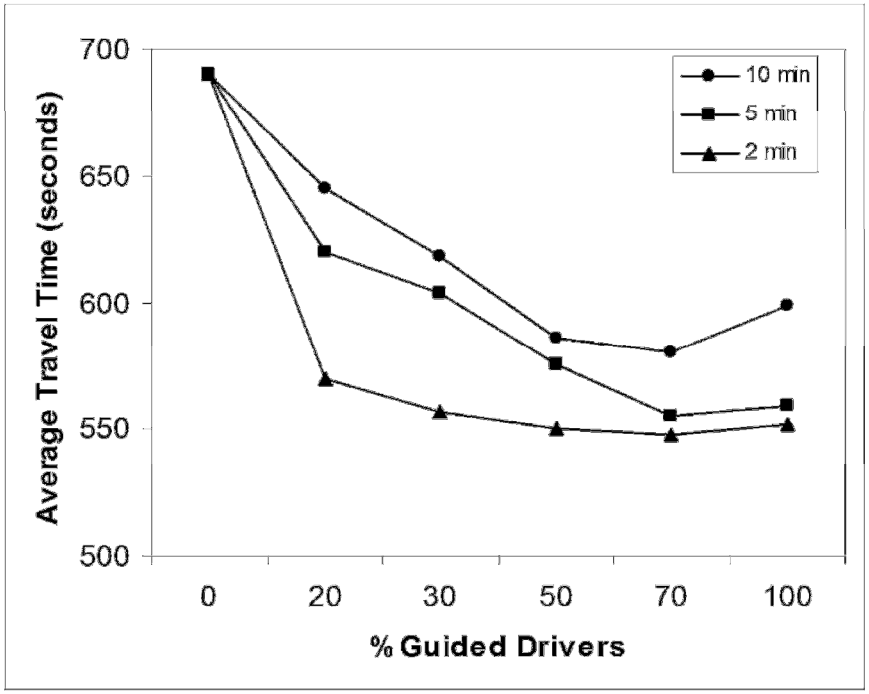


Fig. 6.16. Effect of guidance penetration rate

For this case study, MITSIMLab and DynaMIT use the same OD matrices and route choice model based on the path-size logit structure to represent travel demand. It is unrealistic to expect that guidance generation models to perfectly estimate demand and predict route choices. The impact of errors in these factors was assessed by introducing errors in the

predicted OD flows. Travel time coefficients used in DynaMIT's route choice model were also modified to include an error relative to the "true" value used in MITSIMLab. Table 6.3 summarizes the average travel times in the network for the different scenarios. The results indicate that the effectiveness of the system, as measured by the average travel times, is influenced by the demand and route choice prediction errors used in DynaMIT. The combined effect of error in the OD matrix and the route choice model is greater than the sum of the effects of the two individual sources of error. Differences between these results and those from previous studies may reflect the network specifics, demand characteristics, assumptions of the ATIS design, and the overall structure of the evaluation methodology. The differences also underline the importance of the simulation-based laboratory for detailed evaluations.

Table 6.3. Effect of errors in the demand on the average travel times (sec)

	Route choice parameter error		
OD prediction error	0	-20%	+20%
0	618	620	627
+20%	625	633	634

6.7.2 Evaluation of Advanced Signal Priority Strategies

This case study evaluates bus operations through various conditional signal priority strategies for a Bus Rapid Transit (BRT) line in an urban network in Stockholm, Sweden. The time period of interest is 7:30-8:30 AM. The BRT routes are served by articulated buses equipped with GPS-based AVL systems. The study area is shown in Figure 6.17. Traffic in the side-streets crossing the three arterials is relatively low compared to traffic on the three arterials. There are seven signalized intersections in the study area. One of them is a signalized pedestrian and bicycle crossing. Three local lines and one BRT line operate in this section. Local buses have 15-minute headways during the peak periods, and the BRT articulated buses operate with 7.5-minute headways. The local and BRT services share the bus stops.

The purpose of the case study is to evaluate the extent to which transit signal priorities improve the performance of the bus lines, and to assess its impact on the general traffic in the section. Four priority implementations are compared: (1) no priority (base case), (2) unconditional priority, (3) conditional priority only for buses with more than 30 passengers and (4) conditional priority only for buses with headways that exceed 7.5 minutes. A sensitivity analysis that explores the effects of increased side street demand is also conducted.

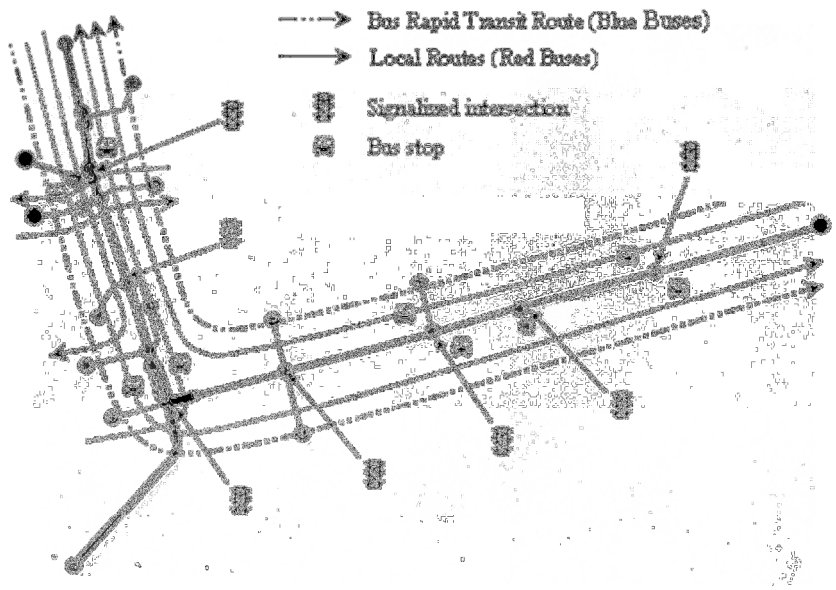


Fig. 6.17. Study network showing bus routes, stops and signalized intersections

Figure 6.18 summarizes the main results. The top part of the figure shows the results for the base-case demand. The average vehicle travel times are shown for different groups of vehicles: all vehicles, BRT, and vehicles crossing the section from the side-streets. Average BRT travel times decreased as the priority conditions became less restrictive. The lowest average travel times occurred under unconditional priority. The signal priority reduced the variability of BRT travel times. The conditional priority strategies can achieve similar BRT travel times compared to the uncondi-

tional priority without granting priority quite as often. With the relatively low base-case demand, the change in average travel time for side-street vehicles is small. It does not support general conclusions about the tradeoffs between transit travel time savings and side-street travel time penalties. Additional simulations were run with a 40% increase in side-street demand. The results are shown in the bottom part of Figure 6.18. The load-based conditional priority yields BRT travel times that are similar to the BRT travel times under unconditional priority. The improvements in BRT travel times under conditional priority have considerably lower adverse impacts on side-street traffic.

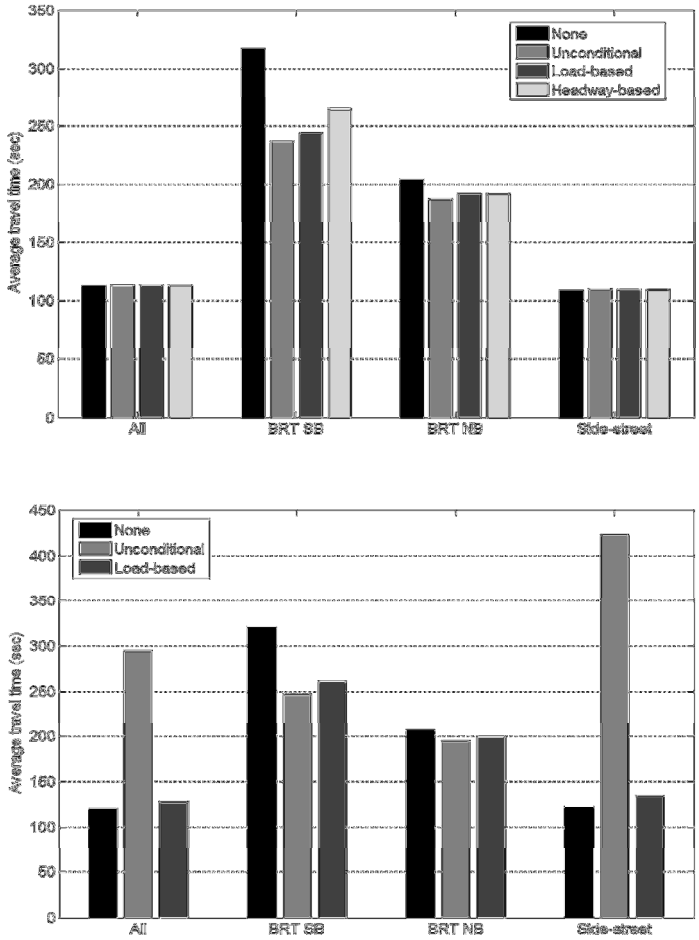


Fig. 6.18. Signal priority impact on travel times: base case (top), increased side-street demand (bottom)

6.8 Advanced Modeling Details

In recent years, the driving behavior models in MITSIMLab have improved in their fidelity to freeway and urban sections under congested conditions. This section presents two developments: the freeway merging model, and the lane-choice and lane changing model for urban arterials.

6.8.1 Freeway Merging Model

This application deals with drivers' merging behavior when entering freeways. Traditional merging models are based on gap acceptance, i.e., drivers merge when an acceptable gap is available. However, in congested traffic, acceptable gaps are often unavailable and more complex merging phenomena are observed. Drivers may merge through courtesy of the lag driver in the target lane or become impatient and decide to force merge, compelling the lag driver to slow down.

To capture this behavior, drivers' selection of a merging tactic needs to be included in the model. The decision framework is presented in Figure 6.19. At each time interval, drivers select a merging plan (tactic) and decide whether they can use this tactic to merge. Critical gaps depend on the chosen plan. The merging plan may evolve dynamically with changing conditions. For example, a driver may initially try to merge normally. But as the driver approaches the end of the merging lane, he may decide to force merge. The probabilities of transitioning between plans are affected by the risk associated with the merge, the characteristics of the driver such as patience level, urgency, and aggressiveness as well as inertia to continue the previously chosen merging tactic (state dependence). These effects are captured by variables such as relative speed and acceleration of the mainline vehicles, delay associated with the merge, density of traffic, distance from the end of the merging lane, etc.

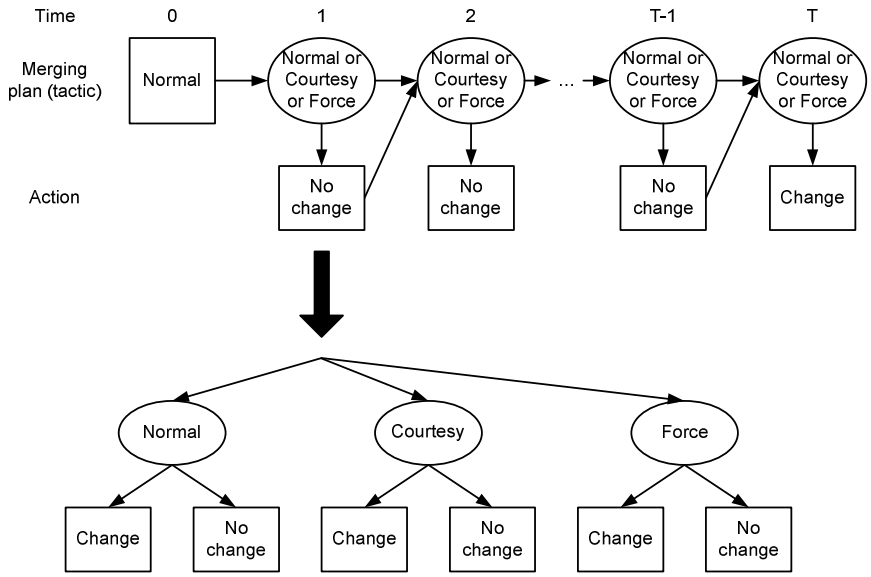


Fig. 6.19. Framework of the merging model

The parameters of the model were estimated with trajectory data collected from I-80 in California (NGSIM 2004) using the maximum likelihood method. In the trajectory data, only the final execution of the merge is observed. The sequences of tactics drivers applied are unobserved. A Hidden Markov Model formulation is used to model these latent tactics. Estimation results showed that the inclusion of the three merging tactics and the differences in critical gaps associated is justified by the data. The final results showed that drivers are willing to accept smaller lead and lag gaps if they perceive that the lag vehicle is courtesy yielding.

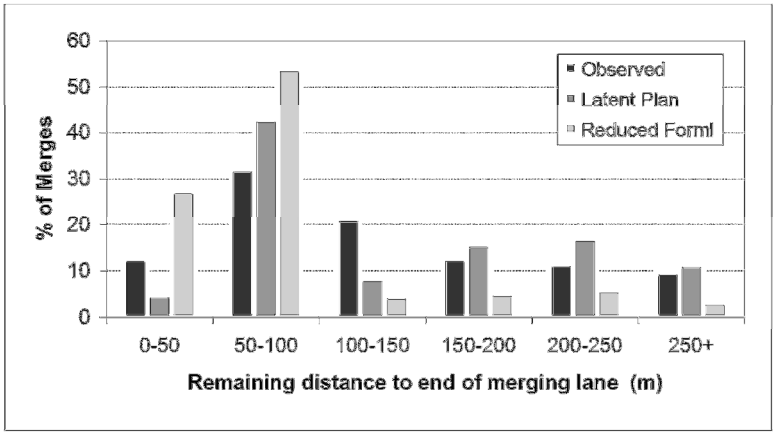


Fig. 6.20. Comparison of location of merges

To demonstrate the benefits of including latent plans, the model described above was compared against a reduced model that does not incorporate latent tactics. In this model, instantaneous single-level gap acceptance was used. The latent plan model showed a significantly better goodness-of-fit in statistical tests. Both models were implemented in MITSIMLab for evaluation using data from a section of US 101 in California (NGSIM 2005). The validation results for the location of merges are presented in Figure 6.20. The latent plan model more realistically replicated the observations on lane-specific flows, speeds and the locations of merges. The detailed model structure, estimation and validation results are presented in Choudhury et al. (2007).

6.8.2 Arterial Lane Changing Model

MITSIMLab has been extended to incorporate a number of integrated driving behavior models appropriate for urban streets. Arterial corridors exhibit a set of varied driving activities that differ by lane and location. These activities encompass trip destination activities (e.g. parking, entering transit stops, right turns, left turns), trip origination activities (e.g. exiting a parking spot, exiting transit stops), and complex routing behaviors (e.g. permissive left turns, pedestrian-impeded right turns). Drivers familiar with the network may be aware of these activities and their likely loca-

tions. They often make appropriate tactical lane positioning decisions to minimize their travel times and driving efforts. The 'look-ahead' or 'plan-ahead' distances (i.e. how far downstream do drivers "see" in advance) can vary significantly among drivers depending on their individual traits (e.g. planning capability) as well as their experience and familiarity with the network.

This look-ahead distance and the associated heterogeneity can substantially affect lane changing behavior in urban arterials, and was explicitly accounted for in the arterial lane changing model. The model also captures the time required to complete the lane change (the time elapsed from the instant an adjacent gap is found to be acceptable to the instant the driver physically moves to the new lane) by introducing an additional level that captures the decision to execute/complete the lane change (Figure 6.21). This shows that although a gap is acceptable, the actual execution of the lane change can depend on different factors (e.g. type and speed of the vehicle, trend of the change in gap size etc.).

The parameters of the model were estimated with trajectory data collected from Lankershim Boulevard in Los Angeles using the maximum likelihood method. Estimation results showed that the path-plan considerations, inertia effect and lane attributes (e.g. queue-ahead variable in particular) are pre-dominant factors behind arterial lane changing decisions as opposed to neighborhood conditions (speed and spacing of adjacent vehicles). The driver's look-ahead distance is normally distributed between within 50m to 500m. In the lane-change execution model, the results showed that drivers tend to execute the lane change faster if the speed of the subject vehicle is high and/or if the corresponding adjacent gap is reducing (the lag vehicle is faster than the lead vehicle). A comparison of estimation results indicates that addressing the heterogeneity in plan-ahead distances and the execution of the lane change significantly improves the fit to the observations.

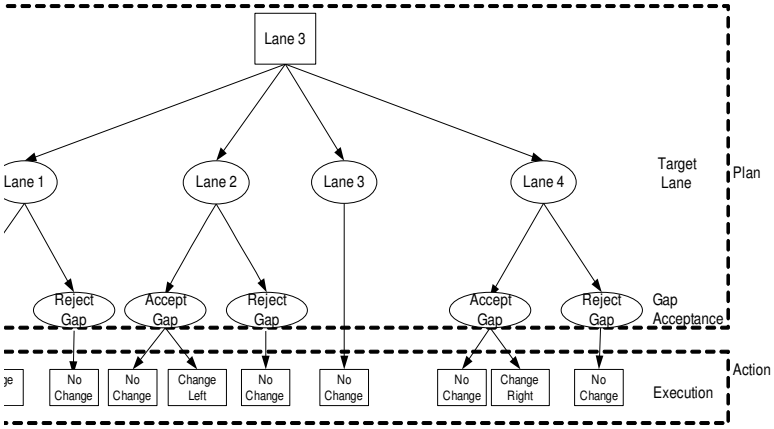
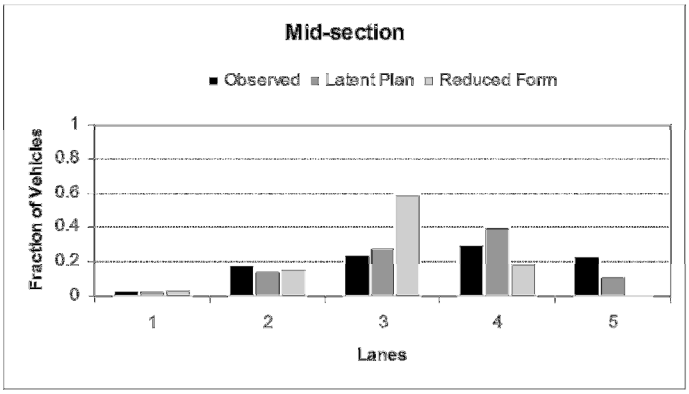


Fig. 6.21. Arterial lane changing model

This was further strengthened by a validation case study within MITSIM-Lab, where the simulation outputs of the urban lane selection model were compared with the MITSIMLab lane changing for freeway traffic models. The results indicated a significant improvement in replicating vehicle distribution among lanes, at mid-sections in particular. The comparison of lane distributions at mid and end sections obtained from each of the models are presented in Figure 6.22. The detailed model structure, estimation and validation results are presented in Choudhury et al. (2008).



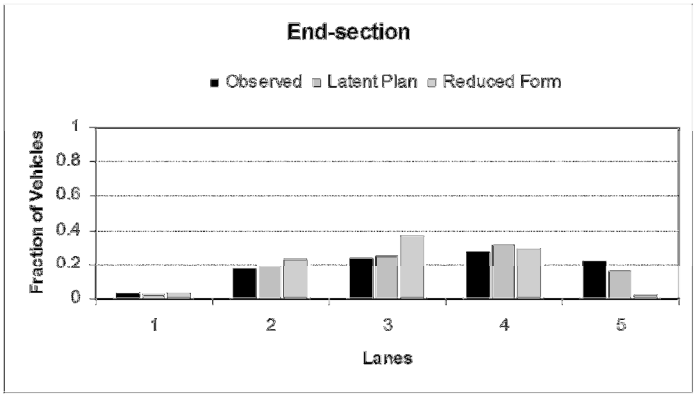


Fig. 6.22. Comparison of vehicle lane distributions

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