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Calibration and Validation of Microscopic Traffic Simulation Tools

Stockholm Case Study

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The calibration and validation approach and results from a case study applying the microscopic traffic simulation tool MITSIMLab to a mixed urban-freeway network in the Brunnsviken area in the north of Stockholm, Sweden, under congested traffic conditions are described. Two important components of the simulator were calibrated: driving behavior models and travel behavior components, including origin–destination flows and the route choice model. In the absence of detailed data, only aggregate data (i.e., speed and flow measurements at sensor locations) were available for calibration. Aggregate calibration uses simulation output, which is a result of the interaction among all components of the simulator. Therefore, it is, in general, impossible to identify the effect of individual models on traffic flow when using aggregate data. The calibration approach used takes these interactions into account by iteratively calibrating the different components to minimize the deviation between observed and simulated measurements. The calibrated MITSIMLab model was validated by comparing observed and simulated measurements: traffic flows at sensor locations, point-to-point travel times, and queue lengths. A second set of measurements, taken a year after the ones used for calibration, was used at this stage. Results of the validation are presented. Practical difficulties and limitations that may arise with application of the calibration and validation approach are discussed.

Traffic simulation tools are increasingly popular for the analysis of the operation of transportation systems. For example, a number of microscopic traffic simulation tools have been used for the study of intelligent transportation systems at the operational level [see Algers et al. (*1*) for a review of tools]. However, the emergence of microsimulation tools raises several questions about their appropriate use and, in particular, calibration and validation for the study they are used for.

Calibration of traffic simulation tools, especially microscopic ones, is not a trivial task. The source of the difficulty is that the data usually available are aggregate measurements of traffic characteristics, which are the emergent results of the interactions between various behaviors of individual vehicles. Therefore, these types of data do not support independent calibration of the various models the microsimulator consists of. As a result, in many cases, simulation tools are applied by using the default parameter values supplied with the simulator. For lack of data, validation is also an activity that does not take place in most studies.

Two groups of parameters require calibration in microsimulators: driving behavior parameters and travel behavior parameters. Driving behavior includes acceleration, lane changing, and intersections models. The major components of travel behavior are the origin–destination (O-D) flows and the route choice model.

The literature on calibration of traffic simulation models is rather limited. Most published studies focus on one component of the simulation model (usually driving behavior), while assuming the others are given. For example, Daigle et al. (*2*), Abdulhai et al. (*3*), Lee et al. (*4*), and Gardes et al. (*5*) calibrate only driving behavior parameters. Ma and Abdulhai (*6*) also include route choice in the calibration but still assume given O-D flows. O-D estimation routines assume known assignment matrices, which capture the effects of route choice and flow propagation. Cascetta and Postorino (*7*) extend the O-D estimation procedure to explicitly include a route choice model but assume that the parameters of that model are given. The calibration is in many cases an ad hoc, sequential procedure. Some parameters are calibrated, often through trial and error. Their values are then fixed for the calibration of a second set and so on. Such procedures do not include feedback loops to capture interactions between the parameters of interest.

The objective of this paper is to present the calibration and validation methods and results from an application of these methods in a case study with data from Stockholm, Sweden, and the microsimulation tool MITSIMLab. The paper is organized as follows: the next section briefly describes MITSIMLab and the parameters to be calibrated within the model. The test network and data used in the case study are presented in the third section. The calibration approach is described in the fourth section, and the validation approach and results are presented in the fifth section. Discussion and conclusions are presented in the last section.

SIMULATION MODEL

MITSIMLab (*8*, *9*) is a microscopic traffic simulation laboratory developed to evaluate advanced traffic management systems and advanced traveler information systems at the operational level. MITSIMLab can represent a wide range of traffic management systems and model the response of drivers to real-time traffic information

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and control. This enables MITSIMLab to simulate the dynamic interactions between traffic management systems and drivers. MITSIMLab consists of three main modules:

1. Microscopic traffic simulator (MITSIM),
2. Traffic management simulator (TMS), and
3. Graphical user interface.

MITSIM represents traffic and network elements. Movements of individual vehicles are represented in detail. The road network is represented by nodes, links, segments (links are divided into segments with uniform geometric characteristics), and lanes. Traffic controls and surveillance devices are represented at the microscopic level. Travel demand is input in the form of time-dependent O-D flows, which are translated into individual vehicles wishing to enter the network. A probabilistic model is used to capture drivers' route choice decisions. Behavior parameters (e.g., desired speed, aggressiveness) and vehicle characteristics are assigned to each vehicle/driver. MITSIM moves vehicles according to detailed driving behavior models, most notably acceleration and lane changing. The acceleration model captures drivers' response to conditions ahead as a function of relative speeds, headways, and other traffic measures. The model assumes three possible regimes, depending on the magnitude of the time headway to the front vehicle: free-flow, car-following, and emergency. The car-following behavior is active when the subject is close to the leader and therefore directly affected by it. The free-flow model describes the behavior of vehicles that are not close to their leaders. Emergency behavior is invoked in near-collision situations. The lane-changing model distinguishes between mandatory and discretionary lane changes. These models assume three levels of decision making: decision to change lane, choice of lane to change to, and execution of the lane change (gap acceptance). The distribution of desired speeds in the population is an important input to both the acceleration and lane-changing models. Merging, drivers' responses to traffic signals and signs, speed limits, incidents, and tollbooths are also captured. A detailed description of driving behavior models implemented in MITSIMLab is presented elsewhere (*10*).

TMS mimics the traffic control system in the network under consideration. A wide range of traffic control and route guidance systems can be simulated. These include intersection controls, ramp control, freeway mainline control, lane control signs, variable speed limit signs, portal signals, variable message signs, and in-vehicle route guidance. TMS can represent different designs of such systems with logic at varying levels of sophistication (pretimed, actuated, or adaptive). An extensive graphical user interface is used for both debugging purposes and demonstration of traffic impacts through vehicle animation.

CALIBRATION METHODOLOGY

In general, calibration of microscopic traffic simulation tools should be based on the framework presented in Figure 1. According to this framework the calibration process consists of two steps. First, the individual models the simulator consists of (e.g., driving behavior and route choice models) are specified and their parameters are statistically estimated with disaggregate data, independent of the overall simulator framework. Disaggregate data include detailed driver behavior information such as vehicle trajectories of the subject and surrounding vehicles. In the second step, aggregate data (e.g., time headways, speeds, flows) are used to fine-tune parameters and calibrate general parameters in the simulator.

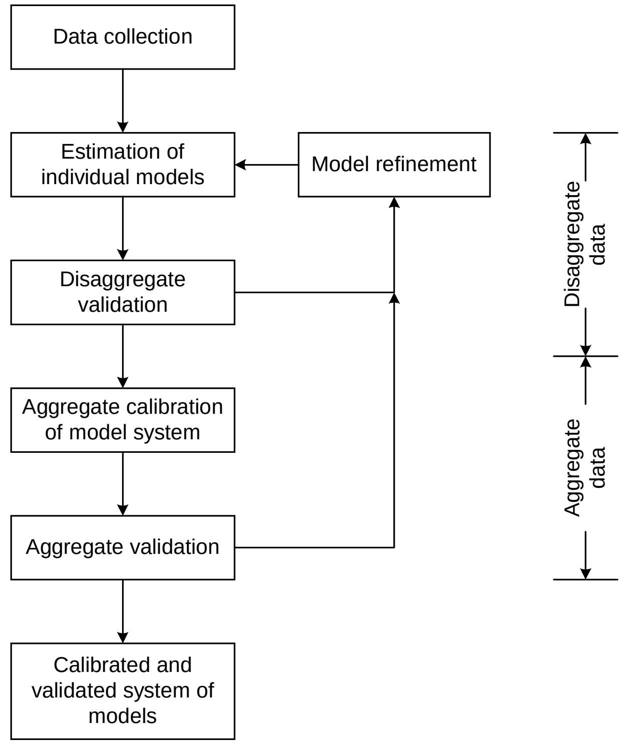

FIGURE 1 Overall calibration framework.

While this two-step approach to calibration is desirable, data availability often dictates what steps are feasible. Most often, as was the case in this study, only aggregate data collected through loop detectors are available and therefore only aggregate calibration is possible. Aggregate calibration is based on a formulation of an optimization problem, which seeks to minimize a measure of the deviation between observed and corresponding simulated measurements. The reason for this approach is that, in general, it is not feasible to isolate the contribution of individual models to the overall error. For example, O-D estimation methods require an assignment matrix as input. The assignment matrix maps O-D flows to traffic counts at sensor locations. Usually the assignment matrix is not readily available and needs to be generated from the simulator. Therefore, the assignment matrix is a function of the route choice and driving behavior models used. Similarly, an important explanatory variable in route choice models is route travel times, which are flow dependent. Simulated flows are a function of the O-D flows, driving behavior, and the route choice model itself. Hence, the following optimization problem, which simultaneously calibrates the parameters of interest (O-D flows, route choice, and driving behavior parameters), may be formulated as follows:

$$\min_{\beta,\theta,OD} f\left(M^{\text{obs}}, M^{\text{sim}}\right) \tag{1}$$

subject to

$$M^{\text{sim}} = g(\beta, \theta, OD)$$

$$OD = \arg\min_{X} \lVert AX - Y^{\text{obs}} \rVert$$

where

β, θ, and OD = vectors of parameters to be calibrated: driving behavior, route choice, and O-D flows, respectively;
$f(\cdot)$ = measure of the discrepancy between M^{obs} and M^{sim}, which are vectors of observed and simulated traffic measurements, respectively;
$g(\cdot)$ = simulation process;
Y^{obs} = observed traffic counts at sensor locations; and
A = assignment matrix.

The preceding problem is very difficult to solve exactly. The O-D constraint, for example, is a fixed-point problem, which is a hard problem on its own merit (*7*). Hence, the iterative heuristic approach presented in Figure 2 is proposed. This approach accounts for interactions between driving behavior, O-D flows, and route choice behavior by iteratively calibrating driving behavior parameters and travel behavior elements. At each step the corresponding set of parameters is calibrated, while the other parameters remain fixed to their previous values. Calibration of the route choice model requires a set of reasonable paths for each O-D and expected link travel times used as explanatory variables in the model. O-D estimation requires generation of an assignment matrix. Hence, the travel behavior calibration step is also iterative: based on the existing O-D flows, parameters of the route choice model are calibrated. The calibrated route choice model is used to generate an assignment matrix and perform O-D estimation. The new O-D flows are used to recalibrate route choice parameters and so forth. In summary, the proposed calibration process proceeds as follows:

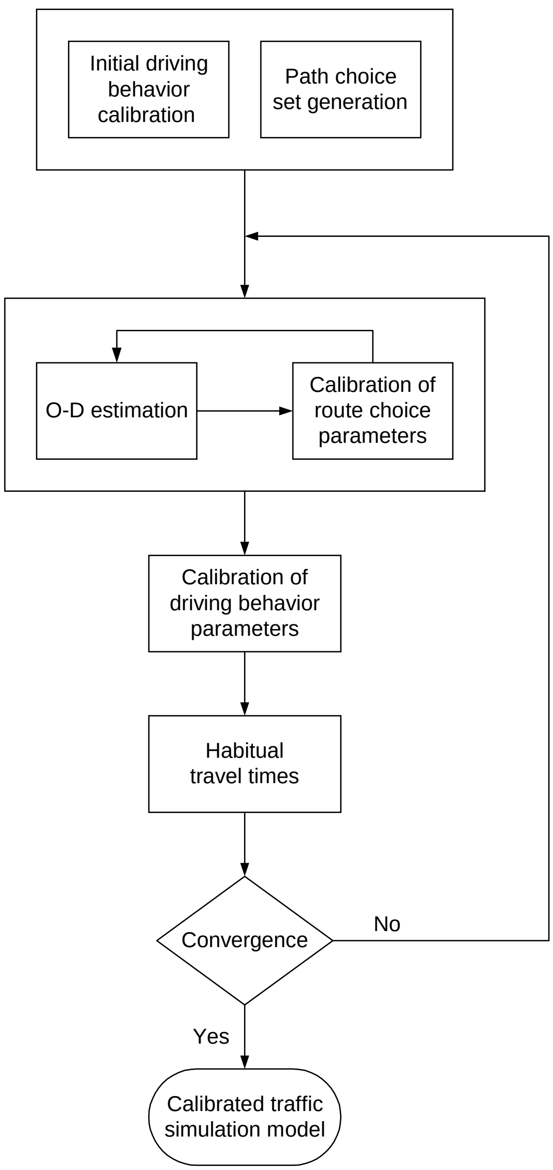

FIGURE 2 Methodology for aggregate calibration of microsimulation models.

Step 1. Initialize parameters, β_0, θ_0, and OD_0.
Step 2. Estimate O-D and calibrate route choice parameters assuming fixed driving behavior parameters.
Step 3. Calibrate driving behavior parameters assuming the O-D matrix and route choice parameters estimated in Step 2.
Step 4. Update habitual travel times using the O-D matrix, route choice, and driving behavior parameters estimated in Steps 2 and 3.
Step 5. Check for convergence: if convergence, terminate. Otherwise, continue to step 2.

CASE STUDY

Study Network and Data

Traffic in Stockholm is growing at an annual rate of 2%. Even if all planned road investments in Sweden were to be allocated to Stockholm, that would not be enough to meet the expected traffic increase in the next 20 years. Hence, road authorities are seeking ways to efficiently manage the use of existing roads, such as advanced traffic management strategies including coordinated traffic control systems, bus priority at signals, and bus-lane operations. MITSIMLab was used to evaluate some of these strategies. A calibration and validation activity was carried out before evaluation. The calibration focused on adjusting key parameters to fit local conditions. Validation focused on demonstrating the ability of the model to replicate observed traffic patterns in conditions other than the ones used for calibration.

A mixed urban-freeway network in the Brunnsviken area, north of the Stockholm central business district, was chosen for the purpose of calibration and validation (Figure 3). This network has been used previously in the DYMO study (*11*). The E4 corridor, on the west side of the network, is the main freeway connecting the northern suburbs to the central business district. The east side of the network is a parallel arterial. These routes experience heavy southbound congestion during the morning peak period.

Morning peak period traffic data from May 1999 were collected for calibration. Similar data were collected a year later, during May 2000, for validation. Sensor and other measurement locations for May 1999 and May 2000 are also presented in Figure 3. Sensor data were available from the motorway control system and additional loop detectors. The validation data also included measurements of point-to-point travel times and queue lengths by probe vehicles. Additional queue measurements were obtained from aerial photographs.

A static morning peak O-D flows matrix, previously developed for planning studies, was available for O-D estimation. Additional information about vehicle mix by type (automobiles, buses, trucks, etc.) and lane-use privilege (i.e., permission to use bus lanes) was

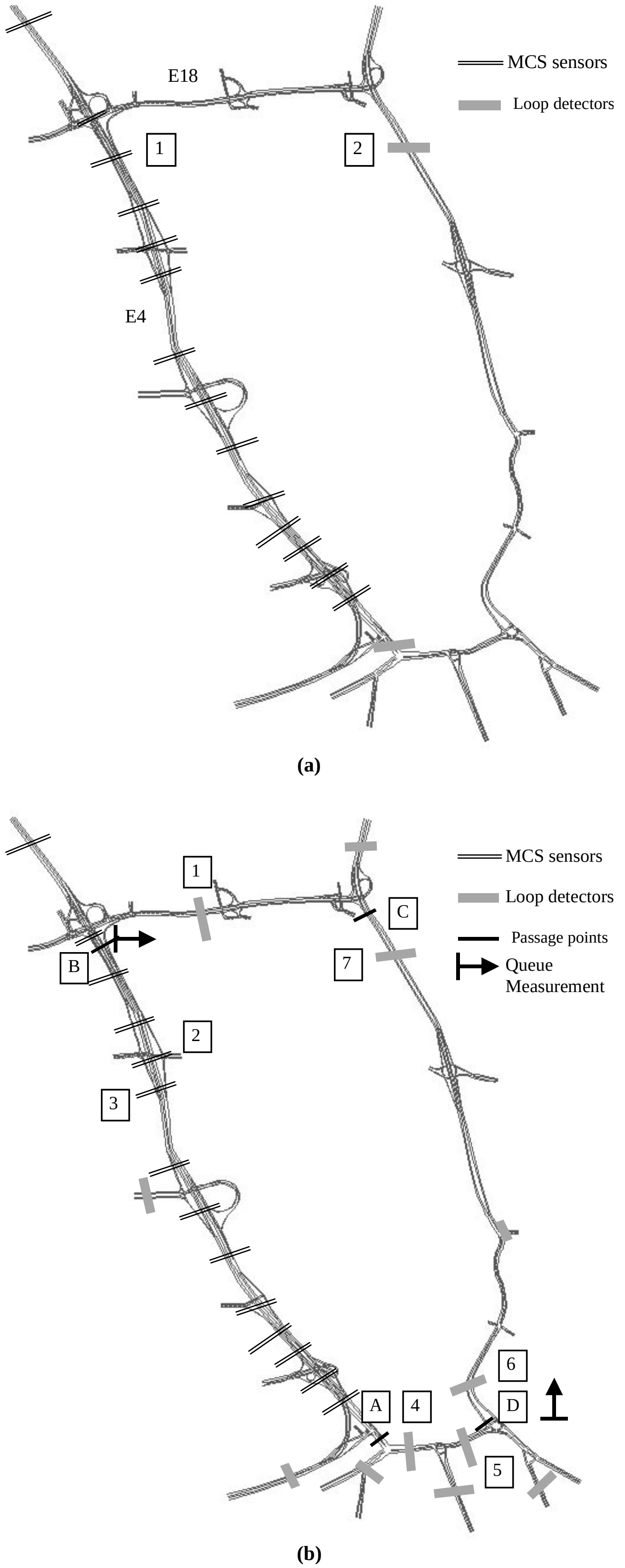

FIGURE 3 Locations of motorway control system (MCS) sensors, loop detectors, passage points, and queue measurements in the Brunnsviken network: (*a*) May 1999, (*b*) May 2000.

used to set corresponding input data for the simulator. The type assigned to a simulated vehicle affects its physical properties (length and width) and performance capabilities (e.g., maximum speed, acceleration and deceleration). The importance of lane-use privileges in this application stems from the extensive bus lanes system in place. Only buses and taxis are allowed to use these lanes. The automobiles category was further split to two separate groups: high-performance and low-performance vehicles. Vehicles in these groups have different performance capabilities.

Now, application of the procedure described in the previous section to the Brunnsviken network is described in more detail.

Initial Parameter Calibration

Driving Behavior Parameters

Of the driving behavior parameters, only parameters of the distribution of desired speeds were estimated independently. The other parameters were calibrated through the optimization approach already discussed.

The desired speed is defined as the speed the driver would choose in the absence of any restrictions imposed by other vehicles or by traffic control devices. This speed is affected by the geometry of the section and by driver and vehicle characteristics. A set of parameters determines the distribution of desired speeds relative to the speed limit. This distribution was inferred from the speeds of unconstrained vehicles. Vehicles crossing the sensor stations at times when the flow rate was less than 600 vehicles (veh)/h/lane were considered unconstrained. This threshold corresponds to the *Highway Capacity Manual* level of service A (*12*). The sensitivity of the desired speed distribution with respect to the flow threshold was analyzed. Desired speed distributions were developed in a similar way, assuming flow thresholds of 300 and 200 veh/h/lane. The results were not significantly different from the one obtained for 600 veh/h/lane.

A small subnetwork extracted from the Brunnsviken network was used to obtain initial values for other driving behavior parameters. Important considerations that led to adopting this approach were as follows:

1. The calibration process is more manageable when performed on a subnetwork.
2. The subnetwork was chosen so that available sensor data can be used to generate accurate O-D flows at 1-min intervals. Moreover, for each O-D pair in the subnetwork only one path exists. Therefore, most of the errors generated by O-D estimation and route choice modeling were eliminated.

The subnetwork and sensor locations within it are presented in Figure 4. This subnetwork was chosen for several reasons including the following:

1. Minimal downstream effects. The location is far from possible spillbacks from the bottlenecks in the network that may affect the behavior but are not represented in the MITSIMLab subnetwork model.
2. Representation of different behaviors. The subnetwork contains on- and off-ramps, thus capturing mandatory and discretionary lane-changing and merging behavior, which are likely to be important behaviors in this case study.

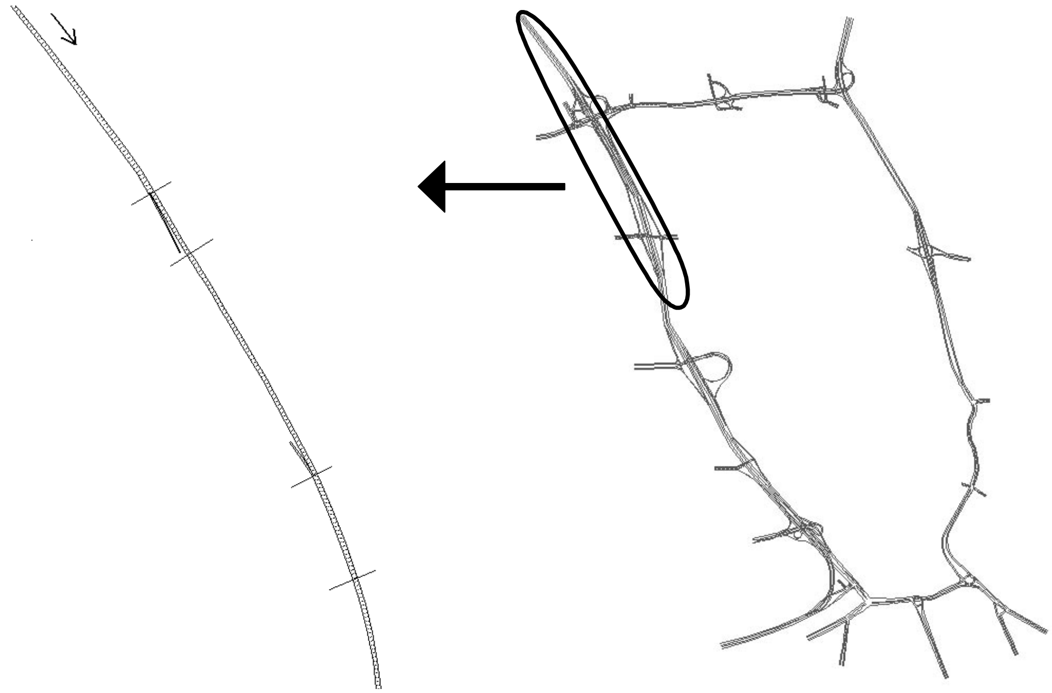

FIGURE 4 Location and details of calibration subnetwork.

The risk associated with this approach is that the calibration may not produce the desired results if the selected subnetwork is not representative of the network. However, because this is only a preliminary calibration step, which would be followed by application of the calibrated models to the entire network, this risk should be negligible.

Because sensor counts were used to extract O-D information for the subnetwork, minimization of the square deviations of simulated sensor speeds from the observed ones was used to calibrate the driving behavior parameters:

$$\min_{\beta} \sum_{t=1}^{T} \sum_{n=1}^{N} (V_{nt}^{\text{sim}} - V_{nt}^{\text{obs}})^2 \tag{2}$$

where

V_{nt}^{obs} and V_{nt}^{sim} = observed and simulated speeds, respectively, measured at sensor n during time period t,
N = number of sensors, and
T = number of time periods.

Path Choice Set Generation

The route choice model requires a set of alternative paths for each O-D pair in the network. The following procedure was used to generate these sets:

1. Generation of a comprehensive path set. A comprehensive path choice set was generated by using a probabilistic link-based route choice model embedded in MITSIMLab, in which each vehicle decides the next link on its path at each node. This choice is based on the shortest-path travel times to the destination via each one of the candidate next links as explanatory variables.
2. Unreasonable path elimination. The link-based route choice tends to generate a large number of paths. Unreasonable paths (e.g., paths using off-ramp and on-ramp immediately afterward) were eliminated.

The path choice set may depend on traffic conditions, and therefore the process should be repeated to ensure that all reasonable paths are captured as O-D flows and the parameters of the route choice model evolve. The structure of the Brunnsviken network facilitates the generation of the path set, because only one or two reasonable paths exist for each O-D pair. Therefore, the path generation exercise was performed only once.

O-D Estimation and Route Choice

O-D Estimation

The O-D estimation problem is often formulated as a generalized least-squares (GLS) problem. The GLS formulation minimizes the deviations between estimated and observed sensor counts while also minimizing the deviation between the estimated O-D flows and seed O-D flows [see, for example, Cascetta et al. (*13*), Cascetta and Nguyen (*14*), and Bell (*15*) for more detail and for review of O-D estimation methods]. The corresponding optimization problem is as follows:

$$\min_{X \geq 0} (AX - Y^H)^T W^{-1}(AX - Y^H) + (X - X^H)^T V^{-1}(X - X^H) \tag{3}$$

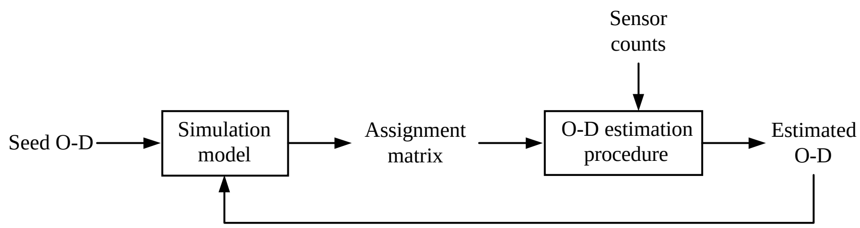

FIGURE 5 O-D estimation process.

where

X and X^H = vectors of estimated and historical (seed) O-D flows, respectively,
Y^H = historical (observed) sensor counts, and
W and V = variance–covariance matrices of the sensor counts and O-D flows, respectively.

However, in the problem discussed here, the assignment matrix is not known. Hence, the iterative process presented in Figure 5 is proposed. First, the simulation is run, using the calibrated parameters and a set of seed O-D flows to generate an assignment matrix. This assignment matrix in turn is used for O-D estimation. Because of congestion effects, the assignment matrix generated from the seed O-D may be inconsistent with the estimated O-D. Therefore, the O-D estimation process must be iterative.

The Brunnsviken network includes a large number of O-D pairs and sensor locations, which made O-D estimation computationally intensive. To overcome this limitation, a sequential estimation technique, which exploits the sparse structure of the assignment matrix, was used. The sequential estimation process is as follows: The seed O-D is taken as fixed for the first time period. An assignment matrix is generated and used to estimate the effect of the first period demand on sensor counts in subsequent periods. The demand in the second period is then estimated, based on the observed counts less the estimated contribution from O-D flows in the first time period. The assignment matrix is used to estimate the effect of second period demand on subsequent periods. This process is continued until O-D flows are estimated for all periods of interest.

This estimation procedure is inferior to a simultaneous one, in which O-D flows for all time periods are estimated jointly. The magnitude of the error it introduces depends on the degree of traffic dynamics in the specific application. The impact that O-D flows in one time period have on subsequent time periods may be used as indicators to this error and therefore to the adequacy of the sequential process. Figure 6 graphically presents an assignment matrix for the Brunnsviken network with nonzero elements indicated as dots. The (almost) block-diagonal structure of the assignment matrix indicates that the contribution of O-D flows in one period is mostly to sensor counts in the same time period and rarely goes beyond the subsequent time period. Therefore, estimating O-D flows one time period at a time is a reasonable compromise.

Route Choice Parameter Calibration

Given the O-D flows, path choice sets, and habitual travel times, parameters of the route choice model were calibrated to match the split between the two sensors marked 1 and 2 in Figure 3*a.* These points were selected because the structure of the network ensures that all vehicles with a choice of paths pass exactly one of them. Splits were used instead of counts to reduce errors from inaccuracies in the scale of the O-D matrix, especially at early stages of the estimation process.

Driving Behavior Parameters

While the initial calibration of driving models included a wide range of parameters, during this step only a limited set of parameters was calibrated. Sensitivity analysis indicated that the calibration could focus on scale parameters of the various models: the sensitivity constants in the acceleration models and alternative specific constants in the lane-changing models. Hence, given O-D flows and route choice parameters, these scale parameters were calibrated with the formulation given in Equation 2, now applied to the entire network. A detailed description of the parameters calibrated and their optimal values is found elsewhere (*16*).

Habitual Travel Times

The route choice model implemented in MITSIMLab uses habitual path travel times as explanatory variables. Calibration of the model parameters requires knowledge of these travel times. While planning

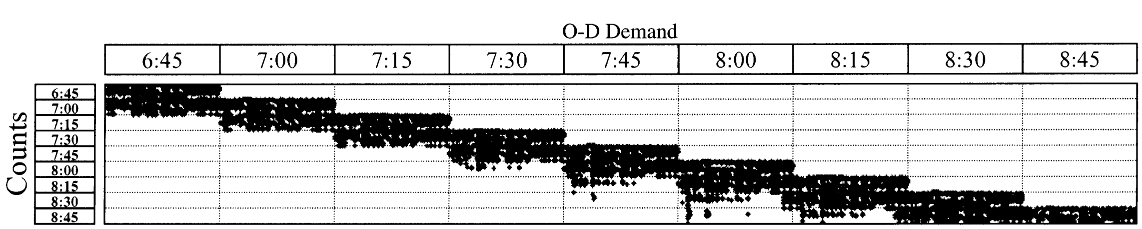

FIGURE 6 Structure of assignment matrix showing nonzero entries as dots.

studies can be used to provide initial values, further refinement is necessary to capture the time-dependent nature of travel times and improve the accuracy of the models. Therefore, an iterative day-to-day perception updating model [see Jha et al. (*17*) for a review] was used to improve initial travel time estimates obtained from planning studies. At each iteration of this process, representing a day, habitual travel times were updated as follows:

$$TT_{it}^{k+1} = \lambda^k tt_{it}^k + (1 - \lambda^k) TT_{it}^k \tag{4}$$

where TT_{it}^k and tt_{it}^k are the habitual and experienced travel times on link *i*, time period *t* on day *k*, respectively, and λ^k is a weight parameter ($0 < \lambda^k < 1$). In this study, a convex combinations approach, which uses a constant $\lambda^k = \lambda$, was implemented.

VALIDATION RESULTS

Three types of measurements were used to validate the calibrated MITSIMLab model—traffic flows, travel times, and queue lengths—by comparing simulated measurements with the corresponding observed measurements. Measurement locations are indicated in Figure 3*b*. O-D flows were estimated from the May 2000 traffic counts and the previously calibrated model parameters.

Traffic Flows

Observed and simulated traffic flows at key sensor locations were compared by using 2 h of morning peak data at 15-min intervals. The results are presented in Figure 7. Two measures of goodness of fit were used to quantify the relationship between observed and simulated measurements: the root-mean-square normalized error (*RMSNE*), which quantifies the total percentage error of the simulator, and the mean normalized error (*MNE*), which indicates the existence of consistent under- or overprediction in the simulated measurements. These measures are calculated as follows:

$$RMSNE = \sqrt{\frac{1}{N}\sum_{n=1}^{N}\left(\frac{m_n^{\text{sim}} - m_n^{\text{obs}}}{m_n^{\text{obs}}}\right)^2} \tag{5}$$

$$MNE = \frac{1}{N}\sum_{n=1}^{N}\frac{m_n^{\text{sim}} - m_n^{\text{obs}}}{m_n^{\text{obs}}} \tag{6}$$

where m_n^{obs} and m_n^{sim} are the observed and simulated measurements, respectively, and *N* is the number of measurement points (over time in this case).

RMSNE values for the different locations range from 5% to 17%. *MNE* values range from −12% to 14%. In general, simulated flows correspond well to the measurements and accurately capture the temporal patterns in traffic flows. Note that sensor flows were used to estimate the O-D flows. Hence, the results emphasize the importance of O-D estimation.

Travel Times

Point-to-point travel times measured by the probe vehicles were compared with average simulated travel times. Only a few probe vehicle observations were available. Therefore, mean observed travel times could not be accurately estimated. Instead, Figure 8 compares average simulated travel times and individual probe vehicle observations. The figure also indicates travel time values corresponding to the average ±2 standard deviations of the simulated travel time. Assuming that simulated travel times follow a normal distribution, these values define an interval containing 95% of simulated travel times. Eighty of the 120 (67%) probe vehicle observations are within these intervals.

Simulated travel times match very well in sections A to B, B to C, and D to C, which are relatively uncongested during the morning peak period. Sections C to D, C to B, and B to A are heavily congested, as indicated by the shapes of the travel time curves. These shapes are rather well replicated, although the simulator underestimates travel times. The largest incomparability between observed and simulated measurements is in sections A to D and D to A. These are short and congested sections dominated by traffic signals and roundabouts. Some of the error in these sections may be attributed to inconsistencies in the traffic counts in this area (e.g., entry flows to an intersection do not match exit flows) that led to poor O-D estimation and to imperfections in the representation of traffic control (e.g., pedestrian and bicycle signals) in the simulation tool.

Queue Lengths

Simulated queue lengths were compared with those measured by the probe vehicles and from aerial photos. Both queues presented in Figure 9 are very significant. At their peak they may interlock and grow beyond the northern boundary of the network. They are well represented in the simulation in terms of both magnitude and time of occurrence. However, the number of observations is very limited, which forbids rigorous statistical analysis of the results.

CONCLUSION

This paper described the calibration and validation methodology of a microscopic traffic simulator applied to the Brunnsviken network in northern Stockholm. An extensive sensor data collection effort was conducted during May 1999 for calibration and May 2000 for validation. In addition, for the validation, point-to-point travel times and queue lengths were measured by probe vehicles and from aerial photographs.

Only sensor data were used to calibrate two important components of the simulation tool: driving behavior models and travel behavior components, including O-D flows and route choice parameters. Such aggregate calibration uses the simulated output, which is a result of the interaction among all components of the simulator. Therefore, it is, in general, impossible to identify the effect of individual models on traffic flow when using aggregate data. The proposed calibration approach accounts for these interactions by iteratively calibrating these components.

The calibrated MITSIMLab model was validated by comparing observed and simulated measurements: traffic flows at sensor locations, point-to-point travel times, and queue lengths. Flow comparisons showed a good fit between observed and simulated flows. Simulated travel times reproduced the observed peaking patterns in most of the sections. Queue lengths also replicated well in the

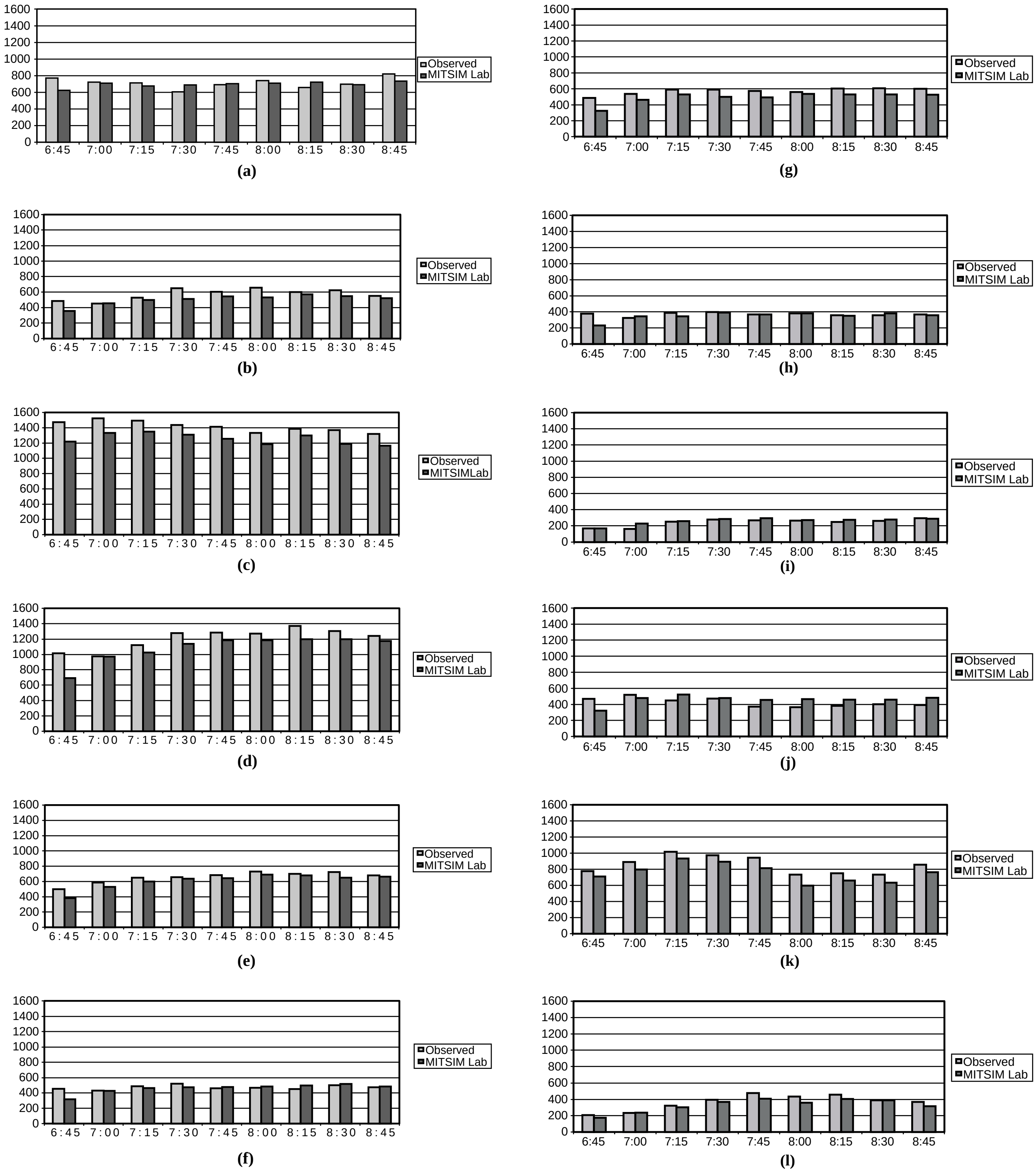

FIGURE 7 Comparison of observed and simulated flows at sensor locations: (*a*) 1 westbound, (*b*) 1 eastbound, (*c*) 2 southbound, (*d*) 3 northbound, (*e*) 4 westbound, (*f*) 4 eastbound, (*g*) 5 westbound, (*h*) 5 eastbound, (*i*) 6 northbound, (*j*) 6 southbound, (*k*) 7 southbound, and (*l*) 7 northbound.

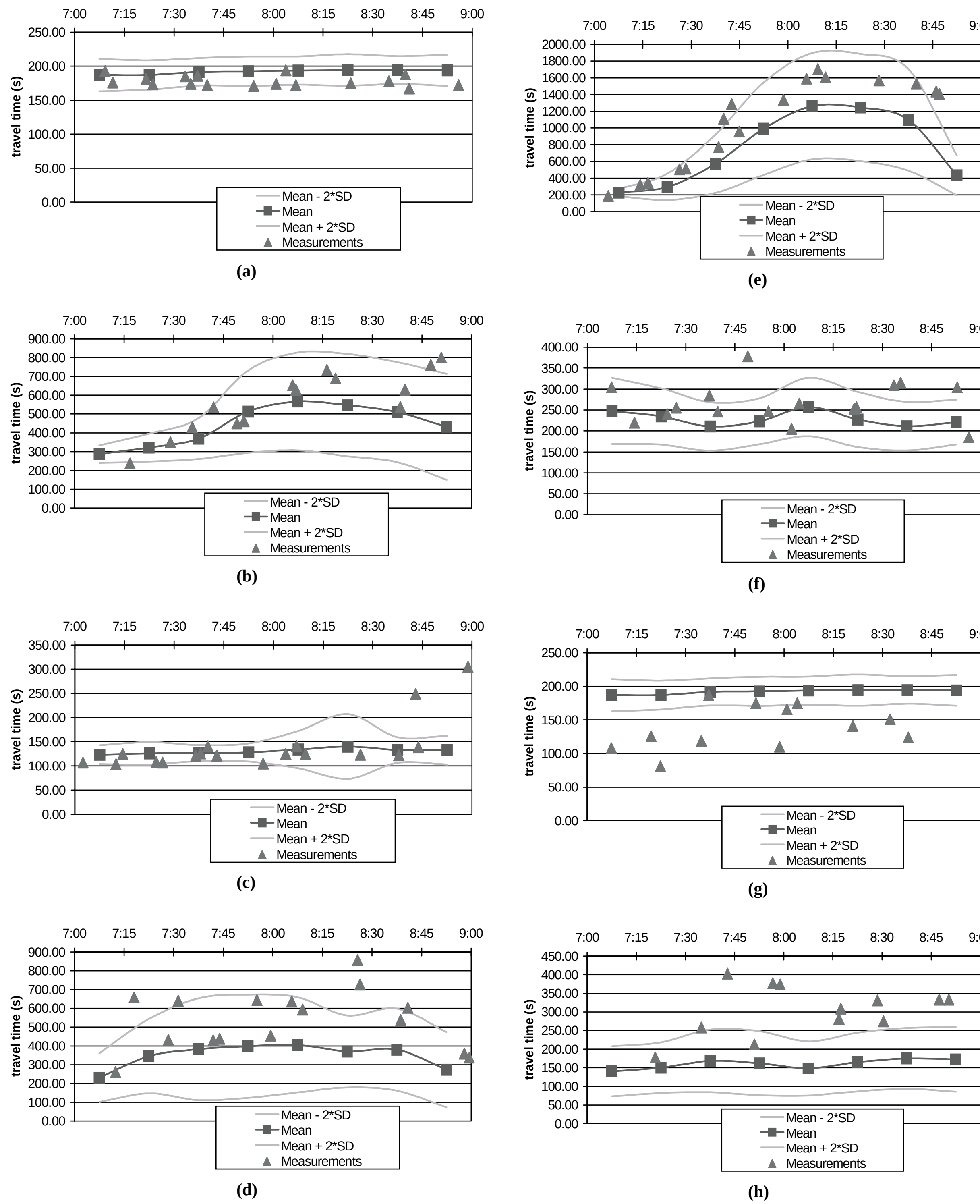

FIGURE 8 Comparison of observed and simulated point-to-point travel times: (*a*) A to B, (*b*) B to A, (*c*) B to C, (*d*) C to B, (*e*) C to D, (*f*) D to C, (*g*) D to A, and (*h*) A to D.

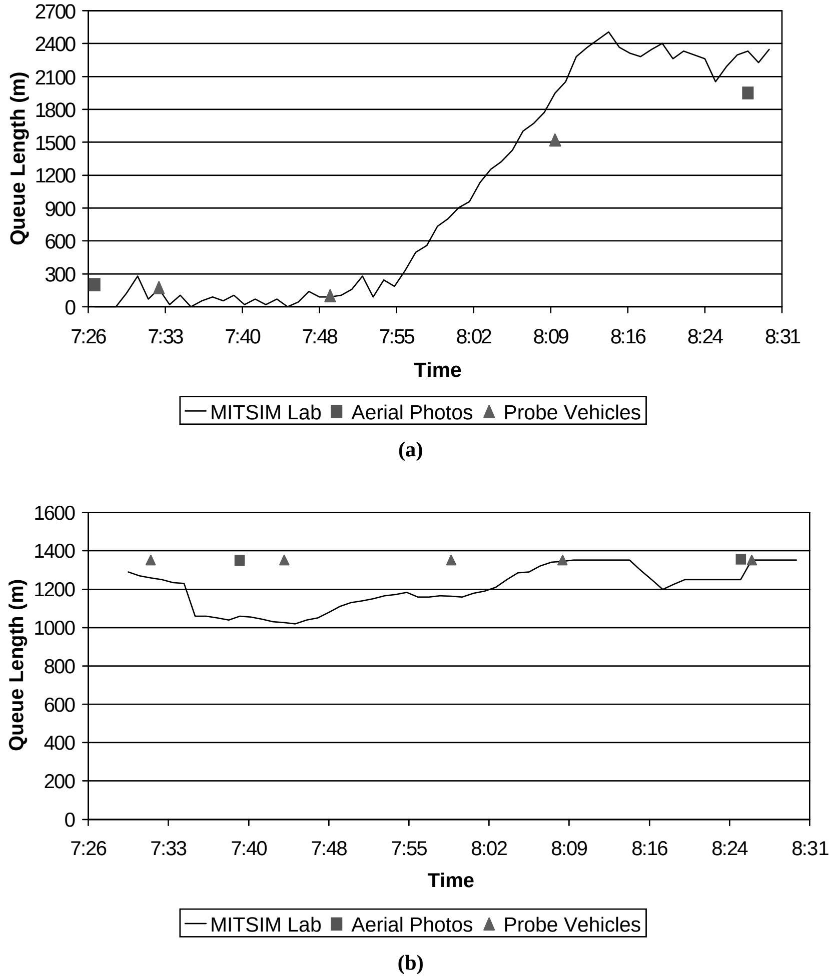

FIGURE 9 Comparison of observed and simulated queue lengths at (*a*) D and (*b*) B.

simulation in terms of both queue dynamics and length. Hence, it may be concluded that the MITSIMLab model for the Brunnsviken network fits the empirical measurements reasonably well.

This study also illustrates the importance of using reliable sensor data with good spatial coverage of the network. Sensor data are prone to significant measurement errors [for example, up to 38% error is reported by Turner et al. (*18*)]. Furthermore, there is significant probability of using measurements from malfunctioning sensors. If sensor data are of poor quality, O-D flows and resulting simulated traffic flows may deviate considerably from reality. Hence, it is important to check and correct data before beginning calibration and validation.

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