Calibration and Evaluation of MITSIMLab in Stockholm

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ABSTRACT

This paper describes results from a case study to calibrate and evaluate of the microscopic traffic simulation model MITSIMLab, to a mixed urban-freeway network in the Brunnsviken area in the north of Stockholm under congested traffic conditions.

In the absence of detailed data, only aggregate data (i.e. speed and flow measurements at sensor locations) was used to calibrate the simulation model. Two important components of the simulation model were calibrated: driving behavior models and travel behavior components, including the OD matrix and the route choice model. An optimization approach to minimize the deviation between observed and simulated measurements was used. This aggregate calibration uses simulation output, which is a result of the interaction among all components of the simulation. Therefore, it is, in general, impossible to identify the effect of individual models on traffic flow when using aggregate data. The calibration approach takes these interactions into account by iteratively calibrating the different components.

The performance of the calibrated MITSIMLab model was evaluated by comparing 3 types of 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 in this stage. Results of the evaluation are presented. Practical difficulties and limitations that may arise with the application of the calibration and evaluation approach are discussed.

1. INTRODUCTION

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. Towards that end, tools to aid in the design and operations of the traffic network are needed. This paper describes results of a case study applying MITSIMLab, a microscopic traffic simulation model, for a mixed urban-freeway network in Stockholm. The purpose of this study is two-fold: to calibrate MITSIMLab for Swedish road conditions and to evaluate the performance of the calibrated model using real-world data. The calibrated model will be used for evaluation of traffic management schemes involving coordinated traffic control systems, bus priority at signals and bus-lane operations.

MITSIMLab is a microscopic traffic simulation laboratory developed to evaluate Advanced Traffic Management Systems (ATMS) and Advanced Traveler Information Systems (ATIS) 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 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)
3. Graphical User Interface (GUI)

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 origin to destination (OD) trip tables. A probabilistic model is used to capture drivers' route choice decisions. OD flows are translated into individual vehicles wishing to enter the network at a specific time. Behavior parameters (e.g. desired speed, aggressiveness) and vehicle characteristics are assigned to each vehicle/driver. MITSIM moves vehicles according to car-following and lane-changing models. The car-following model captures the response of a driver to conditions ahead as a function of relative speed, headway and other traffic measures. The lane-changing model distinguishes between mandatory and discretionary lane changes. Merging, drivers' responses to traffic signals, speed limits, incidents, and tollbooths are also captured.

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 (pre-timed, actuated or adaptive). The simulation laboratory has an extensive graphical user interface that is used for both, debugging purposes and demonstration of traffic impacts through vehicle animation. For a detailed description of MITSIMLab see *[1] and [2]*.

The remaining of the paper is organized as follows: the next section briefly describes the test network and data used in the case study. The calibration approach is described in section 3. Evaluation results are presented in section 4. Discussion and conclusions are presented in the last section.

2. STUDY NETWORK AND DATA

A mixed urban-freeway network in the Brunnsviken area, north of the Stockholm CBD was chosen for the purpose of calibration and evaluation. This network has been used previously in the DYMO study *[3]*. Figure 1 shows an overview of the network. The E4 corridor, on the west side of the network is the main freeway connecting the northern suburbs to the CBD. The east side of the network is a parallel arterial. These routes experience heavy southbound congestion during the AM peak period.

AM peak period traffic data from May 1999 was collected for calibration. Similar data was collected a year later, during May 2000, to be used for evaluation. In addition to sensor data, the second collection effort included measurements of point-to-point travel times between passage points by probe vehicles. The probe vehicles also recorded queue lengths. These were complemented with measurements from aerial photographs. Sensor and other measurement locations for May 1999 and May 2000 are shown in Figures 2a and 2b, respectively. Motorway Control System (MCS) sensors measured average flows and speeds at 1-minute intervals. The additional loop detectors measured average flows at 15 min. intervals.

A static AM peak OD matrix, which has been previously developed for planning studies on the same network, was available for OD estimation.

Additional information about vehicle mix by type (i.e. passenger cars, buses, trucks etc.) and lane-use privilege (i.e. permission to use bus lanes) was used to set corresponding input data for the simulation model. The type assigned to a simulated vehicle in MITSIMLab affects its physical properties (length and width) and performance capabilities (e.g. maximum speed, maximum acceleration and deceleration). The importance of lane-use privileges in this application stems from the extensive bus lanes system in place. The vehicle mix specified in MITSIMLab and shown in Table 1 was directly based on AM peak traffic observations.

Simulated buses and taxis were allowed to use the bus lanes. All other vehicles were not permitted to use the bus lanes, although a small percentage of drivers may use bus lanes in violation of the lane regulations. The Autos category was further split into two separate groups: high-performance vehicles and low-performance vehicles. This division was based on statistics about the distribution of vehicle by age and brand in Stockholm.

3. CALIBRATION

The MITSIMLab calibration framework is shown in Figure 3. In general, the calibration process consists of two steps. First, using disaggregate data, individual models can be calibrated and estimated. Disaggregate data includes information on detailed driver behavior such as vehicle trajectories of the subject and surrounding vehicles. Aggregate data (e.g. time headways, speeds, flows, etc.) is used to fine-tune parameters and estimate general parameters in the simulator.

In the absence of detailed data, only aggregate data is used to calibrate the most critical parameters. Aggregate calibration uses optimization techniques to minimize the deviation between observed and corresponding simulated measurements. A generalized least squares (GLS) estimator is commonly used. The objective function for calibration is:

$$\min Z = \left(X^{sim} - X^{obs}\right)^T V^{-1} \left(X^{sim} - X^{obs}\right) \qquad (1)$$

where, X^{sim} and X^{obs} are vectors of simulated and observed measurements. V is the variance-covariance matrix of errors associated with the measurements.

Two main groups of parameters were calibrated in this study: driving behavior parameters and travel behavior parameters. Driving behavior in MITSIMLab is based on car-following, lane-changing, and intersection models. The parameters of these models have been previously calibrated against Boston data *[4]*. The two major components of travel behavior in MITSIMLab are the OD matrix and the route choice model.

Aggregate calibration uses simulation output, which is a result of the interaction among all these components. In general, it is impossible to identify the effect of individual models on traffic flow. For example, OD estimation methods require an assignment matrix as input. The assignment matrix maps OD flows to counts at sensor locations. Usually the assignment matrix is not readily available and needs to be generated from the model. Therefore the assignment matrix is a function of the route choice and driving behavior models used. Similarly, one of the most important explanatory variables in route choice models is route travel times, which are flow-dependent. Simulated flows are affected by the OD matrix, driving behavior models and the route choice model itself.

The calibration methodology outlined in Figure 4 takes these interactions into account by iteratively calibrating the different components. The route choice model calibration requires two preliminary stages: determination of a set of reasonable paths for each OD and link travel times that correspond to the route choice behavior. As mentioned above, the OD estimation process requires generation of an assignment matrix. The process iterates between a route choice calibration step and an OD estimation step. At each iteration, based on the existing OD matrix, input for the route choice model is generated and parameters of this model are calibrated. The calibrated route choice model is used to generate an assignment matrix, required in the OD estimation process. The new OD matrix is used to re-calibrate route choice parameters and so on. Scale parameters for the driving behavior models are also adjusted periodically.

3.1 Calibration of driving behavior parameters

This category includes parameters that govern the behavior of vehicles as they maneuver in traffic. Two important models affect driving behavior in MITSIMLab: the acceleration model and the lane-changing model. The acceleration model determines the longitudinal movement of a vehicle under 3 possible regimes: free-flowing, car-following and emergency. The car-following behavior is active when the subject vehicle is directly affected by the vehicle in front of it. The free-flowing model describes the behavior of a vehicle that is not affected by the vehicle in front (when it is far away from it). Emergency behavior is invoked in near collision situations. The lane-changing model captures a lane-changing action with three levels of decision-making: the decision to change lane, the choice of lane to change to and the gap acceptance behavior to perform the lane change. The distribution of desired speeds in the population is an important input to both acceleration and lane-changing models. A detailed description of the models implemented in MITSIMLab is presented in *[4]*.

Driving behavior parameters were calibrated in 3 stages: first, the distribution of desired speeds was inferred directly from sensor data. Next, a sub-network was used to initially calibrate car-following and lane-changing behavior parameters. Finally, the calibrated parameters were applied to the whole network and scale parameters of the models were modified to best replicate the state of the network in an iterative process that included calibration of travel behavior parameters.

The key parameter in the free-flowing acceleration behavior is the desired speed of the vehicle. The desired speed is defined as the speed that 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 characteristics. MITSIMLab uses the speed limit as a basis for the distribution of desired speeds in the driver population. A set of parameters determines the distribution of desired speeds relative to the speed limit.

The distribution of desired speeds was inferred from the sensor data using the speeds of unconstrained vehicles. Vehicles crossing the sensor stations at times when the flow rate was less than 600 veh/hr/lane were considered unconstrained. This threshold corresponds to the Highway Capacity Manual (HCM) maximum flow for level of service A *[5]*. The speed limit in the section of E4 studied is 70 km/hr.

An analysis of the sensitivity of the desired speed distribution with respect to the flow threshold was performed. The desired speed distributions for flow thresholds of 300 and 200 veh/hr/lane were not significantly different.

A small sub-network of the Brunnsviken network was used in order to calibrate other driving behavior parameters. The main considerations that led to adopting this approach were:

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

The location and details of the sub-network are shown in Figure 5. Numbers shown indicate sensor identification numbers. This sub-network was chosen for several reasons including:

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 sub-network model.
2. Representation of different behaviors – The sub-network contains geometric elements that are likely to demonstrate most of the behaviors that are represented in MITSIMLab. The network contains on- and off-ramps, allowing capturing mandatory and discretionary lane changing, and merging behavior.

Sensor counts were used to extract OD information for the sub-network and therefore could not be used for the calibration objective function. Instead, the square deviations of simulated sensor speeds from the observed speeds were minimized:

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

where, V_{nt}^{obs} and V_{nt}^{sim} are the observed and simulated speeds at sensor *n* at time *t*, respectively. *N* and *T* are the number of sensors and time periods used, respectively.

3.2 Calibration of travel behavior parameters

Path choice set generation

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

1. Generation of a comprehensive path set – The MITSIMLab model was run using the default link-based route choice model. In this route choice model a vehicle decides the next link on its path at each node. The next link choice is based on a logit model with the shortest path travel times to the destination via each one of the possible 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 after that) were eliminated. A special utility in MITSIMLab's graphical user interface was used to visualize paths and assist in the elimination process.

The path set may depend on traffic conditions, in which case the process should be repeated as the OD matrix and route choice model evolve to ensure that all reasonable paths are captured. The structure of the Brunnsviken network facilitates the generation of the path set, since only one or two reasonable paths exist for each OD pair. Because of this structure the path generation exercise was only performed once.

Habitual Travel Times

The route choice model implemented in MITSIMLab uses expected or equilibrium path travel time as an explanatory variable. In order to calibrate the parameters of the model knowledge of these travel times is required. An iterative day-to-day learning model was used to develop these travel times. At each iteration of this process, representing a day, MITSIMLab was run using the current expected travel times estimates. Experienced travel times from the MITSIMLab run were used to update the expected travel times:

$$TT_{it}^{k+1} = \lambda^k tt_{it}^k + \left(1 - \lambda^k\right) TT_{it}^k \tag{3}$$

where, TT_{it}^k is the expected travel time on link *i*, during time period *t* on day *k*. tt_{it}^k is the experienced travel time on day *k*. λ^k is the weight parameter for the experienced travel time ($0 < \lambda^k < 1$).

Route Choice Parameters

Parameters of the route choice model were calibrated to match the split between the two sensors marked 1 and 2 in Figure 2a. These points were selected because the structure of the network ensures that all vehicles with a choice of paths pass either of these points. Splits rather than counts were used in order to reduce errors from inaccuracies in the scale of the OD matrix especially at early stages of the estimation process.

OD Estimation

The OD estimation process is shown in Figure 6. MITSIMLab, with its previously calibrated parameters, was used to generate the assignment matrix from the seed OD matrix.

The OD estimation process minimizes the deviations between estimated and observed sensor counts while also minimizing the deviation between the estimated OD matrix and the seed matrix. The formulation of the corresponding optimization problem is:

$$\min_{x \geq 0} \left(Ax - y^H\right)^T W^{-1} \left(Ax - y^H\right) + \left(x - x^H\right)^T V^{-1} \left(x - x^H\right) \tag{4}$$

where, *x* and x^H are the vectors of estimated and historical (seed) OD flows, respectively. y^H is the vector of historical (measured) sensor counts. *A* is the assignment matrix. *W* and *V* are the variance-covariance matrices of the sensor counts and OD flows, respectively.

The large number of OD pairs and sensor locations in the Brunnsviken network, made the estimation computationally too intensive. To overcome this limitation, a sequential estimation technique was employed. This technique exploits the sparse structure of the assignment matrix. Figure 7 graphically shows an assignment matrix for the Brunnsviken network with non-zero elements shown as dots. Travel times in the network are such that usually OD flows in one period have no effect beyond the subsequent time period. Furthermore, much of the effect of the OD is felt in the same time period. Therefore, estimating the OD matrix a single time period at a time is a reasonable compromise.

The sequential estimation process is as follows: The seed OD is taken as fixed for the first time period. The 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 the first period OD flows. The assignment matrix is used to estimate the effect of second period demand on subsequent periods. This process is continued until OD flows are estimated for all periods of interest.

Due to the effects of congestion within the network, the assignment matrix generated from the seed OD is not necessarily consistent with the estimated OD. Therefore, the OD estimation process must be iterative.

4. EVALUATION

The performance of the calibrated MITSIMLab model was evaluated by comparing 3 types of observed and simulated measurements: traffic flows, travel times and queue lengths. An OD matrix was estimated from the May 2000 traffic counts and using the previously calibrated model parameters.

MITSIMLab is a stochastic simulation model. Therefore, average results of several simulation runs need to be used. Assuming that the outputs from different simulation runs are normally distributed, the minimum number of replications required is:

$$R = \left(\frac{\hat{s}\, t_{\alpha/2}}{\hat{y}\varepsilon} \right)^2 \qquad (5)$$

where, $\hat{y}$ and $\hat{s}$ are estimates of the mean and standard deviation of the measurements, respectively. ε is the allowable error. $t_{\alpha/2}$ is the critical value of the t-distribution at a significance level α.

This value was calculated for all measurements of interest (travel times, flows, and queue lengths). The most critical (highest) value of R should be used. To get initial estimates for the means and variances, the simulation was run 10 times. Application of equation (5) to the simulation outputs resulted in R values which were lower than 10. Hence, the analysis was based on the outputs from these 10 replications.

4.1 Results

All measurement locations are indicated in figure 2b.

Traffic flows

Observed and simulated traffic flows at key sensor locations were compared using two hours of AM peak data at 15 min. intervals. The results are presented in Figure 8. Two Measures of goodness of fit were used to quantify the relationship between the actual and simulated measurements. The root mean square (RMS) percent error quantifies the total percentage error of the simulator. The mean percent error indicates the existence of consistent under- or over-prediction in the simulated measurements. These measures are calculated by:

$$RMS = \sqrt{\frac{1}{N} \sum_{n=1}^{N} \left(\frac{y_n^s - y_n}{y_n} \right)^2} \qquad (6)$$

$$Mean\ Percent\ Error = \frac{1}{N} \sum_{n=1}^{N} \frac{y_n^s - y_n}{y_n} \qquad (7)$$

where, y_n and y_n^s are the observed and simulated measurements, respectively. *N* is the number of measurement points (over time in this case).

RMS percent errors range from 5% to 17%. The mean percent error ranges from –12% to 14%. In general, simulated flows correspond well to the measurements. Note that sensor flows were used to estimate the OD matrix. Hence, the results emphasize the importance of OD estimation.

Travel times

Point to point travel times measured by the probe vehicles were compared against the average simulated travel times and their standard deviations for the relevant 15 min. intervals. Results are shown in Figure 9. It is important to account for the variability between drivers when comparing observed and simulated travel times. Figure 9 shows the average simulated travel times and travel time values corresponding to the average ±2 standard deviations of the simulated mean travel time as well as observed values. A good fit between observed and simulated travel times is indicated by a large proportion of observations falling within the range defined by the average ±2 standard deviations values.

Sections A-B, B-C and D-C are relatively uncongested during the AM peak period. Simulated travel times match very well in these sections. Sections C-D, C-B and B-A are heavily congested. This can be seen from the shapes of the travel time curves. These shapes are rather well replicated, although the simulation underestimates travel times. Some of this error is explained by the presence of bus lanes in sections C-D and C-B (as well as sections B-C and D-C). The probe vehicles did not use these lanes, but the calculation of simulated travel times includes vehicles using these lanes. Travel times on the bus lanes were significantly shorter. Hence, the calculation of average simulated travel times is biased down. The largest incomparability between observed and simulated measurements is in sections A-D and D-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 that led to poor OD estimation.

Queue Lengths

Simulated queue lengths were compared against those measured by the probe vehicles and from aerial photos. Both queues, shown in Figure 10, 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, although the number of comparisons is limited.

5. DISCUSSION AND CONCLUSIONS

This paper described the calibration and evaluation of MITSIMLab to the Brunnsviken network in Northern Stockholm. An extensive sensor data collection effort was conducted during May 1999 for calibration and May 2000 for evaluation. In addition, for the evaluation, point-to-point travel times and queue lengths were measured by probe vehicles and from aerial photographs.

Only sensor data was used to calibrate the simulation model. Such aggregate calibration uses simulation output, which is a result of the interaction among all components of the simulation. Therefore, it is, in general, impossible to identify the effect of individual models on traffic flow when using aggregate data. The calibration approach takes these interactions into account by iteratively calibrating the different components. Two important components of the simulation model were calibrated: driving behavior models and travel behavior components, including the OD matrix and the route choice model.

Sensor data is the basis for estimating the OD matrix. Sensor data is prone to measurement errors of up to 25%. Furthermore, there is significant probability of using measurements from malfunctioning sensors. Hence, OD flows and resulting simulated traffic flows may deviate considerably from reality.

The performance of the calibrated MITSIMLab model was evaluated by comparing 3 types of observed and simulated measurements: traffic flows at sensor locations, point-to-point travel times and queue lengths. Flow comparisons showed an acceptable fit between observed and simulated flows. Simulated travel times reproduced the peaking patterns observed in reality in most of the sections. Queue lengths were also replicated well in the simulation both in terms of queue dynamics and length.

It may be concluded that the MITSIMLab model for the Brunnsviken network fits the empirical measurements reasonably well.

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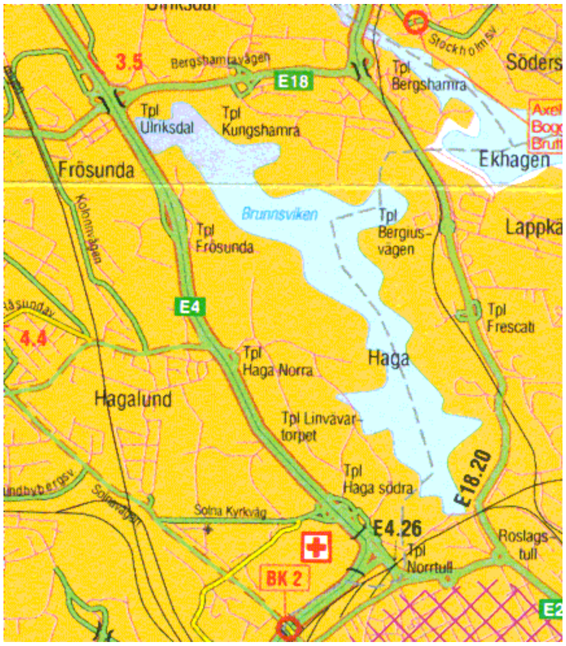
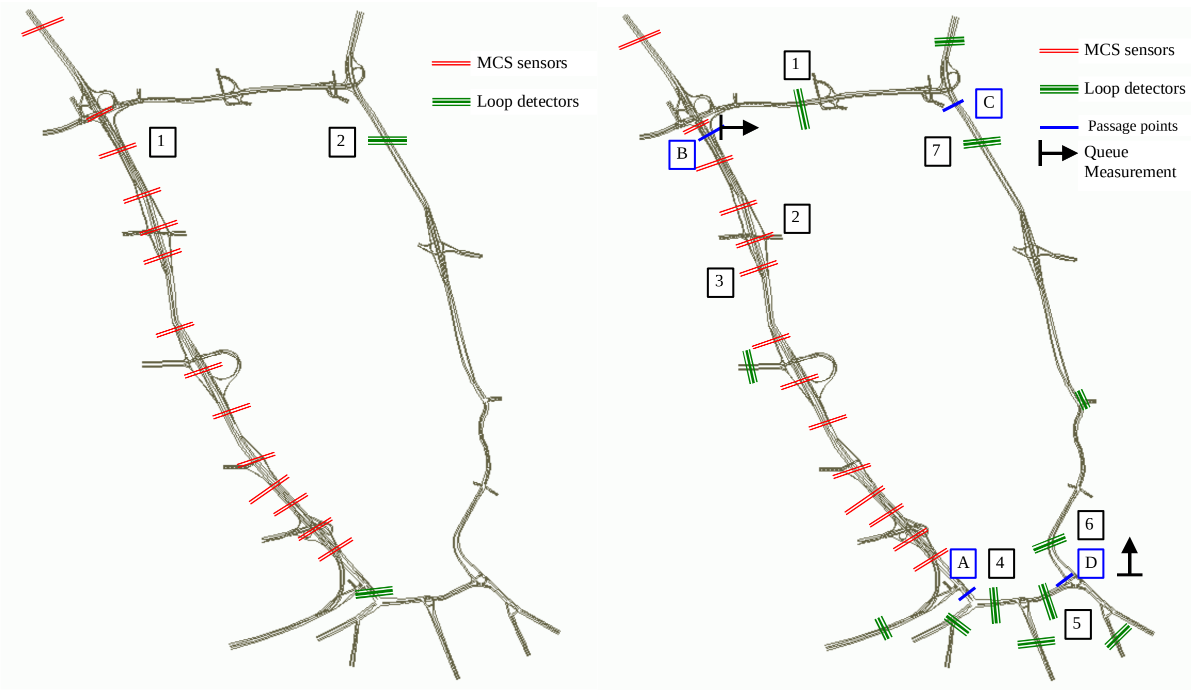


FIGURE 1 The Brunnsviken network



(a) May 1999

(b) May 2000

FIGURE 2 Measurement locations

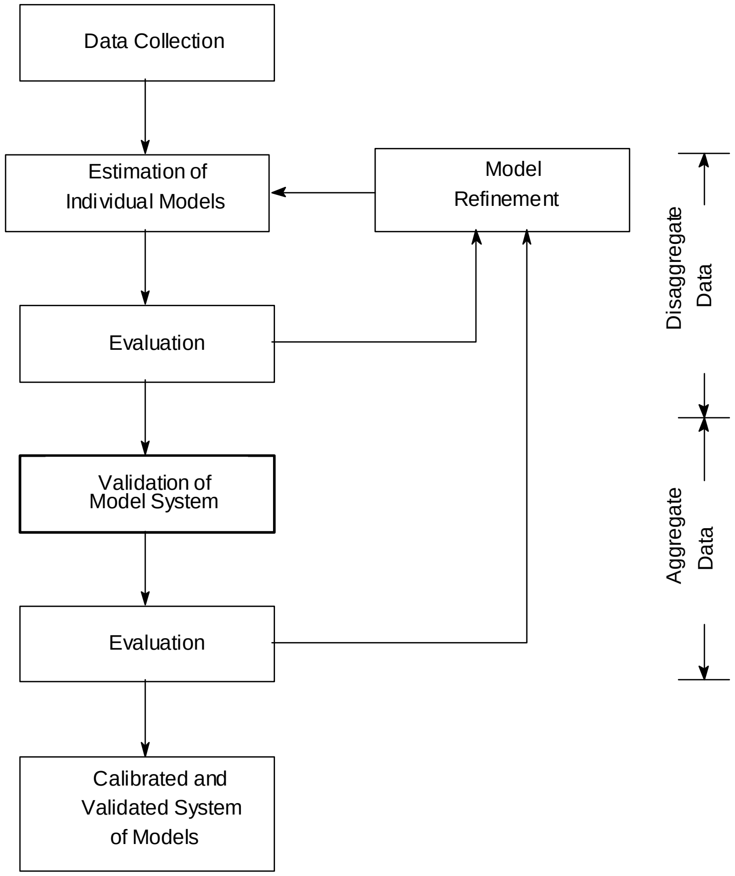


FIGURE 3 Calibration framework

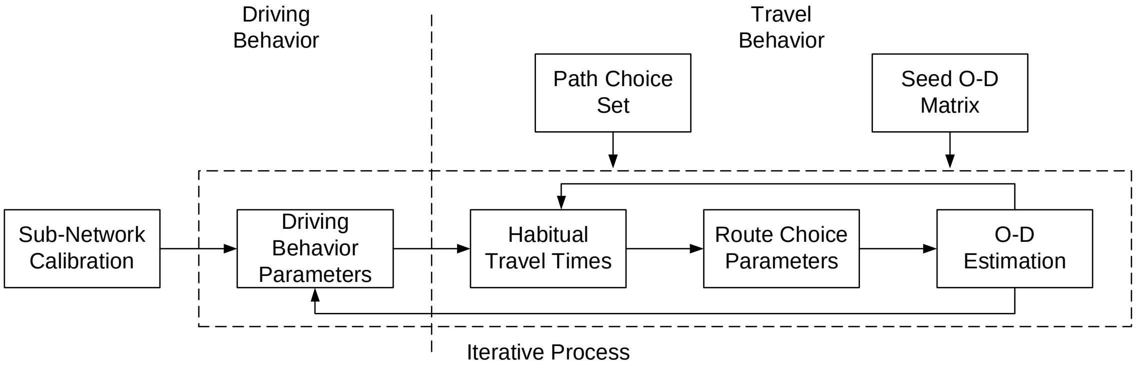


FIGURE 4 Methodology for aggregate calibration of traffic simulation models

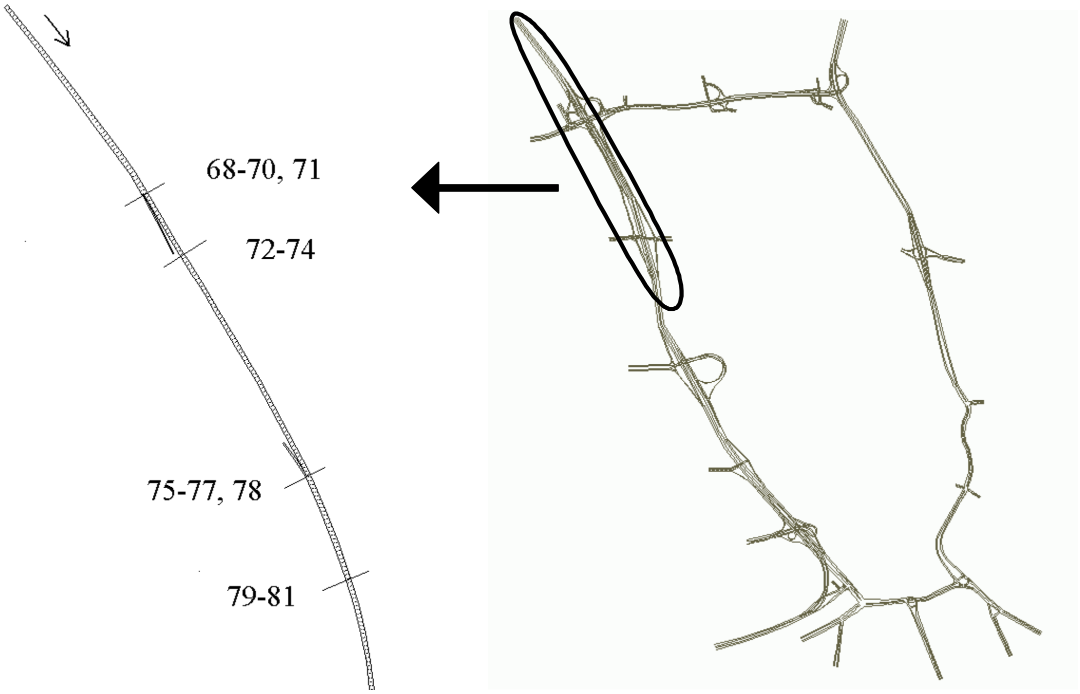


FIGURE 5 Location and details of the calibration sub-network

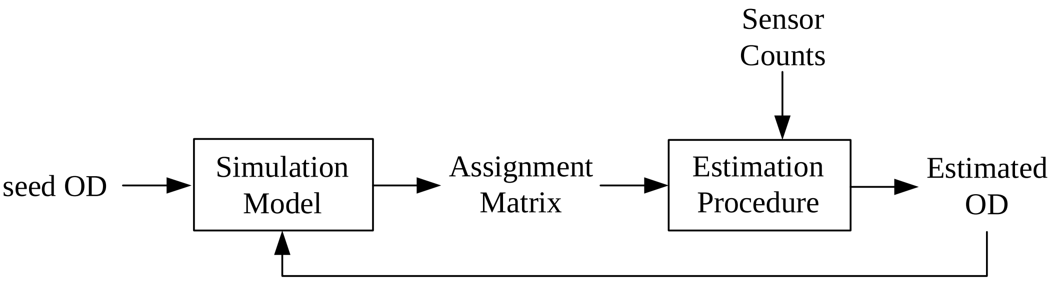


FIGURE 6 OD estimation process

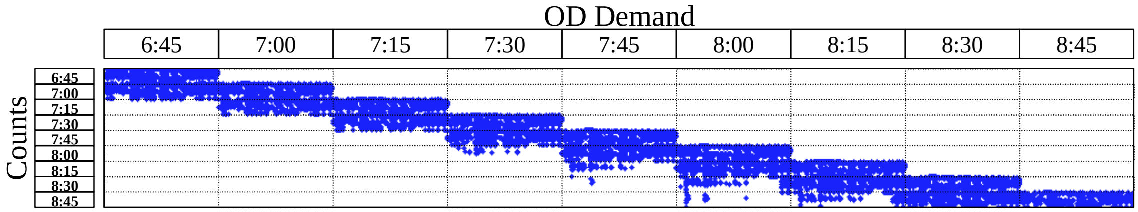


FIGURE 7 An assignment matrix

FIGURE 8 Comparison of observed and simulated flows at sensor locations

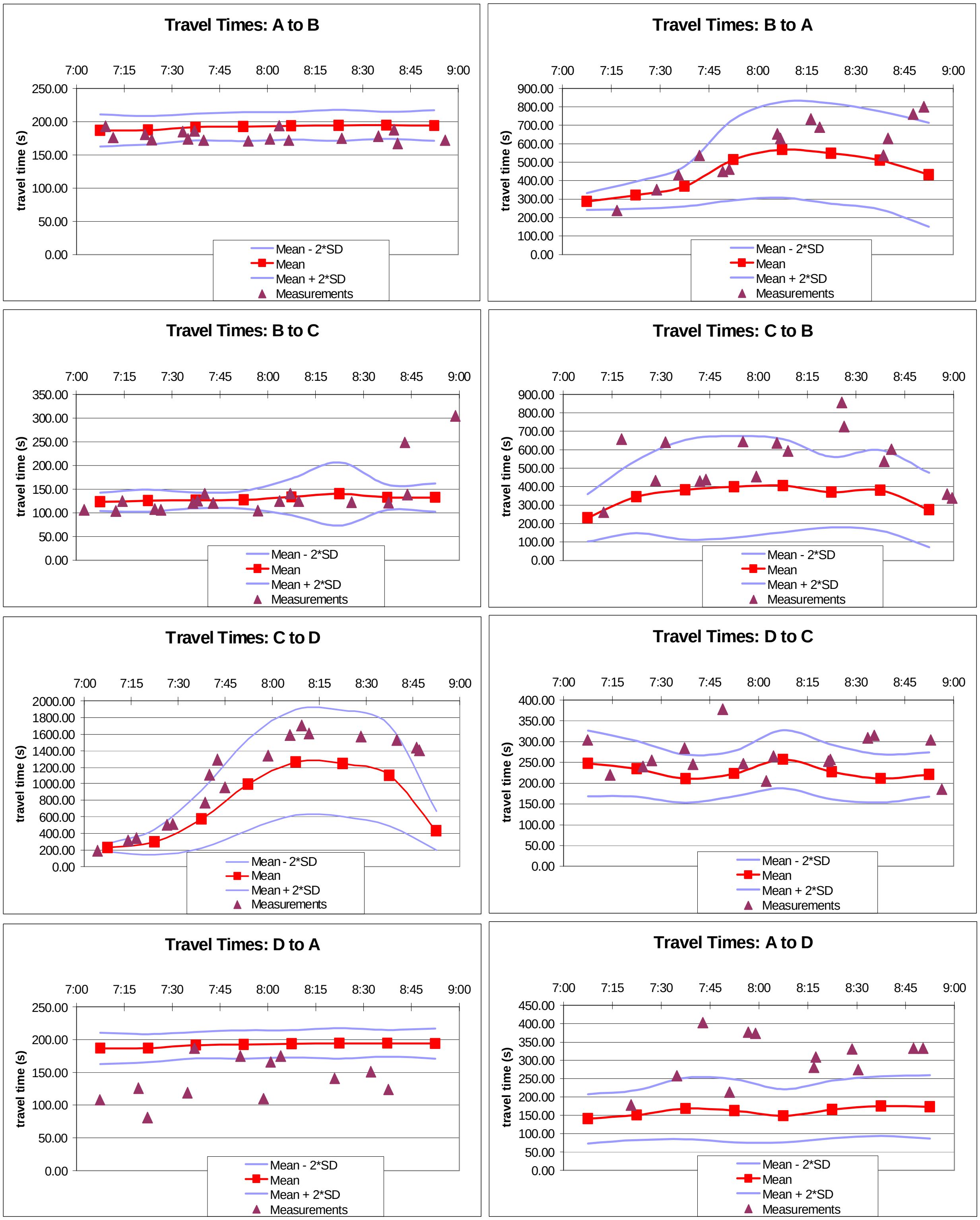


FIGURE 9 Comparison of observed and simulated point-to-point travel times

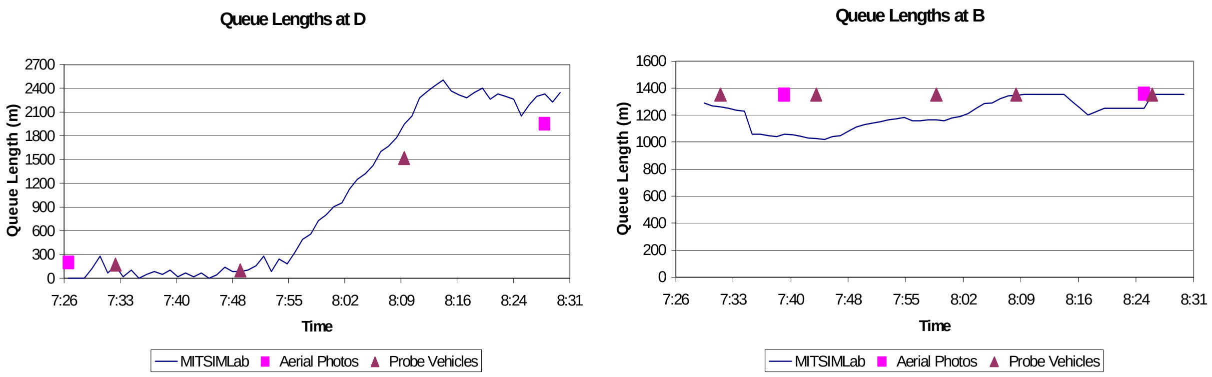


FIGURE 10 Comparison of observed and simulated queue lengths

TABLE 1 Vehicle mix data

Vehicle Type	Fraction
Autos	0.81
Taxis	0.10
Buses	0.06
Heavy Trucks	0.03