Development and Calibration of a Large-Scale Microscopic Traffic Simulation Model

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The development and the calibration of a microscopic traffic simulation model, using MITSIMLab, for the entire metropolitan area of Des Moines, Iowa, are presented. The primary contributions include the application of a microscopic model on such a large-scale network and an effort for joint calibration of the model parameters and estimation of origin–destination flows. The application of microscopic traffic simulation models to very large networks such as this poses a number of methodological and practical challenges that are not faced with smaller applications. Solutions to these problems are both heuristic and analytical. The solutions presented are generic and hence applicable to any large-scale microscopic traffic modeling.

Microscopic traffic simulation models have drawn significant attention from both practitioners and academicians in recent years. However, their applications are limited to small to medium-sized networks. Furthermore, the calibration of the simulation model is limited to ad hoc changes in a few driving parameters to match field conditions. Although such calibration methods often result in satisfactory performance for small networks, a much more thorough calibration that includes both estimation of origin–destination (O-D) flows and route choice and driving behavior parameters is needed for large-scale applications. This paper presents the development and calibration of a large-scale microscopic traffic simulation model using MITSIMLab (*1, 2*) for the metropolitan area of Des Moines, Iowa, and derives insights from this application.

Simulation models have been applied to perform operational analysis of highways for a number of decades. However, their application to complex networks is fairly recent. With the development of new traffic simulation models such as AIMSUN (*3*), MITSIMLab, PARAMICS (*4*), and VISSIM (*5*), it is now possible to simulate increasingly larger networks with complex scenarios that involve intelligent transportation system (ITS) elements, incident scenarios, highway construction, and such. Even though the simulation of large networks is similar to that of small ones at the abstract level, it poses a number of practical (and sometime theoretical) difficulties concerning the development and calibration of such models. Some of these difficulties have not been addressed in the literature so far and are therefore a significant obstacle to the application of microscopic traffic simulation models to large-scale networks.

Researchers have long been concentrating their efforts toward the calibration of microscopic simulation tools to match the field conditions. Most studies have focused on either parameter calibration or O-D estimation, but not both. Some of the methodologies adopted for calibrating parameters include simple search techniques (*6*), genetic algorithms (*7, 8*), and a simplex-based approach (*9*). Approaches that have been adopted for O-D estimation include generalized least squares (GLS) (*10, 11*), maximum likelihood (*12, 13*), and entropy maximization or information minimization (*14*).

It is only recently that O-D estimation and parameter calibration are being done jointly. Liu and Fricker (*15*) sequentially estimate O-D flows and route choice parameters for uncongested networks by first fixing route choice parameters and estimating O-D flows and then using the estimated O-D flows as inputs to estimate the route choice parameters. Toledo et al. (*16*) propose an iterative approach to calibrate model parameters jointly and estimate O-D flows with aggregate data and apply the method to calibrate MITSIMLab for a test network in Stockholm, Sweden, under congested traffic conditions. This approach is also applied in Darda (*17*) for a network in Irvine, California.

The rest of this paper is organized as follows: the next section describes the project and input development followed by a brief description of our methodology for calibration and O-D estimation. Practical challenges that were faced in the development and calibration of large-scale models are described next, followed by presentation of calibration and validation results. Finally, we provide some concluding remarks concerning the future applications of such models.

PROJECT DESCRIPTION

The Des Moines Area Metropolitan Planning Organization (MPO) and Iowa Department of Transportation (DOT) jointly decided to develop a large-scale microscopic traffic simulation model using MITSIMLab for the entire Des Moines area. This model is intended to complement the existing regional planning model and would enable the agencies to perform detailed operational analyses of traffic ranging from studying the impact of a planned reconstruction project that would cause significant route diversions to evacuation planning. Traditionally, only regional models are used for both short- and long-term policy decisions. In the immediate application the

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MITSIMLab model is used to evaluate the impact of various construction staging scenarios and devise traffic management plans for the I-235 reconstruction.

The Des Moines area network consists of approximately 200 mi^2 of various types of roads including freeway, principal arterials, and other major roads. The scope of the network is shown in Figure 1. The network consists of three major freeways: I-35, I-80, and I-235. I-235 traverses through the downtown area and connects the two major interchanges between I-35 and I-80 in the northeast and southwest corners of the network. The two interchanges are commonly known as NE and SW Mixmasters because of the complex connections among the three freeways. I-35 and I-80 merge in the area between the Mixmasters and act as a bypass for traffic passing through the metropolitan area. The freeway network includes approximately 35 interchanges of various configurations. In addition to the freeways, all other major roads shown in Figure 1 have been included in the model. In total the Des Moines model consists of 1,479 nodes, 3,756 links, 5,479 segments (a segment is a part of a link with uniform geometric properties), 10,657 lanes, 1,979 sensors, and traffic signals at about 250 intersections. The total roadway within the network is approximately 2,500 lane-miles. To the best of our knowledge, this is the largest network that has been modeled in a microscopic simulation model to date.

MODEL DEVELOPMENT

This section describes the development of the simulation model and discusses some of the practical approaches to problems that arise with the large-scale application.

Network Development

Development of a simulation model at this scale requires procedures to automate the network preparation phase, which is otherwise prohibitively expensive and time consuming. In this study various sources were utilized to obtain network information. The most useful source of network information is the regional planning model maintained by the MPO. The basic network database for the MITSIMLab model was directly imported from this model. Additional information that was not included in the planning model, such as the number of

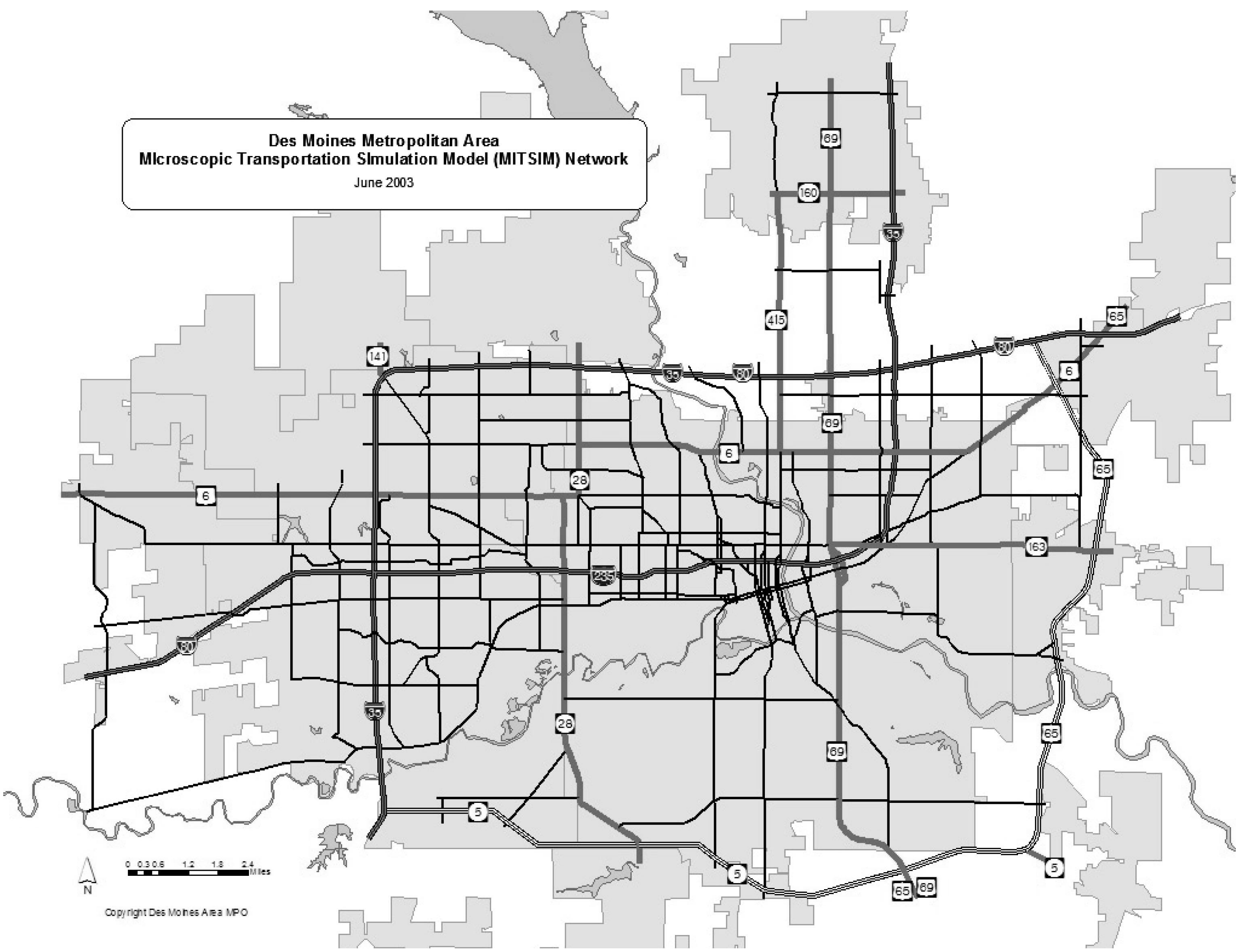


FIGURE 1 Des Moines area network.

lanes and detailed representations of intersections and interchanges, were supplemented from the Iowa state geographic information system (GIS) database. Design details, such as locations, lengths, and configurations of turning lanes, were extracted from design drawings and available aerial photographs. Locations of the surveillance and control devices and the specifications of their operation were obtained in a similar fashion. The MITSIMLab graphical network editor was used to edit the corresponding properties of lanes, segments, links, signals, and sensors.

Travel Demand

Travel demand is input into MITSIMLab, as well as most other traffic simulation models, in the form of time-dependent O-D flows. However, accurate estimates of these flows were not readily available. Therefore, O-D matrices were estimated as part of the model calibration effort, which is described in the next section. The O-D estimation process requires as input a seed O-D matrix, which represents prior beliefs on the structure of O-D flows. In this study, the seed O-D matrix was derived from the existing planning model. However, planning models are static and often provide only daily O-D flows. This poses a significant challenge in making the derived O-D flows useful for simulation studies. The authors provide a brief overview of the issues involved and our approach to solve them.

The planning model for Des Moines metropolitan area consists of about 400 traffic analysis zones (TAZs) that translate to approximately 150,000 O-D pairs. An interesting observation regarding the number of O-D pairs is that more than 80% of the O-D pairs have a volume of less than 1 vehicle per hour. A significant number of O-D pairs have volumes that are less than 0.1 vehicle per hour. While this property does not pose a problem in planning models because the flow is a continuous variable, it has serious implications for simulation models, which utilize discrete vehicles and interpret these volumes as a probability of making trips. For example, 0.1 vehicle per hour would indicate one trip in 10 days (or 10 simulation runs). The simulation model applies time-dependent O-D flows, at 15-min intervals in this case. Therefore, a demand of 0.1 vehicle per hour during a particular time interval would translate to one trip per 15-min period in 40 time intervals (and hence on average 40 simulation replications would be needed to realize this demand). It is also worth mentioning here that O-D pairs with less than 1 vehicle per hour contributed to approximately 15% of the total demand in the network. Thus we could not simply remove them without creating significant underestimation of demand.

Clearly, an aggregation was needed in order to create O-D matrices that would not have unrealistically low volumes. For that purpose, a number of TAZs were combined to form "super zones." The number of trips from each TAZ to destination super zones was calculated by adding up the vehicles that originated from that TAZ and had destinations in one of the nodes within the super zone. Then, origin and destination nodes were assigned within the respective super zones for each O-D pair. The zone aggregation was performed only on those O-Ds that had demand levels of less than 1 vehicle per hour. O-D matrices that were obtained after aggregation do not include any demands that are less than a unit. Even though the smallest entries in the O-D matrix were a unit, this still translated to 0.25 vehicle per 15-min interval. Therefore, multiple replications were still required to realize the demand and generate assignment matrices, as is discussed in the next section. This effort was performed for both the a.m. and p.m. peak periods. The two static seed O-D matrices that were generated include around 19,000 and 21,000 O-D pairs, respectively.

Signal Data

The study area includes approximately 250 signalized intersections. The controllers are actuated in about 200 of these. The other 50 are fixed-time signals. While coding them in a microscopic model is just time consuming, obtaining all the relevant data is tedious and involves significant agency coordination. Signals are typically controlled and operated by the local city or county. The number of agencies with jurisdictions in the area covered by such a large model can be significant. For example, the Des Moines area consists of 20 counties. Thus the project team had to contact a large number of individuals in various counties to obtain the signal data. Furthermore, these agencies do not follow a common approach for the implementation of actuated signal control algorithms. In brief, signal data, which are widely believed to be readily available, are perhaps one of the most difficult data sets to obtain for microscopic model development.

CALIBRATION AND O-D ESTIMATION

In addition to the difficulties in developing the model, calibration of a microscopic traffic simulation model for this size of network with various kinds of roads, signals, and other controls poses significant problems that are not realized in small-scale networks. Some critical issues in the model calibration include route choice modeling, obtaining historical travel time estimates, and estimation of time-dependent O-D flows. In this study the process of jointly estimating time-dependent O-D flows and calibrating behavior parameters was automated. This automatic calibration process used the available 15-min sensor data. A naïve calibration approach, based on trial and error, could not be applied for a network of this magnitude. This section presents the calibration approach and results.

Calibration Methodology

The parameters and inputs to be calibrated include four elements: parameters of the driving behavior models (i.e., acceleration, lane changing, etc.), parameters of the route choice model, O-D flows, and habitual travel times (which are used as explanatory variables in the route choice model). Ideally, all these should be calibrated jointly. However, the scale of the problem and the computational time implications led us to calibrate driving behavior parameters separately from the others. For the other parameters, an iterative approach in which one group of parameters is calibrated while others remain fixed was used.

First, driving behavior parameters were calibrated with a single freeway section on I-235 westbound. This section was selected such that the O-D matrix for this section could be inferred directly from available sensor counts and there was no route choice for the vehicles within this small section. This approach allowed us to reduce errors from estimating O-D flows and eliminate the effect of route choices. Thus the impact of driving behavior on the performance of the simulation could be isolated and calibrated separately.

Once driving behavior parameters were calibrated for the specified freeway section, their values were fixed, and the iterative process to jointly calibrate route choice parameters and estimate O-D flows and habitual travel times was performed. This process can be succinctly described as follows:

1. Set the seed O-D flows and the initial route choice parameters as the current estimates of O-D flows and route choice parameters, respectively.
2. Use the current estimate of O-D flows and route choice parameters to calculate habitual travel times.
3. Generate an assignment matrix, which maps O-D flows to sensor counts.
4. Use the assignment matrix to obtain new estimates of the O-D flows.
5. Recalibrate route choice parameters using the habitual travel times calculated in Step 2 and O-D flows estimated in Step 4.
6. Check convergence, based on the magnitude of change in the route choice parameters, O-D flows, and habitual travel times from previous estimates. If convergence is achieved, stop; otherwise, go back to Step 2.

A detailed discussion of this approach is given in Toledo et al. (*16*). Equilibrium travel times were generated through an iterative process, which estimates habitual travel times as a weighted average of a sequence of experienced travel times.

$$TT_{it}^{\mathrm{hab},k+1} = \lambda^k TT_{it}^{\mathrm{exp},k} + (1-\lambda^k) TT_{it}^{\mathrm{hab},k} \quad (1)$$

where $TT_{it}^{\mathrm{hab},k}$ and $TT_{it}^{\mathrm{exp},k}$ are the habitual and experienced travel times on link i at time period t on iteration k, respectively; and λ^k is a weight parameter ($0 < \lambda^k < 1$). A constant value of 0.8 was used in this study.

The calculation of habitual travel times is the most time-consuming component in the entire calibration process. In the case of large networks, it is likely that unrealistic congestion in some parts of the network will occur during these iterations. Using the experienced link travel times that will be generated to estimate habitual travel times may lead to overcompensation that would shift significant flows to other paths in the next iteration and cause congestion of these paths. Therefore, a large number of iterations would be required to obtain the equilibrium travel times, which would be achieved when the difference between experienced travel times and habitual travel times (maximum over all the links and time periods) is below a predefined criterion. In order to make the process more efficient, there is a need to adopt heuristic mechanisms to bound the values of experienced (and habitual) travel times. From the travel time data available, it was observed that it was realistic to bound experienced travel times such that they were not more than five times the free-flow travel times:

$$TT_{it}^{\mathrm{hab},k+1} = \lambda^k \min\left(TT_{it}^{\mathrm{exp},k}, 5TT_{it}^{ff}\right) + (1-\lambda^k) TT_{it}^{\mathrm{hab},k} \quad (2)$$

where TT_{it}^{ff} is the free-flow travel time on link i at time period t.

O-D Estimation

The O-D estimation in this study was performed with the GLS formulation (*10*), to minimize a weighted function of the deviations between estimated and observed traffic counts and between the estimated O-D flows and seed O-D flows. The GLS formulation is given by

$$\min_{X \geq 0} (AX - Y^{\mathrm{obs}})^T W^{-1} (AX - Y^{\mathrm{obs}}) + (X - OD^o)^T V^{-1} (X - OD^o) \quad (3)$$

where

Y^{obs} = vector of observed traffic counts at sensor locations,
A = assignment matrix that maps O-D flows to counts at sensor locations,
OD^o = seed (a priori) O-D matrix, and
W and V = variance–covariance matrices of sensor counts and O-D flows, respectively. For a given seed O-D and weights for sensor, the problem has a unique solution.

The assignment matrix is not directly observable and so has to be estimated from the simulation model itself. A significant number of the O-D flows in this large network have a very small demand for a 15-min interval. Therefore, an assignment matrix calculated from a single realization would not reflect the path choice fractions. In order to reduce the effect of the simulation stochasticity, an average assignment matrix calculated from five replications was used for O-D estimation.

The size of the O-D flow matrix raised a computational difficulty. In this case, the p.m. O-D matrix included 20,953 O-D pairs, which were estimated for four 15-min intervals with data for three 15-min peak period intervals at 404 sensors. Estimation of O-D flows for the additional interval at the beginning of the peak hour (the first time interval) was necessary to capture the contribution of O-D flows from previous time intervals on traffic counts rather than assume that the network is initially empty. Although simultaneous estimation of all O-D flows across all time periods was desirable, it was computationally intensive and perhaps infeasible to estimate 83,812 O-D flows using standard equipment. But, it was clear that the O-D flows from each period would have contributed significantly toward traffic counts for subsequent periods. Thus sequential estimation could not be applied directly as the authors had to estimate O-D flows for four time intervals to match sensor counts of three intervals. Therefore, the authors estimated O-D flows for the first two time intervals simultaneously. For the other time intervals, sequential estimation was used after subtracting the contributions of O-D flows from previous time intervals from the sensor counts in the third and fourth time intervals.

CHALLENGES IN LARGE-SCALE TRAFFIC SIMULATION

Development of a large-scale microscopic traffic simulation model poses a number of practical challenges. The following sections present some of these issues and discuss approaches to address them and the limitations associated with these approaches.

Data Collection

The development, calibration, and validation of large-scale microscopic traffic simulation models require considerable amount of detailed data. There are two types of problems associated with the data collection. The first is that data collection at this scale is tedious and requires significant amount of time and agency coordination. Clearly, obtaining and coding the network configuration, signal locations, and timings fall into this category. Another type of problem is related to the unavoidable inaccuracy, uncertainty, and lack of coverage within the available traffic data, such as speed, count, and travel time measurements. Although these problems are confronted in almost all traffic simulation studies, their impact may be more serious for large-scale networks. For example, the available data may be collected by various agencies at different times with different equipment and methods. These uncoordinated efforts may give rise to temporal inconsistencies. In this study, the authors were generally able to avoid this problem by using data from a comprehensive data collection program by Iowa DOT.

Computational Requirements and Problem Size

Microscopic traffic simulation models are widely perceived to be computationally intensive to the extent that many researchers believe that they are not applicable to large-scale networks. This study clearly demonstrated that this was not necessarily true. The authors performed the simulation runs on a P4 laptop with 512 MB memory and a processor speed of 1.8 GHz. While the authors did not perform a detailed analysis for CPU use, it took approximately 90 min to simulate traffic for 75 min. Thus the time required for model run is by no means prohibitive. However, the computational requirement for calibration of the model is a more relevant problem than that for performing the model runs and requires special attention. In this study, approximately 300 simulation runs, which translated to 450 hours, were required for the calibration. The reason for this significant effort was in the comprehensive calibration framework. A complete iteration that included several runs to calculate habitual travel times, generation of an average assignment matrix from a few simulation runs, O-D estimation, and calibration of route choice parameters required about 25 replications. A total of 12 iterations for a.m. and 15 iterations for p.m. were performed to obtain the final results.

Conversion of Planning O-D to Simulation O-D

Almost all simulation studies derive their demand data from planning models. The conversion of planning O-D flows to dynamic O-D matrices poses several challenges. A number of theoretical issues involved in the conversion have been discussed elsewhere and therefore the authors focus on practical aspects of this problem in the context of large-scale models. As discussed previously, planning O-D matrices must be aggregated in order to be useful for simulation models. Thus the number of trips from an origin (or to a destination) is higher in the simulation model compared to that in the corresponding planning model. Furthermore, unlike planning models, simulation models incorporate hard capacity constraints at links and loaders. This may give rise to problems in network loading. The number of vehicles from an origin is often so high that it is impossible to load all of them on the network, which results in unrealistic spillbacks at the centroids. These spillbacks negatively impact route assignment and the results of O-D estimation. A detailed discussion of the implications of this spillback is beyond the scope of this paper. However, the authors found that a successful conversion of planning O-D flows to simulation O-D matrices required applying heuristic rules that would avoid unrealistic spillbacks. The heuristics included appropriately aggregating centroids, ignoring sensor data located close to the centroids, and imposing constraints that would have prohibited O-D estimation algorithms to increase from such origins.

Impact of Small Errors

Microscopic traffic simulation models are unforgiving. For example, a simple error in signal coding could have detrimental impacts on the route assignment for the entire network and through that affect the course of the calibration. The impact of such small errors is exponentially magnified in large networks resulting in significant additional effort in calibration. In this respect, unrealistic spillbacks have similar impacts to coding errors. Clearly, efforts should be made to make the model free of such errors before running it in the automated fashion. A simple approach to achieve this objective is to first visually inspect the model results to ensure that traffic behavior is reasonable.

RESULTS

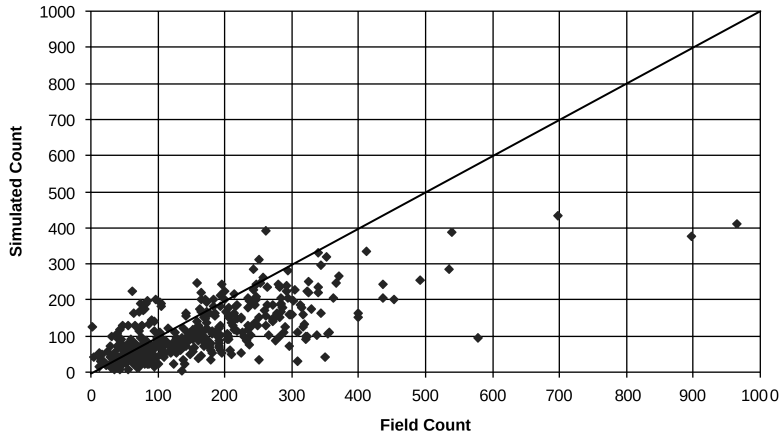
Calibration Results

As mentioned previously, 15-min data were available at 404 sensor locations for calibration. These data were collected over a period of 5 weeks on Tuesdays, Wednesdays, and Thursdays. The average count data over the 15 days were used for calibration. In addition, travel time data that were collected using floating cars were available for 1 week. Three trips were made each day during the peak period for 3 days. The available travel time data are an average of nine observations. The travel times for individual trips were not available. These data were used for validation of the calibrated model.

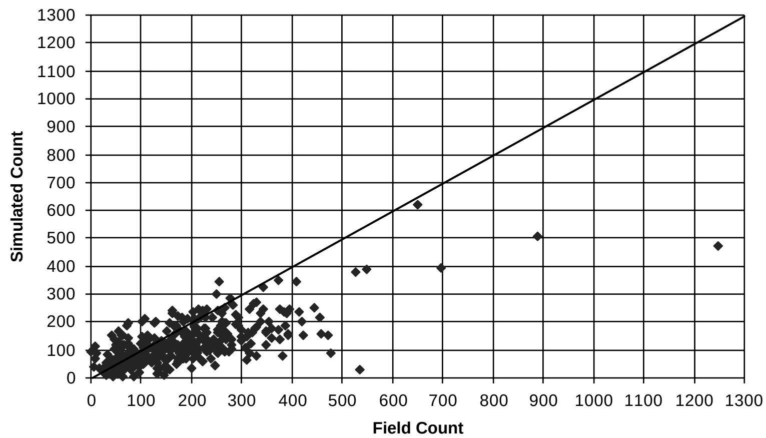
Time-dependent traffic flows in the Des Moines area showed that the morning and afternoon peak periods were between 7:30 and 8:15 a.m. and 4:30 and 5:15 p.m., respectively. In order to allow an initial warm-up period and a dissipation period at the end of the simulation run it was decided to perform the simulation runs for peak periods of 75 min between 7:15 and 8:30 a.m. and 4:15 and 5:30 p.m.

The authors compared 15-min count data at the 404 sensor locations before and after O-D estimation for three time intervals. The calibration results are presented for both the a.m. and p.m. peak. Figures 2 and 3 present the scatter plots for the a.m. peak period between 7:30 and 8:15 a.m. before and after calibration, respectively. Figures 4 and 5 present the scatter plots for the p.m. peak period between 4:30 and 5:15 p.m. Each point on these figures indicates the field count (on the *x*-axis) and simulated count (on the *y*-axis) for one sensor at the given time interval. If a straight line is drawn at a 45% angle, a perfect calibration would result in all points falling on this line. In addition, Figures 6 and 7 present histograms of the differences between field and simulated counts before and after calibration, respectively. The bins are defined by ranges of 100 vehicles. For example, all observations of differences between –50 and 50 vehicles are in the bin designated as zero. The figures show the improvements in fit induced by the calibration and O-D estimation process. The initial results generally underestimate the observed traffic counts. In the final results, approximately 90% of the total data points have an error of less than 100 vehicles.

These figures indicated that the joint calibration and O-D estimation made a significant improvement in the model fit. Errors in the field measurements inhibited further improvement of the fit. In a large network such as the Des Moines model, errors in sensor data affect the calibration of route choice parameters, habitual travel times, and O-D flows. Thus a large error in sensor data not only made it impossible for simulated count to match field count, it also affected the calibration on alternate routes. For example, University Avenue in West Des Moines served as an alternative to I-235 freeway. Field



(a)



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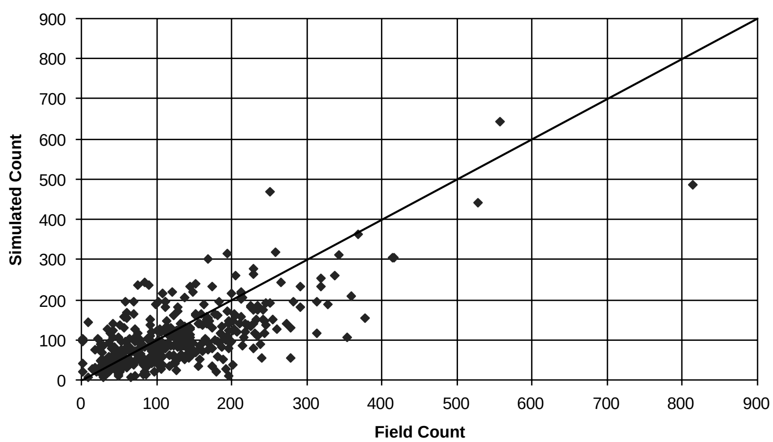

(c)

FIGURE 2 Scatter plot of field and simulated a.m. counts before calibration: (*a*) 7:30–7:45, (*b*) 7:45–8:00, and (*c*) 8:00–8:15.

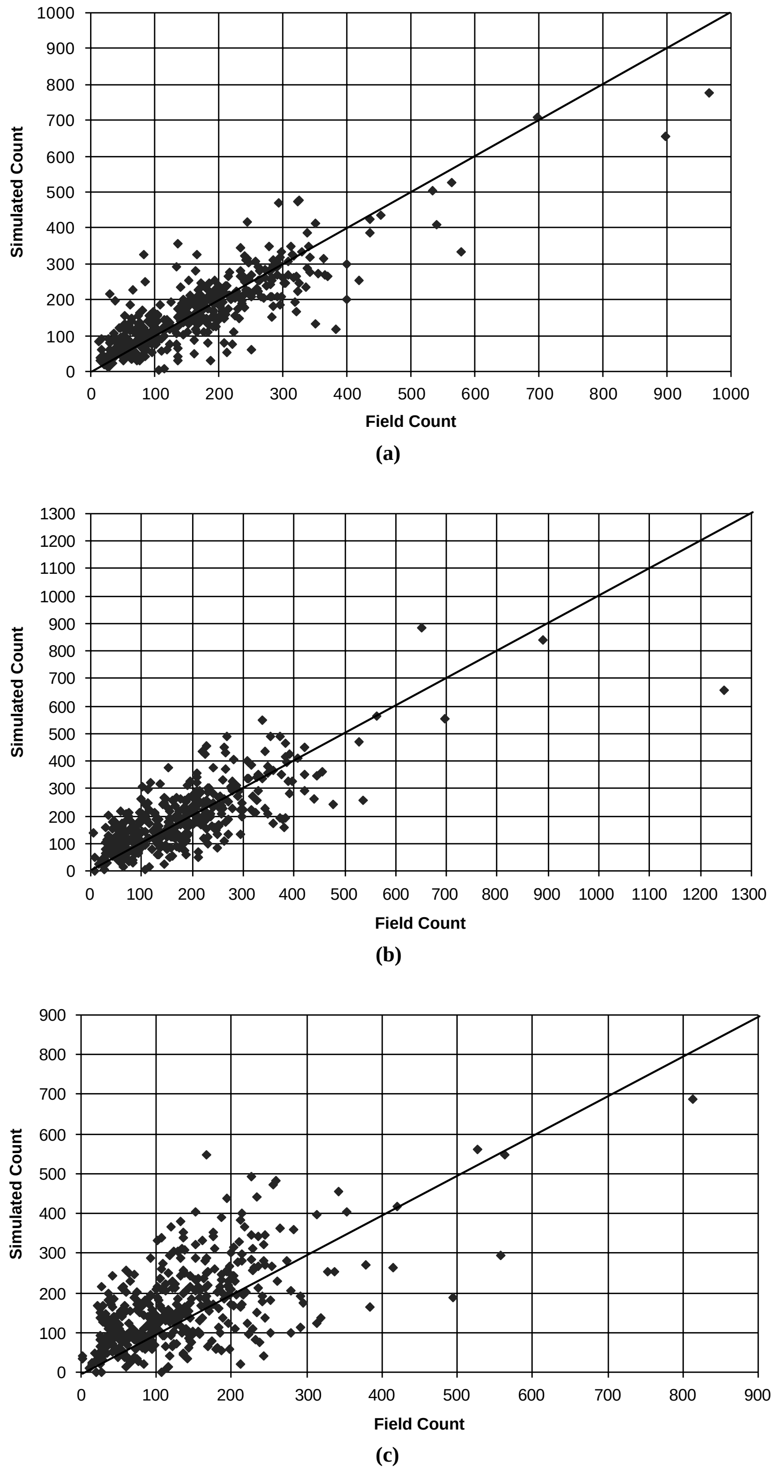

FIGURE 3 Scatter plot of field and simulated a.m. counts after calibration: (*a*) 7:30–7:45, (*b*) 7:45–8:00, and (*c*) 8:00–8:15.

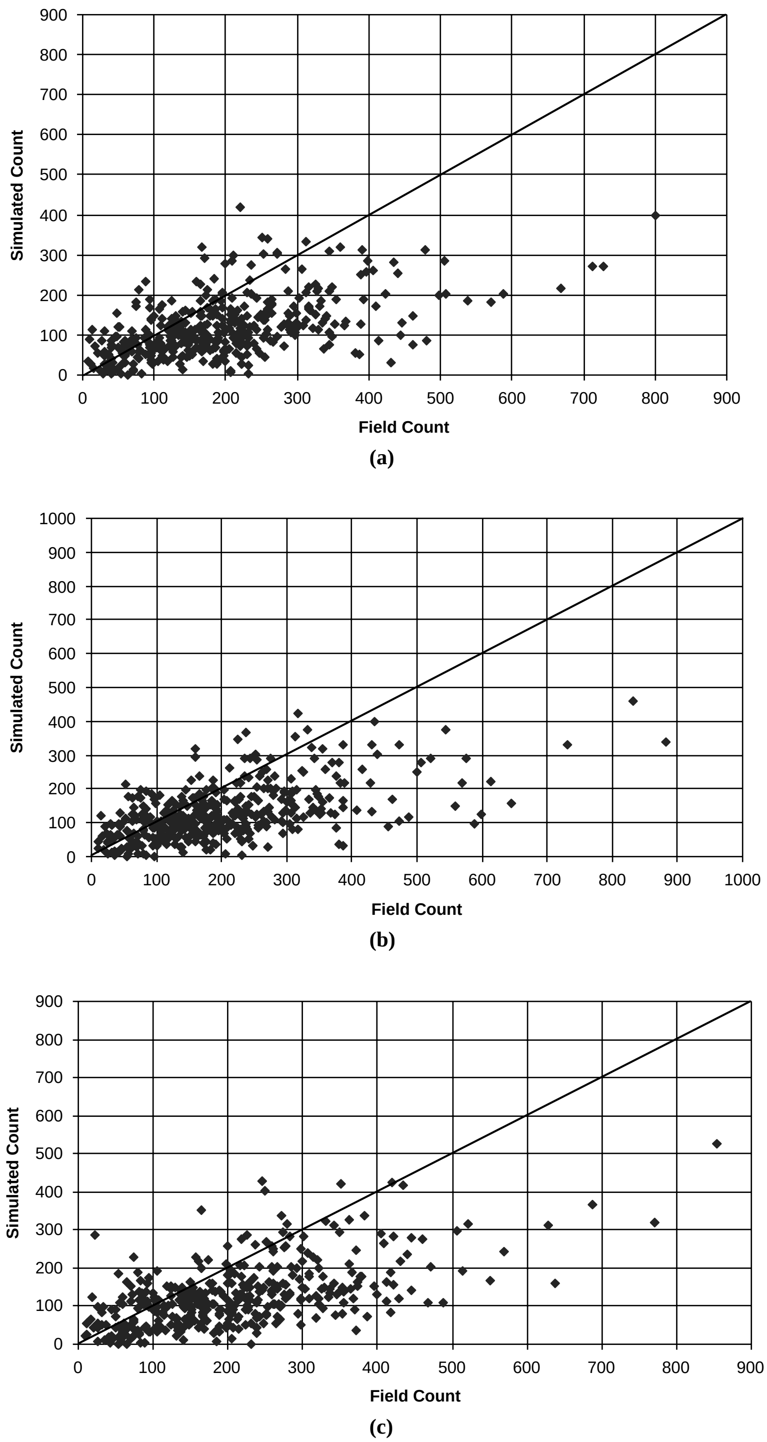

FIGURE 4 Scatter plot of field and simulated p.m. counts before calibration: (*a*) 4:30–4:45, (*b*) 4:45–5:00, and (*c*) 5:00–5:15.

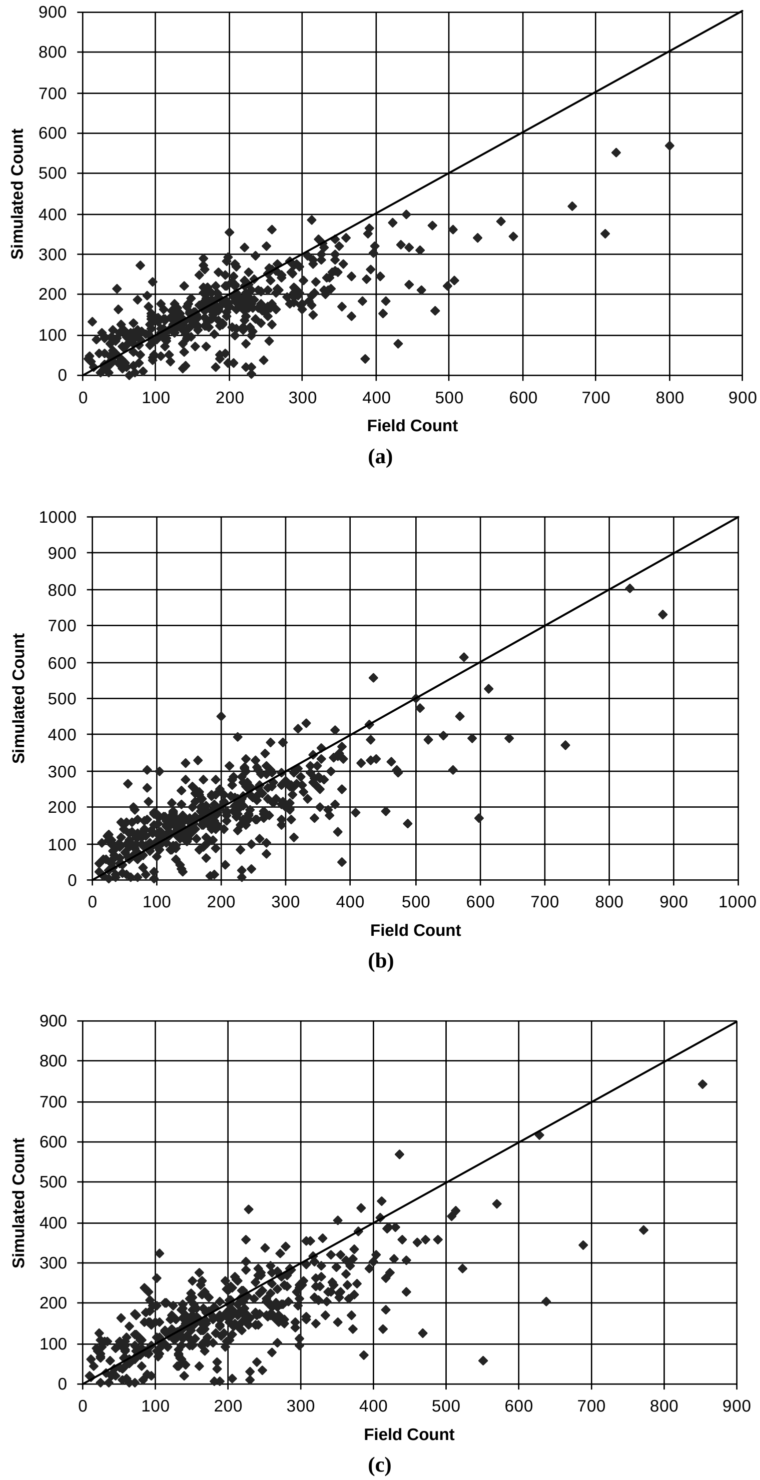

FIGURE 5 Scatter plot of field and simulated p.m. counts after calibration: (*a*) 4:30–4:45, (*b*) 4:45–5:00, and (*c*) 5:00–5:15.

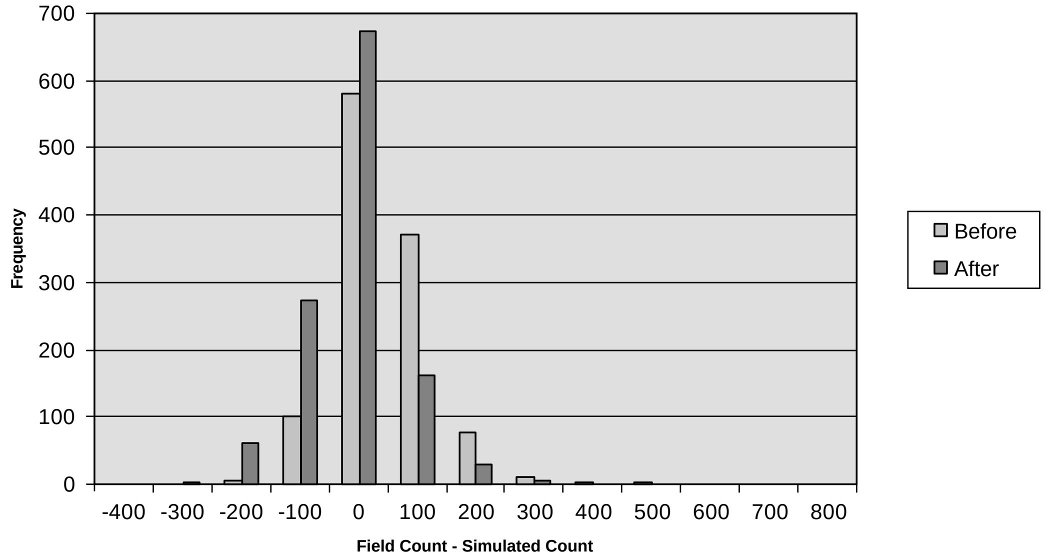

FIGURE 6 Histogram of difference between field and simulated traffic a.m. counts before and after calibration.

counts at two intersections in University Avenue were significantly biased downward. This affected both the total demand for O-D pairs that used University Avenue and the route choice parameters that determined the split between University Avenue and the I-235 alternatives. However, route choice parameters are global and so also affect other parts of the network. Although this problem poses no new theoretical issue, it has an important practical significance.

Validation

Travel times in four corridors were collected with floating cars during the a.m. peak period for validation purposes. These travel times were not used in the calibration and so formed an independent set of observations for validation. The travel time comparison, although a good validation measure, should be interpreted with caution. Simulated travel times were based on the average travel time over the entire analysis period, whereas observed travel times were the averages of nine trips made in 3 days.

The travel time comparisons for four corridors are presented in Table 1. The first corridor was the I-235 freeway from 74th Street in West Des Moines to 31st Street in Des Moines. For this corridor, the average simulated travel time of 776 s was 27 s higher than the observed average travel time. Thus the error was approximately 4%. Corridors 2, 3, and 4 followed major arterials. Compared with field observations, the simulated travel times were 13 s or 3% higher in Corridor 2, 38 s or 5% lower for Corridor 3, and 241 s or 40% higher for Corridor 4. The large difference in the last results was due to unre-

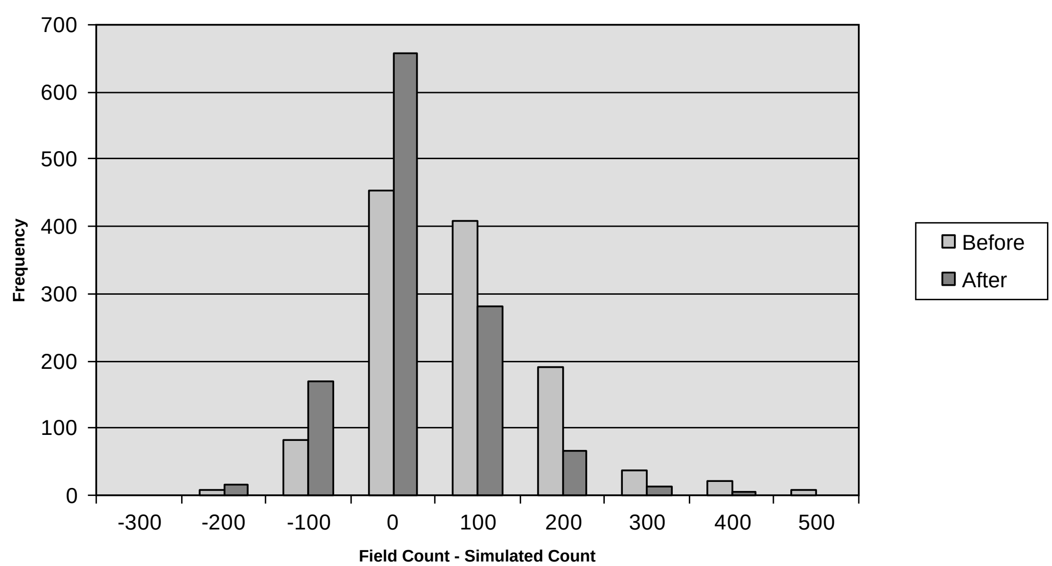

FIGURE 7 Histogram of difference between field and simulated traffic p.m. counts before and after calibration.

TABLE 1 Observed and Simulated Travel Times

	Corridor	Travel Times (sec)	
		Observed	Simulated
1	I-235, from 74th St to 31st St	749	776
2	Douglas Ave/Euclid Ave, from Beaver Ave to NE 14th St	550	563
3	Grand Ave, from EP True Pkwy to 18th St	868	830
4	86th St/22nd St, from I-35/80 to I-235	599	840

alistic congestion in MITSIMLab at one of the intersections along this corridor (Hickman Road and 86th Street). Further investigation of this intersection revealed that the count data at this intersection might have been erroneous and resulted in unrealistic congestion in MITSIMLab.

SUMMARY

This paper presented the development, calibration, and validation of a microscopic traffic simulation model for a large-scale network. The network included all major roads in the entire Des Moines metropolitan area. MITSIMLab was used for developing the model. The MITSIMLab model was one of the largest networks modeled in a microscopic simulation model to date. Joint calibration of model parameters and O-D estimation was performed. Calibration and validation results were promising. However, some obvious errors in sensor data that adversely affected the calibration results were detected. It was suggested that accuracy of sensor data should be investigated before applying the automated calibration for future applications. Although some erroneous sensor may be difficult to identify, it is still possible to identify sensor measurements that have large error, which could dramatically improve the performance of the calibration.

A significant area of research in this direction lies in empirical investigation of convergence of the calibration. Each component within the calibration module relies on some convergence criterion. The properties of convergence are not well known. Also, the impacts of various levels of aggregation, such as time intervals for habitual travel time and the O-D flows, need to be studied.

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