LARGE-SCALE MICROSCOPIC TRAFFIC SIMULATION MODELING

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Abstract

This paper presents the development and calibration of a microscopic traffic simulation model, using MITSIMLab, for the entire metropolitan area of Des Moines, IA. The primary contributions of this paper include the application of microscopic model at such a large scale network and an joint calibration and estimation of origin-to-destination (OD) flows effort. The paper demonstrates that microscopic traffic simulation of very large networks such as this poses a number of methodological and practical challenges that are not faced during small application. Solutions to these problems are both heuristic and analytical. The solutions presented in this paper are generic and hence applicable to any large-scale microscopic traffic modeling.

Keywords: Traffic simulation; Calibration; OD estimation
Topic area: D3 Integrated Supply / Demand Modeling

1. Introduction

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 size networks. Furthermore, the calibration of the simulation model is limited to ad-hoc changes in a few driving parameters to match field conditions. While such calibration methods often result in satisfactory performance for small networks, a much more thorough calibration that includes both estimation of origin to destination (OD) 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 (Yang and Koutsopoulos 1996, Yang et al. 2000) for the metropolitan area of Des Moines IA, and derive insights from this large-scale application.

Simulation models have been applied to perform operational analysis of highways for a number of decades. However, their application to complex network is fairly recent. With the development of new traffic simulation models such as AIMSUN (Barcelo et al. 1999), MITSIMLab, PARAMICS (Smith et al. 1994) and VISSIM (Fellendorf 1994), it is now possible to simulate increasingly larger networks with complex scenarios that involve 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 towards the calibration of microscopic simulation tools to match the field conditions. Most studies have focused on either parameter calibration or OD estimation, but not both. Some of the methodologies adopted for calibrating parameters include simple search techniques (Daigle et al. 1998), genetic algorithms (Abdulhai et al. 1999, Lee et al. 2001) and a simplex based approach (Kim and Rilett 2003). Some of the approaches adopted for OD estimation include generalized least squares (Cascetta et al. 1993, Bell 1991), maximum likelihood (Maher 1983, Spiess 1987) and entropy maximization or information minimization (Venzuylen and Willumsen 1980).

It is only recently that OD estimation and parameter calibration are being done jointly. Liu and Fricker (1996) sequentially estimate OD flows and route choice parameters for uncongested networks by first fixing route choice parameters and estimating OD flows and then using the estimated OD flows as inputs to estimate the route choice parameters. Toledo et al. (2003) proposed an iterative approach to jointly calibrate model parameters and estimate OD flows using aggregate data, and apply the method to calibrate MITSIMLab for a test network in Stockholm, Sweden, under congested traffic conditions. This approach was also applied by Darda (2002) using data from Irvine, California.

All the studies mentioned above were tested on networks that range from small to medium scale. However, the methods used, might not be applicable, as they are, for networks of a very large scale due to some practical issues.

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 OD estimation. Practical challenges faced in development and calibration of such a large-scale model is described next. It should be noted that the primary contribution of this paper lies in demonstrating the application of a microscopic simulation model at a very large scale. Calibration and validation results are presented next. Finally, we provide some concluding remarks concerning the future applications of such models.

2. 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 impacts of a planned reconstruction project that would cause significant route diversions to evacuation planning. Furthermore, the model will be used to support various policy decisions. Traditionally, only regional models are used for both short and long term policy decisions. In the immediate application the MITSIMLab model is used to evaluate the network level impact of various construction staging scenarios and devise work zone traffic management system for the I-235 reconstruction program.

The Des Moines area network consists of approximately 200 square miles 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 north-east and south-west corners of the network. The two interchanges are commonly known as NE and SW Mixmasters due to the complex connections among the three freeways. I-35 and I-80 merge in the area between the Mixmasters and act as a bypass freeway for through traffic. 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 1479 nodes, 3756 links, 5479 segments (a segment is a part of a link with uniform geometric properties), 10657 lanes, 1979 sensors, and traffic signals at about 250 intersections. The total lane length in this network is approximately 2,500 miles. To the best of our knowledge, this is the largest network that has been modeled in a microscopic simulation model to date.

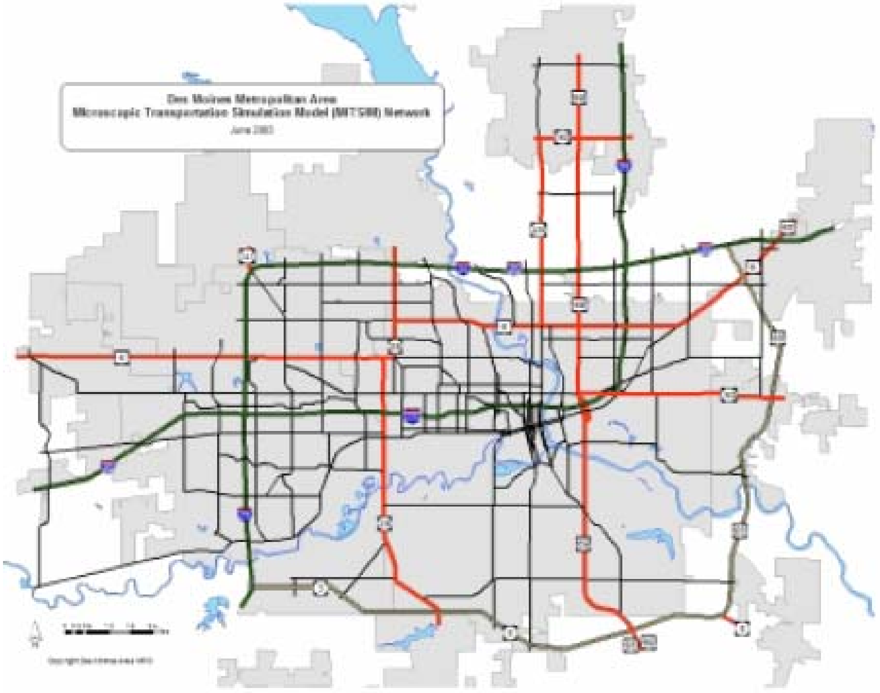

Figure 1 The Des Moines area network

3. Model development

In this section we describe the development of the simulation model and discuss some of the practical approaches to problems that arise with the large-scale application.

3.1. 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 is not included in the planning model, such as the number of lanes and detailed representations of intersections and interchanges were supplemented from the Iowa state GIS database. Design details, such as locations, lengths and configurations of turning lanes, were extracted from design drawings and available aerial photographs. Locations and specifications of the surveillance and control systems 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.

3.2. Travel demand

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

The planning model for Des Moines metropolitan area, a medium size network, consists of about 400 traffic analysis zones (TAZs) that translates to approximately 150,000 OD pairs. An interesting observation regarding the number of OD pairs in a medium to large size network is that more than 80% of the OD pairs have a volume of less than 1 vehicle per hour. A significant number of OD pairs have volumes less than 0.1 vehicles/hour. While it does not pose a problem in planning models because the flow is a continuous variable, it has serious implications for simulation model, which interpret these volumes as a probability of making trips. For example, 0.1 vehicles per hour would indicate one trip in ten days (or ten replications in simulation). As mentioned above, the simulation model applies time dependent OD flows, at 15 minutes intervals in this case. Therefore, a demand of 0.1 vehicles per hour during a particular time interval would translate to one trip per 15-minute 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 OD pairs with less than 1 vehicle per hour contributed to approximately 15% of the total demand in the network. Thus, we could not just remove them without creating significant underestimation of demand. Also, a direct conversion of planning OD to simulation OD would not be feasible.

Clearly, an aggregation was needed in order to create OD matrices that would not have unrealistically low volumes. A number of TAZs were combined to form an “area”. First, an origin to area OD matrix was developed. The number of vehicles from a TAZ to a destination “area” was calculated by adding vehicles that originated from that TAZ and had destination as one of the nodes in destination “area”. Finally, a destination node was assigned within the destination “area”. Selection of destination node was such that each node in origin “area” had a distinct destination node in destination “area”. It is worth re-mentioning here that the aggregation was performed only on those ODs that had volume of less than 1 vehicle per hour. The OD matrices that were obtained after aggregation did not have any number less than one. It is important to notice that even though the smallest number in OD matrix was one, it translated to 0.25 vehicles per 15 minutes interval. Therefore, multiple replications were still required to realize the demand and generate assignment matrices, as will be discussed in the next section. This effort resulted in a static seed OD matrix for both the AM and PM peek periods. The two matrices include around 19,000 and 21,000 OD pairs, respectively.

3.3. Signal data

The study area includes approximately 250 signialized intersections: about 200 of these are actuated and 50 are fixed time signals. While coding them in a microscopic model is an easy task, 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 counties in such a large model could 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 any common approach for the implementation of a particular actuated signal control algorithm. In brief, the signal data that are widely believed to be readily available is perhaps one of the most difficult data set to obtain for microscopic model development at this large scale.

4. Calibration and OD estimation

It is critical to note that 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 control poses significant problems that are never realized in a small-scale network. Therefore, it should be considered as a separate class of problem than small size network or more commonly corridor simulations. Some critical issues in the calibration of the network model include route choice modeling, historical travel time estimates and time-dependent OD estimation. In this study we automated the process of jointly estimating time dependent OD flows and calibrating behavior parameters. This automatic calibration process was performed on this network using 15 minutes sensor data at some 400 locations. A naive ad hoc calibration approach, based on trial and error, could not have been applied for a network of this magnitude. In this section we present the calibration approach and results.

4.1. 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, OD 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 of that scale led us to calibrate driving behavior parameters separately from the others. For the other parameters, an iterative, heuristic approach in which at each step one group of parameters are calibrated while others remain fixed to their current values is group of parameters was used.

As mentioned above, first, driving behavior parameters were calibrated using a single freeway section on I-235 westbound. This section was selected such that the OD matrix for this section could be inferred directly from the counts and also such that there was no route choice for the vehicles within this small section. This approach allowed us to reduce errors from estimating OD flows and eliminate the effect of route choices. This way, the impact of driving behavior on the performance of the simulation could be evaluated separately.

Once driving behavior parameters were calibrated to match observed traffic speeds on the specified freeway section, their values were fixed and the iterative process to jointly calibrate route choice parameters and estimate OD flows and habitual travel times was performed. This process can be described as follows:

i. Use seed OD and initial route choice parameters to calculate habitual travel times
ii. Generate an assignment matrix, which maps OD flows to sensor counts.
iii. Use the assignment matrix to OD estimate new OD flows
iv. Re-calibrate route choice parameters for the habitual travel times from (i) and OD flows from (iii)
v. Check convergence, based on changes in the route choice parameters, OD flows and habitual travel times. If convergence is achieved stop, otherwise go to step (i).

A detailed discussion of this approach is given in Toledo et al. (2003). 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:

$$TT_{it}^{hab,k+1} = \lambda^k TT_{it}^{\exp,k} + \left(1-\lambda^k\right) TT_{it}^{hab,k} \qquad (1)$$

,

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

These travel times are essential for the methodology being adopted and is also the most time consuming section in the entire process. In the case of large networks, during these iterations, it is likely that unrealistic congestion in some parts of the network will occur. Using these experienced link travel times to estimate habitual travel times would cause over-compensation in the next iteration by shifting significant flow to other paths causing congestion of these paths. Therefore, a large number of iterations would be required to obtain the equilibrium travel times. The model is applied until 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 some heuristics to bound the values of experienced (and habitual) travel times. Based on the travel time data available, it was observed that the travel time on each link is not more than five times its free flow travel time. This information has been used to bound habitual travel times:

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

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

4.2. OD estimation

The OD estimation formulation used in this study follows the GLS formulation (Cascetta et al. 1993), which seeks to minimize a weighted function of the deviations between estimated and observed traffic counts and between the estimated OD flows and seed OD flows. The GLS formulation is given by:

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

Y^{obs} is the vector of observed traffic counts at sensor locations. *A* is the assignment matrix that maps OD flows to counts at sensor locations. OD^o is the seed (a priori) OD matrix. *W* and *V* are the variance-covariance matrices of sensor counts and OD flows, respectively. It is important to note that for a given seed OD and weights for sensor, the formulation has a unique solution.

The assignment matrix is not directly observable, and therefore, has to be estimated from the simulation model itself. However, an assignment matrix obtained from a single realization of simulation cannot be used for OD estimation. This is because a significant number of the OD flows are less than 1 vehicle per 15 min. (which is the OD interval) and an assignment matrix calculated from a single realization would not reflect the path choice fractions. Therefore, and in order to reduce the effect of the simulation stochasticity, an average assignment matrix calculated from a few replications has been used for OD estimation.

The Des Moines network includes 20953 OD pairs, with three 15-minute peak hour counts for 404 sensors. The size of the O-D flow matrix raises a computational difficulty. While simultaneous estimation of all O-D flows across all time periods is desirable, the need to estimate 83812 OD flows makes it computationally intensive and perhaps infeasible on a typical PC. On the other hand, it is clear that the OD flows from the first period would contribute significantly towards the count data for the second period. Thus, sequential estimation could not be applied directly as we have to estimate OD flows for four time intervals to match sensor counts of three intervals. We estimated OD flows for the first two intervals simultaneously. For the other time intervals, sequential estimation was used because it was easy to account for contribution of 2nd and 3rd time period O-Ds towards sensor counts in the 3rd and 4th time periods, respectively

5. Challenges in large scale traffic simulation

Development of a large-scale microscopic traffic simulation model poses a number of practical challenges. We present some important ones and our approach to address them and limitations.

Data collection: It is obvious that the development, calibration and validation of large-scale microscopic traffic simulation models require a large amount of detailed data. There are two types of problems in data collection. The first is that data collection at this scale is tedious and requires significant amount of time and agency coordination. Clearly, network configuration, signal location and timings fall into this category. However, the other type of problem is related with inaccuracy, uncertainty and lack of coverage. Traffic data such as speed, count and travel times fall into this category.

While the second type of problem is almost always confronted in all simulation studies, it becomes an even bigger issue for a large-scale network. One of the major reasons for this problem that is absent from small network study stems from the fact that traffic data is collected by various agencies at different times using different devices. In other words, data collection by various agencies in their part of the network is seldom coordinated giving rise to temporal inconsistencies. Therefore, in the study decribed in this paper, it was decided to use only those data that were collected by the Iowa DOT as a part of a comprehensive data collection program.

Computational requirements and problem size: Microscopic traffic simulation models are widely perceived to be computationally intensive often to an extent that lead many researchers to believe that they are not applicable to a large scale network. This study clearly demonstrated the applicability of a microscopic simulation model to a very large network for various practical applications. We performed the simulation runs on a P4 laptop with 512 MB memory and a processor speed of 1.8GHz. While we did not perform a detailed analysis for CPU use, it took approximately 90 minutes to simulate traffic for 75 minutes. Thus, the time required for model run is by no means prohibitive. However, it is worth mentioning here that the computational requirement for calibration of such large network is much larger and requires careful attention. Our experience with this network demonstrated that computational requirement for calibration is a more relevant problem than that for the model run. While it required only 90 minutes to perform one simulation run, the total number of runs for completing the calibration was found to be approximately 300. Thus, the total computational time required for completing the calibration for one peak period is approximately 450 hours. The reason for such a significant number of runs lie in our comprehensive calibration framework. For each OD estimation, five replications were performed to generate assignment matrix. After OD estimation, five iterations were performed to obtain habitual travel times. Thus, one complete iteration that included OD estimation, habitual travel time and generation of assignment matrix required 25 replications. A total of 12 iterations for AM and 15 iterations for PM were performed to obtain the final results.

Conversion of planning OD to simulation OD: Almost all simulation studies derive their demand data from a planning model. The conversion of planning ODs to dynamic OD matrices poses several challenges. A number of theoretical issues involved in the conversion have been discussed elsewhere and therefore we focus on practical aspects of this problem in the context of a large-scale model. As mentioned above, planning ODs have to be aggregated in order to make them useful for simulation. Thus, for a given origin (or destination) the number of vehicles in the simulation model is higher than that in the corresponding planning model. Furthermore, planning models do not have a capacity constraint. The two observations, i.e., aggregation and lack of capacity constraint, give rise to a network loading problem. The number of vehicles from an origin is often so high that it is impossible to load them. This results in unrealistic spillbacks at the centroids. These spillbacks have several negative impacts on route assignment and OD re-estimation. A detailed discussion of the implications of this spillback is beyond the scope of this paper. However, we strongly believe that a successful conversion of planning OD to simulation OD requires a set of heuristics that will avoid unrealistic spillbacks. The heuristics include appropriate aggregation of centroids, ignoring sensor data that are located close to the centroids and imposing constraints that would prohibit OD estimation algorithms to increase from such origins.

Impact of small errors: Microscopic traffic simulation models are known to be *unforgiving*. For example, a simple error in signal coding could have detrimental impact on the entire network assignment and future course of calibration. The impact of such small errors is exponentially magnified in the case of very large network resulting in significant loss of time. Apart from coding errors, unrealistic spillbacks have similar impacts. 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 through visual inspection of the model run before running the iterations.

6. Results

6.1. Calibration Results

As mentioned above 15 minute data were available at 400 sensor locations for calibration. These data were collected over a period of five weeks on Tuesdays, Wednesdays and Thursdays. Thus, the average count data over fifteen days were used for calibration in this study. Furthermore, travel time data using floating cars were available for one week. Three trips were made each day during the peak period for three days. The available travel time data is an average of nine observations. We do not have travel time data for individual trip.

The peak simulation periods in simulation were between 7:15-8:30AM and 4:15-5:30PM. While peak periods for a number of large urban areas last well beyond above time periods, time dependent volume data in Des Moines area, not presented here, clearly showed that the morning and afternoon peak traffic are observed between 7:45-8:15 and 4:45-5:15, respectively. Therefore, we decided to select the duration of the peak period for simulation as 75 minutes.

We compare 15-minute count data at 400 locations for the three time intervals before and after OD estimation. The calibration results are presented for both the AM and PM peak. Figures 2 and 3 present the scatter plots for the AM peak time periods between
7:30 and 8:15. Figures 4 and 5 present the scatter plots for the PM peak time periods between 16:30 and 17:15. Each point on these figures indicates the filed count (on X axis) and simulated count (on Y axis) for a sensor for the time period. In other words, each point represent field and simulated count for one observation. If we draw a straight line at a 45% angle, a perfect

calibration would result in all points falling at this line. In addition, Figures 6 and 7 present histograms of the differences between field and simulated counts for before and after calibration. The bins are defined such that all differences between –50 and 50 vehicles fall in the bin designated as zero. The figures clearly show the improvements in fit induced by the calibration and OD estimation process. The histograms show that approximately 90% of the total data points have error of less than 100 vehicles. In general the initial values and seed OD flows gave rise to lower count than observed.

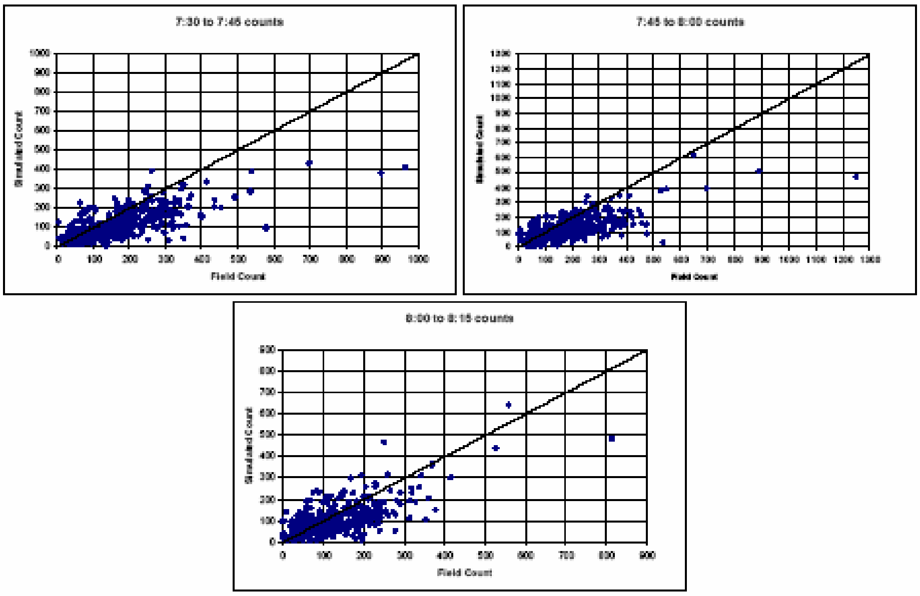

Figure 2 Scatter plot of field and simulated AM counts before calibration

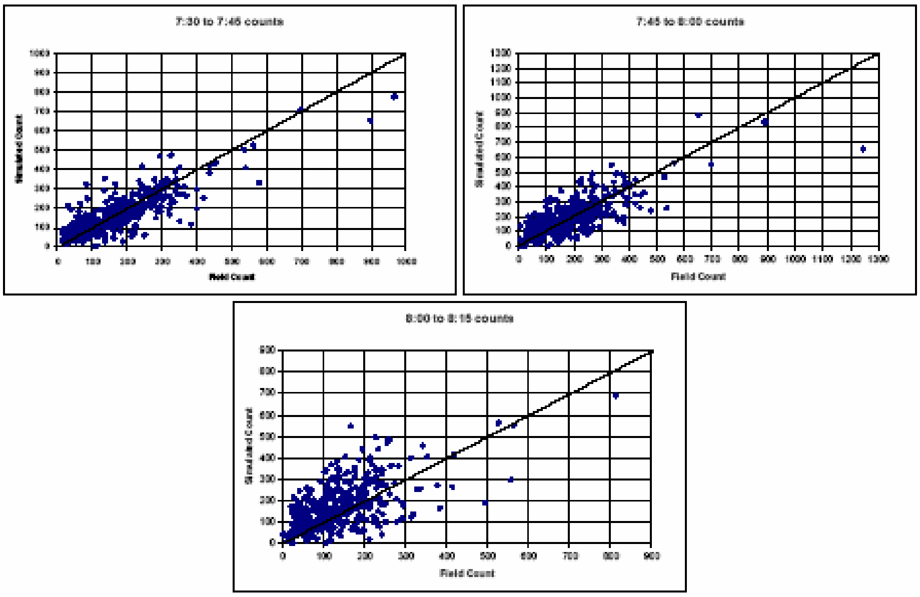

Figure 3 Scatter plot of field and simulated AM counts after calibration

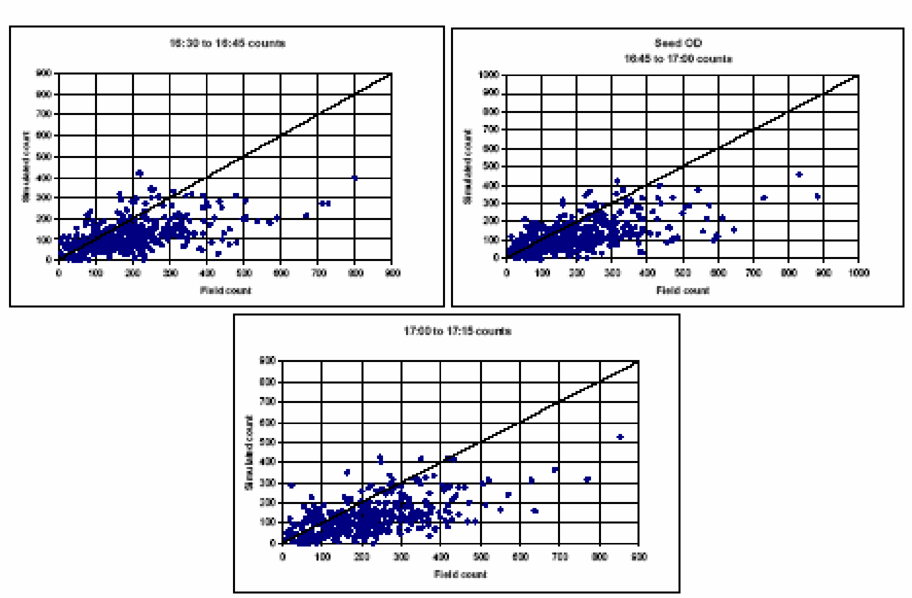

Figure 4 Scatter plot of field and simulated PM counts before calibration

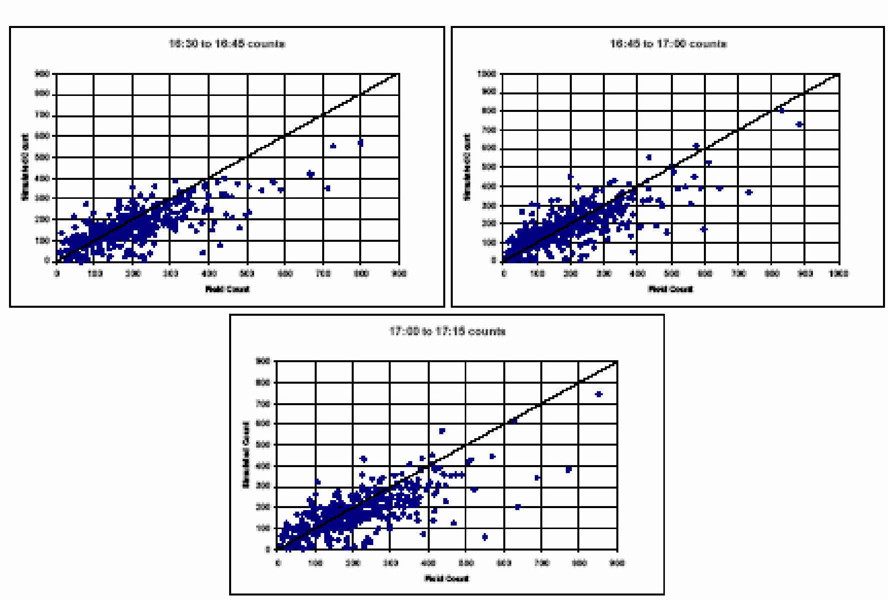

Figure 5 Scatter plot of field and simulated PM counts after calibration

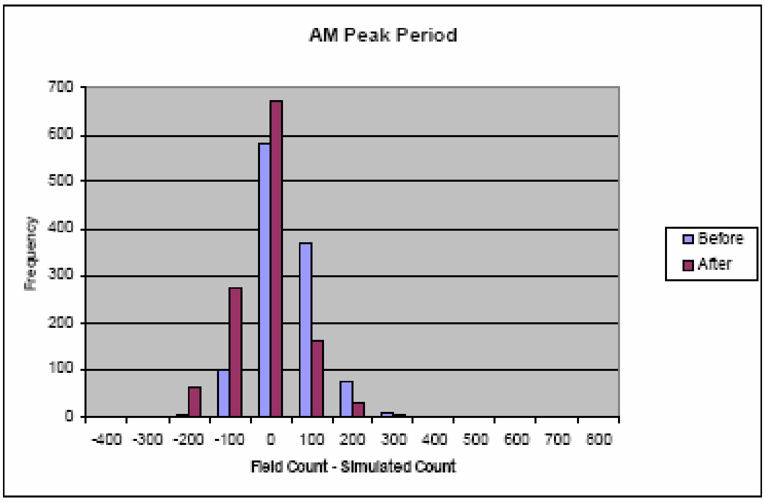

Figure 6 Histogram of the difference between field and simulated traffic AM counts before and after calibration

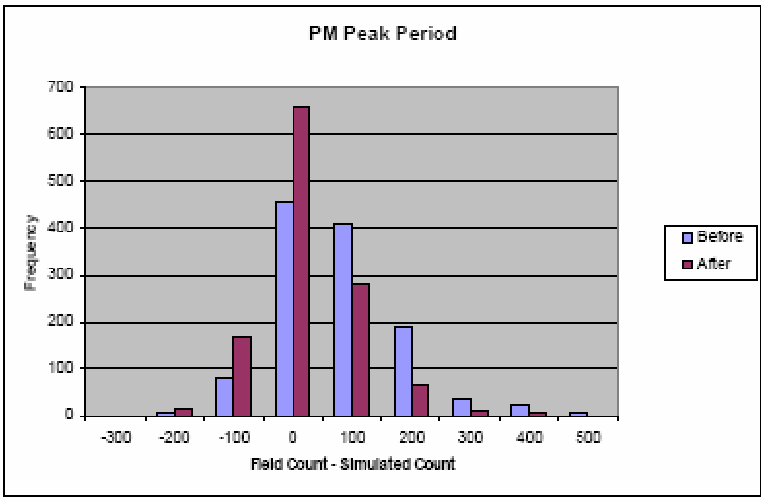

Figure 7 Histogram of the difference between field and simulated traffic PM counts before and after calibration

It is clear from above figures that the joint calibration and OD estimation made a significant improvement. The simulated data are shown to be much closer after calibration than before. The biggest problem in achieving any further progress lies in errors in field counts. Such errors do not have much impact in smaller networks because they affect the calibration only at local level. In a very large network such as Des Moines area, errors in sensor data affect the parameters in route choice model, habitual travel times and OD. Thus, a large error in sensor data not only makes it impossible for simulated count to match field count; it also affects the calibration on alternate routes. For example, University Avenue in West Des Moines serves as an alternative to I-235 freeway. The original field counts on two intersections on the University Avenue were much lower than the “real counts”. At the first glance, it would appear that calibration procedure would result in a smaller count data (in order to match the erroneous data). However, the impact is far reaching. It was found that it was impossible to match field count on I-235 due to errors on University Avenue because an increase in volume on I235 could not be obtained without increasing volumes on the University Avenue. A few such locations were identified and corrected. While it poses no new theoretical issue, it has an immense practical significance because a network of this size is bound to have a number of such sensors.

6.2. Validation

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

The travel time comparisons are presented in Table 1. The first corridor is a freeway, I-235, that traverses from the 74th Street in West Des Moines to 31st St in Des Moines. For this corridor, the average simulated travel time of 776 seconds is 27 seconds higher than the observed average travel time of 749 seconds. Thus, the error is approximately 4%. Corridor 2 is the Douglas and Euclid Avenues from Beaver Avenue to NE 14th St in Des Moines. For this corridor the average simulated travel time of 563 seconds is 13 seconds higher than the survey of 550 seconds. In this case the error is less than 3%. Corridor 3 is Grand Avenue from EP True Pkwy in West Des Moines to 18th Street in Des Moines. For this corridor the average simulated travel time of 830 seconds was 38 seconds faster than the survey of 868 seconds. Thus, the error is approximately 5%. Corridor 4 is 86th Street and 22nd Street from Interstate 35/80 in Urbandale to Interstate 235 in West Des Moines. For this corridor the average simulated travel time of 840 seconds is 241 seconds higher than the survey of 599 seconds. This large difference in travel time is due to unrealistic congestion in MITSIMLab at the intersection of Hickman Rd and 86th Street. Further investigation of this intersection revealed that the count data at this intersection might be erroneous. While this location is still under investigation, the preliminary conclusion is that the count data is much higher than the capacity, resulting in an unrealistic congestion in MITSIMLab. The overall average for the 18 corridors compared to the observed travel time data showed that simulated travel times were about 38 seconds lower then observed travel times.

Table 1 Observed and simulated travel times

Travel times (sec)			
Corridor		**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

7. Summary

This paper presented the development, calibration and validation of a microscopic traffic simulation model for a very large network. The network included all major roads in the entire Des Moines metropolitan. MITSIMLab was used for developing the model. The MITSIMLab model is one of the largest networks that have been modeled in a microscopic simulation model to date. Joint calibration of model parameters and OD estimation was performed. Calibration and validation results are promising. However, some obvious errors in sensor data were detected that adversely affected the calibration results. It is suggested that accuracy of sensor data should be investigated before applying the automated calibration for future applications. While some erroneous sensor data could be hard to identify, it is authors' opinion that it is still possible to get rid of the sensor data that have large error. These sensors could dramatically improve the performance of the calibration.

A significant area of research in this direction lies in empirical investigation of convergence. Each component within the calibration module notably travel time and OD matrices rely on some sort of convergence criterion. The properties of convergence are not well known. Also, the impacts of various levels of aggregation such as time interval for habitual travel time estimation or OD need to be studied.

References

Abdulhai, B., Sheu, J.B. and Recker, W., 1999. Simulation of ITS on the Irvine FOT Area Using 'Paramics 1.5' Scalable Microscopic Traffic Simulator: Phase I: Model Calibration and Validation, California PATH Research Report UCB-ITS-PRR-99-12.

Barceló, J., Casas, J., Ferrer, J.L., and García, D., 1999. Modeling Advanced Transport Telematic Applications with Microscopic Simulators: The case of AIMSUN, in: Traffic and Mobility, Simulation, Economics, Environment, W. Brilon, F. Huber, M. Schreckenberg and H. Wallentowitz, Eds., Springer Verlag.

Bell, M.G.H., 1991. The Estimation of Origin-Destination Matrices by Constrained Generalized Least-Squares, Transportation Research Part B, 25, 13-22.

Cascetta, E., Inaudi, D., and Marquis, G., 1993. Dynamic Estimators of Origin-Destination Matrices Using Traffic Counts, Transportation Science, 27, 363-373.

Daigle, G., Thomas, M., and Vasudevan, M., 1998. Field Applications of CORSIM: I-40 Freeway Design Evaluation, Oklahoma City, OK, in Proceedings of the 1998 Winter Simulation Conference, D.J. Medeiros, E.F. Watson, J.S. Carson and M.S. Manivannan, eds.

Darda, D., 2002. Joint Calibration of a Microscopic Traffic Simulator and Estimation of Origin-Destination Flows, MS Thesis, Dept. of Civil and Environmental Engineering, Massachusetts Institute of Technology.

Fellendort, M., 1994. VISSIM: A Microscopic Simulation Tool to Evaluate Actuated Signal Control Including Bus Priority, paper presented at the 64th ITE annual meeting, Dallas, TX.

Kim, K., and Rilett, L.R., 2003. Simplex Based Calibration of Traffic Micro-Simulation Models Using ITS data, in Preprints of the 82nd Transportation Research Board Annual Meeting, Washington DC.

Lee, D.H., Yang, X., and Chandrasekar, P., 2001. Parameter Calibration for PARAMICS Using Genetic Algorithm, in Preprints of the 80th Transportation Research Board Annual Meeting, Washington DC.

Liu, S.S., and Fricker, J.D., 1996. Estimation of a Trip Table and the Theta Parameter in a Stochastic Network, Transportation Research Part A, 30, 287-305.

Maher, M.J., 1983. Inferences on Trip Matrices from Observations on Link Volumes - a Bayesian Statistical Approach, Transportation Research Part B, 17, 435-447.

Smith, M., Druitt, S., Cameron, G., and MacArthur, D., 1994. PARAMICS final Report, Technical Report EPCC-PARAMICS-FINAL, University of Edinburgh.

Spiess, H., 1987. A Maximum-Likelihood Model for Estimating Origin Destination Matrices, Transportation Research Part B, 21, 395-412.

Toledo, T., Koutsopoulos, H.N., Davol, A., Ben-Akiva, M.E., Burghout, W., Andréasson, I., Johansson, T., and Lundin, C., 2003. Calibration and Validation of Microscopic Traffic Simulation Tools: Stockholm Case Study, in Preprints of the 82nd Transportation Research Board Annual Meeting, Washington DC.

Vanzuylen, H.J., and Willumsen, L.G., 1980. The Most Likely Trip Matrix Estimated from Traffic Counts, Transportation Research Part B, 14, 281-293.

Yang, Q., and Koutsopoulos, H.N., 1996. A Microscopic Traffic Simulator for Evaluation of Dynamic Traffic Management Systems, Transportation Research Part C, 4, 113-129.

Yang, Q., Koutsopoulos, H.N., and Ben-Akiva, M., 2000. A Simulation Laboratory for Evaluating Dynamic Traffic Management Systems, Transportation Research Record, 1710, 122-130.