CONSTRUCTION AND CALIBRATION OF A LARGE-SCALE MICRO-SIMULATION MODEL OF THE SALT LAKE AREA

H. Rakha
M. Van Aerde
Center for Transportation Research
Virginia Polytechnic Institute & State University
Blacksburg, VA 24061
(540) 231-2261 Fax: (540) 231-5214

L. Bloomberg
TransCore
2000 Powell St., Suite 1090
Emeryville, CA 94608
(510) 428-2550, Extension 115

X. Huang
Utah Department of Transportation
4510 South 2700 West
Salt Lake City, UT 84114
(801) 965-3866

ABSTRACT

The objective of this paper is three-fold. First, the paper demonstrates the feasibility of modeling a large-scale network at a microscopic level of detail. Second, the paper describes the unique data collection challenges that are involved in constructing and calibrating a large-scale network microscopically. Third, the paper describes the unique opportunities and applications from the use of a microscopic as opposed to a macroscopic simulation tool.

The paper demonstrates that it is possible and feasible to model a large-scale network using a microscopic simulation model. The requirements of a validated microscopic model for large-scale modeling are: (a) the model must be capable of modeling O-D demand tables, (b) the model must be capable of modeling dynamic traffic routing, and (c) the model must be capable of modeling the dynamic interaction of freeway/arterial facilities.

The data collection and coding exercise for microscopic models is more intensive than for macroscopic models. The calibration exercise for a microscopic model to a large-scale network, while feasible, is by no means an easy task, and does require expert assistance. The Salt Lake metropolitan region study has demonstrated that the data collection, coding, and calibration exercise is approximately a 4-person-year exercise.

Model execution times during peak periods are still quite high (from 2 to 17 times the simulation time depending on the number of vehicles) for the PC platform (Pentium 200 with 64 Mbytes of RAM). Consequently, tools that can extract portions of the large-scale network can allow the modeler to conduct various types of sensitivity analyses within a more realistic time-frame.

INTRODUCTION

In the past, modeling large networks (with more than 1,000 links) was only possible through the use of a macroscopic model. Macroscopic models approximate traffic as being similar to the homogeneous and continuous flow of a fluid through a pipe. In contrast, capturing the car-following and lane-changing characteristics of each individual vehicle permits microscopic models to consider the non-homogeneous flow of different vehicle types in individual lanes. Macroscopic models are capable of modeling large-scale networks, however they do not capture the details of vehicle-to-vehicle or vehicle-to-traffic-control interactions. Consequently, it becomes necessary to incorporate the microscopic level of detail in traffic simulation if the model is to be utilized to evaluate different types of traffic signal control, ramp metering control, variable message signs (VMS), and other types of Intelligent Transportation System (ITS) applications.

Typically, microscopic simulation models have been limited in their scope and scale of application. Specifically, these models were limited in the domain of application (arterial versus freeway network models) and the network size in terms of links, nodes, and number of vehicles that could be simulated. Furthermore, the majority of microscopic simulation models could not capture the dynamic routing of traffic.

The need to model large-scale networks at a microscopic level of detail has created a unique challenge and opportunity for traffic model developers. This paper describes the steps taken to permit the application of the INTEGRATION microscopic simulation and assignment model to a network representing the greater Salt Lake metropolitan region. It must be noted, at this point, that the INTEGRATION model has been subjected to rigorous validation exercises. These exercises include validating the car following and lane changing logic (1) validating the queue formation and delay estimates at signalized intersections (2), validating the gap acceptance logic within the model (1), and validating the shockwave formations and delays upstream recurrent of and non-recurrent bottlenecks (1). Consequently, the objective of this paper is not to demonstrate the validity of the model; instead, the objective of the paper is three-fold. First, the paper demonstrates the feasibility of modeling a large-scale network at a microscopic level of detail. Second, the paper describes the unique challenges that are involved in modeling a large-scale network microscopically. Third, the paper describes the unique opportunities and applications from the use of a microscopic as opposed to a macroscopic simulation tool.

BACKGROUND

In order to plan alternative responses to traffic congestion arising from special events and roadway construction, the Utah Department of Transportation (UDOT) determined that a large-scale simulation study of the Salt Lake metropolitan region was desired. A major reconstruction project for I-15 (a billion-dollar, multi-year project on the central spine freeway in Salt Lake City) and the looming 2002 Winter Olympics (with its transportation repercussions throughout a large area) were particularly instrumental in prompting UDOT's action. The basic needs of UDOT for this large-scale simulation study included transportation systems analysis, traffic management analysis, and traveler information generation, as noted:

- Transportation systems analysis was identified as critical to gain a better understanding of travel demand by time-of-day in the Salt Lake area. An improved understanding of changes in travel behavior, such as route selection or detouring during congestion and construction-related lane closures, was desired.
- Traffic management analysis was the second key element because UDOT wanted to estimate the impact of various traffic control strategies to be implemented in the Salt Lake area. These included ramp metering, VMS, and traffic signal timing on major arterial routes.
- Traveler information generation was the third pressing need for UDOT. For instance, the I-15 reconstruction will prompt the traveling public to demand advisory information about expected delay times and suitable detour routes.

Based on these needs, UDOT identified a set of requirements for a comprehensive yet very detailed simulation study. First, UDOT recognized that, in order for the simulation effort to be successful, the model must include an accurate, subsequently region-wide origin-destination (O-D) table in order to capture traffic diversion. Second, UDOT identified that a microscopic simulation would be needed for the analysis, in order to assess the impacts of individual lane closures and to generate response plans such as changes to signal timing plans involving complex permissive and protected phases. The third requirement for the study was that freeway and surface street traffic must be simulated concurrently and consistently. Ideally, there should be no artificial transition between the simulation of the freeway system and the surface street system.

Finally, UDOT needed a simulation model that runs on a standard IBM-compatible PC. This is the standard platform for UDOT engineers, as well as the standard platform of the future Transportation Operations Center (TOC).

Based on its needs, UDOT selected the INTEGRATION model (3) for the study, as described in (4). The modeling of the Salt Lake area using the INTEGRATION model formally began in August 1996. The study network, was loosely defined as the entire Salt Lake metropolitan area, including all freeways and major arterials. Ultimately, more detail was added to the network, as described later in this paper. A 24-hour model was needed because construction impacts could potentially be more severe in the off-peak hours. Unlike other daily models that might produce only a single average daily traffic value at a particular location, the study was intended to produce a time-series of traffic conditions throughout a typical spring 1997 weekday, varying by hour.

Three overlapping model development phases were involved in executing this project, namely: data collection and coding, model testing and calibration, and sample model applications. At each stage, the work presented unique challenges, and many lessons were learned about how to succeed in the task of developing such a large-scale, yet detailed model. This paper attempts to extract and distill the most important lessons learned in order to be of assistance to others who are contemplating conducting a similar such task.

INPUT DATA

This section describes the data and level of effort required to generate the basic INTEGRATION input files that were required in order to simulate the Salt Lake metropolitan region. The focus of the description is to provide some insight into the lessons learned from the project in terms of how much and what type of data are required.

Data Collection

The importance of data collection is often overlooked in planning a simulation project, but it usually turns out to be the most time-consuming and critical step in the entire process. The INTEGRATION model, while being less data intensive than other microscopic models, is still highly data dependent, and with the size and scope of the Salt Lake network, significant resources were required for collecting data.

The data to be collected were organized into three categories: supply, demand, and control. Supply data included geometric (e.g., number of lanes) and traffic (e.g., capacity) characteristics. Most of these data were available from existing macroscopic planning as opposed to simulation models (MINUTP). MINUTP, originally developed by COMSIS (5), is a PC-based four-step transportation-planning tool that is used by the metropolitan planning organization (MPO) in the Salt Lake area. Additional field observations were required, however, to determine lane geometries (i.e., number of lanes, turning movements, and lengths of turn bays) at approaches to signalized intersections. Clearly, the impact on diversion of turn bays, lane sharing, and permissive phasing could not be considered without these geometric details.

Demand data primarily included traffic counts at screenlines and turning movement counts at major intersections. Three sources were used for assembling these data: automated traffic recorders (at approximately 20 freeway stations), tube counts at all freeway ramps and major arterial screenlines, and turning movement counts at 163 signalized intersections. The end result was a database of 163 peak-period turning movement counts and 826 daily (24-hour) screenline counts. Approximately 16% of the tube counts and 58% of the turning movement counts were collected specifically for the INTEGRATION modeling effort. These data were used in conjunction with an approximation of a maximum likelihood tool to compute the most likely O-D demand tables that generated these flows in the first place. The details of the O-D demand estimation exercise are described later in the paper.

The control data were 24-hour signal timing plans at major intersections. There are about 600 signalized intersections in the study area: of these, UDOT identified the 163 most important intersections for detailed modeling. These signals included a mixture of fixed-time and actuated controllers, maintained by different jurisdictions. Since INTEGRATION uses a unique format for entering signal data, an input form was developed and distributed to the signal engineers, who translated their controller data into INTEGRATION format.

For this project, the data collection effort was aided by a number of fortunate circumstances. In particular, the sponsoring agency (UDOT) took a major role in collecting data. Specifically, most of the key roadways (freeways and major arterials) are UDOT facilities, and there was a significant base of data collected as part of previous studies. Even with these advantages, the data collection process took much longer than originally anticipated: the original schedule called for nine weeks of new primary data collection (ending in mid-October 1996), but the actual effort was not completed until mid-March 1997 (after about thirty weeks). Winter weather conditions were a large contributor to the delay in the data collection exercise.

The main lessons learned from the data collection exercise are as follows:

- Do not underestimate the time and resources needed to collect data.
- Develop a data collection plan and corresponding resource requirements.
- Factor weather into the data collection plan.
- Produce a database at the end of the project that can be distributed to other agencies and contractors.
- Give responsibility for collecting data on a facility to the jurisdiction that owns that facility.

Input Coding

What would be expected to be the biggest task of coding was actually the easiest: creating the basic node and link files that described the physical network. Fortunately, a travel demand network model was available for the Salt Lake City area that served as the "skeleton" for the INTEGRATION code. The travel demand model (in MINUTP) included the links and nodes for the entire network. Consequently, the MINUTP files were first simply converted to INTEGRATION format. The MINUTP network was much more detailed than the original INTEGRATION study network (which included only freeways and major arterials). Since there was no additional effort needed to convert these "extra" roadways as well, the study INTEGRATION network was expanded to include much more detail.

The next step in the conversion process was to add the various details of the traffic characteristics (e.g., capacity, free flow speed, number of lanes, speed at capacity) to the link file that were important to micro-simulation but irrelevant to the macro-planning model. The MINUTP network did have some of these data available, but capacities and speeds are often coded differently in a macro-planning model than in a micro-simulation model. An example is a signal approach with a green split of 60 percent that would be coded in a travel demand model as having a capacity of 1200 veh/h, but in INTEGRATION would be coded as a saturation flow rate of 2000 veh/h of green plus a signal timing plan that is green 60 percent of the time. This was the case here, so the traffic characteristics were updated appropriately. The link file was also updated to reflect the intersection approach configuration at major intersections (e.g. turning bays, lane striping, etc.).

The demand data, together with the link flow and turning movement counts, were used primarily as input to the QUEENSOD origin-destination (O-D) synthesis model. The O-D generation can be a complex task and can be considered a calibration exercise. Consequently, a separate section of this paper is dedicated entirely to the description of this process.

In summary, a total of 3365 nodes and 7926 links were used in coding the model. There were 163 signalized intersections coded explicitly, with 576 signalized approach links for which detailed striping (lane assignments) was specified. The O-D input data included 24 hours of screenline volumes (from 683 to 826 per hour), and about 9 hours of turning movement counts (6-9 AM, 11 AM-1 PM, and 3-7 PM). A total of 565 zone centroids were used as origins and destinations in the network.

The lessons learned from coding the supply side of INTEGRATION on a large-scale network are:

- Do not "reinvent the wheel;" use other model networks as a base or "skeleton."

- Spreadsheet and programming expertise are essential in working with and manipulating large input files.
- Automate input processes as much as possible so that new data can be easily added as they become available.

Typical Day-to-Day Variations in Traffic Counts

The calibration effort for a simulation model ultimately requires comparing simulated data with field-observed data. Because field observations vary from day to day due to the stochastic nature of traffic, it is paramount to quantify the typical field variation in traffic counts before embarking on a large-scale calibration exercise. This section attempts to quantify the typical variability in link flow and turning movement counts for the Salt Lake metropolitan region as a first step in this calibration exercise. It must be noted at this point that the authors do realize that a statistically rigorous approach that would quantify the variability in the simulated data relative to the field data would be to conduct a two-factor Analysis of Variance (ANOVA). The first factor would be the link number and the second factor would be whether the data were simulated versus observed in the field data. The approach would require repeating a set of simulation runs for a number of times using different random seeds and comparing results against field data observed across different days. However, the approach that is described in this study did not utilize ANOVA techniques because of the lack of available resources. Nevertheless, it is recommended that ANOVA comparisons be conducted and presented in a forthcoming study.

In order to quantify the variability in link flows, a number of numeric and non-numeric measures were utilized. These included the relative Least Squared Error (LSE), the Least Poisson Error (LPE), and visual inspection of the data. The relative LSE is computed as the average squared error divided by the average observed link flow, as indicated in Equation 1. For a constant average observed link flow, the LSE is sensitive to the absolute error as opposed to the relative error. In other words, an error of 1 veh/h for a flow of 10 veh/h is equivalent to an error of 100 veh/h for a flow of 1000 veh/h. Clearly, this should not be the case. The LPE error normalizes the error relative to the square root of the observed flow, as demonstrated in Equation 2. Assuming a Poisson count distribution, the LPE error normalizes the error relative to the standard deviation. In other words, the LPE is the number of standard deviations of the link flow from the observed link flow.

$$LSE = \frac{\sqrt{\dfrac{\sum_i (q_{1i} - q_{2i})^2}{n}}}{\dfrac{\sum_i q_{1i}}{n}} \qquad (1)$$

$$LPE = \sqrt{\frac{\sum \frac{(q_{1i} - q_{2i})^2}{q_{1i}}}{n}} \quad (2)$$

where q_{1i} = first source link flow on link i
q_{2i} = second source link flow on link i
n = number of link flows

When comparing flows between days, the LSE was found to vary from 1.7 to 3.6 percent of the mean flow, while the LPE was found to vary from 3.2 to 5.2, as demonstrated in Table 1. A visual inspection of the data demonstrated that the hourly volumes were scattered around the line of unbiased correlation (45-degree line). It is important to note that the LPE and LSE scores do not necessarily coincide with the visual inspection. The fact that, in some cases, the error estimates do not coincide with the visual inspection is an indication that none of the above measures can, separately, sufficiently quantify the error. However, collectively, the measures do provide an indication of how well the observed flows match each other from one day to the next.

Issues Related to Traffic Count Data

In addition to the typical day-to-day variations, the link counts that were utilized for O-D demand estimation and calibration purposes were collected from a number of sources over a relatively long time frame (eight years in some cases). The inconsistency in data collection has resulted in a number of issues, including the following:

- Counts were only available for approximately 10 percent of the links in the network. The majority of the counts were available for the freeway links, while only 5 percent of the arterial links had observed counts available.
- Only 6 percent of the freeway mainline volume were actual field counts, while the other 94 percent were simulated flows from the FREQ model.
- Freeway mainline field counts were taken over a two-year period (1995-1996). Freeway ramp data were collected over four years, from 1993 to 1996, while arterial counts were collected over eight years, from 1990 to 1997. Volume changes over such time spans could be large. In addition, volume variations due to factors such as weather, construction, and incidents could have large impacts on the final data.

SYNTHETIC O-D GENERATION

The generation of O-D demands from link flows is a complex task for several reasons. First, even if the link flows are known exactly (which typically is not the case), the problem is under-specified (i.e. the number of constraints is less than the number of unknowns). This means that, potentially, there are multiple solutions to the synthetic O-D problem. Consequently, the most likely solution needs to be selected from these multiple solutions. Second, since typically there are errors in the link flow counts and/or time lags in observing the flows, there will not be any solution that exactly matches the observed flows. Instead, the objective is to find the most likely solution that minimizes the link flow error. The approximation is that by minimizing the link flow error, the O-D demand error is also minimized (i.e. by matching the flows, the O-D demands are matched). Third, the actual O-D demand is typically unknown, so it is impossible to quantify the extent to which the solution is correct.

The QUEENSOD model was developed to provide a robust yet practical means of estimating both static and dynamic origin-destination traffic demands (6). These O-D demands are required as input to the INTEGRATION model. An optional seed can be provided to the model to expedite the search and to allow the model to converge to a solution that resembles the seed.

Currently, the QUEENSOD model provides two options to compute the O-D demand, as illustrated in Figure 1. In the first option, the vehicles are routed based on an all-or-nothing (AON) traffic assignment, and the model searches for the O-D demand that minimizes the link flow error given this AON traffic assignment (ends with the dotted lines). In the second option, the model computes multiple trees and corresponding tree weights, and observes O-D demands that minimize the link flow error for this multi-path input. The second option involves a larger amount of computation because an optimum O-D is computed for each tree weight combination. Figure 2 illustrates how the computation time varies for option 1 and for option 2 for two trees. Option 1 was executed with a maximum of 10 iterations, while option 2 was modeled with 10 iterations and tree weight steps of 5 percent. It can be noted that the addition of a second tree typically resulted in a two-fold to ten-fold increase in the execution time. It is not clear at this point why the execution times for time slices 7, 11, and 15 were much higher for the two-tree option. Figure 2 demonstrates that for a single AON tree, the hourly O-D demand can be computed within 10 minutes. The addition of a second tree puts the execution time into the range of one hour.

Figure 2 also illustrates the variation in the total synthetic O-D demand as a function of the time-of-day. It is clear from Figure 2 that the AM peak starts at 7 AM and continues until 9 AM. There also appears to be a minor mid-day peak at 1 PM, and a PM peak from 4 PM to 7 PM. By comparing the execution time to the total demand, there does not appear to be any strong correlation between the total O-D demand and the execution time for either of the options (one-tree or two-tree).

Figure 3 demonstrates the variation in the LSE and link flow coefficient of correlation (r) as a function of the time-of-day. The figure demonstrates two findings. First, the link flow error increases as the level of congestion increases. This could also have resulted from the fact that during the peak hours, more observed link flows were available (i.e. more constraints were imposed on the solution). Second, it suggests that the addition of a second tree always reduces the link flow error. In some cases, the link flow error is reduced by up to 50 percent.

Figure 3 also illustrates that the variation in the link flow coefficient of correlation (r) as a function of the time-of-day is consistent with the variation in the link flow error. Specifically, that the link flow coefficient of correlation decreases as the level of congestion increases, and the link flow coefficient of correlation increases with the addition of a second tree. It must be noted that the coefficient of correlation is in excess of 0.95 for the entire day.

Figure 3 also illustrates the variation in the coefficient of correlation between the seed and estimated O-D as a function of the time-of-day. This figure demonstrates that the addition of a second tree results in an O-D that is marginally correlated with the seed O-D. Based on Figure 3, it can be concluded that by adding a second tree, the link flow error is reduced. In doing so, the O-D demand is adjusted, resulting in an O-D demand that has little resemblance to the seed O-D demand. Consequently, two potential conclusions can be made: (1) that the 24-hour seed O-D demands were not consistent with the observed hourly link flows that were provided to the synthetic O-D model, or (2) that minimizing the link flow error does not necessarily result in minimizing the O-D estimate error. Further work is required to further investigate and analyze these findings, however, this is beyond the scope of this paper.

Figure 4 illustrates the variation in the LSE as a function of the iteration number for the various tree and tree weight combinations. The figure demonstrates that the largest reduction in the LSE occurs for a single tree (1.00 legend) from 65 veh/h to 30 veh/h after 10 iterations. A shift of 5 percent to the second tree (2.05 legend) reduces the LSE further from 30 veh/h to 28 veh/h. However, the number of iterations has only a marginal impact on the LSE. The same trend occurs for the various tree weight combinations (2.10, 2.15, 2.20, 2.25, and 2.75). The final tree weight contribution reduces the LSE from 30 veh/h to 15 veh/h with 75 percent of the O-D demand using the second tree.

Figure 4 also illustrates a similar reduction in the LSE as a function of the iteration number and tree weight combination for the AM O-D demand. However, the tree weight has a marginal impact on the LSE. The fact that the tree weight has a large impact for the off-peak conditions and a marginal impact for the peak conditions is consistent with the findings of Figure 4. These findings could have resulted from the larger number of link flow observations during the peak demands, thus providing more constraints in terms of the O-D estimation and requiring less traffic re-routing to reduce the link flow error. It is not clear at this point if these results are specific to the Salt Lake network or if these findings can be generalized to other network and traffic configurations.

The lessons learned from generating the O-D demands on a large-scale network are:

- Generation of O-D demands is essential for modeling traffic routing.
- O-D demands from other macroscopic planning models could be used as a seed for the O-D demand generation.
- A minimum of 10 iterations and 2 trees should be used for O-D generation.
- Computer RAM can be the most effective means to speed up the O-D demand generation.

MICROSCOPIC SIMULATION RESULTS

This section describes some of the simulation findings at this stage of the project. The simulation results are presented to illustrate calibration findings rather than findings with respect to specific strategies (e.g. traffic signal control, incident management, etc.).

The LPE was found to vary from 3, during the off-peak, to 14, during the peak demand, as illustrated in Figure 5. Furthermore, the variation in LPE, as a function of the time-of-day, was consistent with the variation in the total demand (Figure 4). The relative LSE was found to vary from 0.2 to 0.4. Again, the variation in the LSE was consistent with the variation in the total demand. The results of Figure 5 demonstrate that both the LSE and LPE are correlated with the total demand. In terms of the physical interpretation of these results, they indicate that for the majority of time periods, the link flow error (simulated versus observed) was, on average, 30 percent the mean link flow and only during two time periods reached 60 percent the mean link flow.

Figure 6 illustrates that the simulated link flows produced by the INTEGRATION model were consistent with the actual flows that were observed in the field during the off-peak period (time slice 11). The simulated flows and actual flows were highly correlated and symmetric about the line of unit correlation. The results for the 10-11 time slice are representative of the scatter plots for the other 23 time slices that, due to limited space, are not presented. While the scatter in the link flows may be equivalent to what is typically observed for macroscopic models, the use of a microscopic model allows us to capture microscopic levels of control that cannot be captured in a macroscopic model.

The execution time for each of the hour simulations ranged from 2 hours during the off-peak demands up to approximately 17 hours for the peak demands, as illustrated in Figure 7. Based on these results, it would require approximately 215 hours (9 days) to simulate the entire day on a 200 Mhz Pentium PC with 64 Mbytes of RAM.

Clearly, these execution times are feasible, but they are not practical for many applications.

A comparison of link flow errors from Table 1 to the simulation results in Figure 5 demonstrates that the simulation link flow error exceeds the typical day-to-day link flow error. However, as discussed earlier in the paper, not only were the observed link flows gathered over an eight-year time frame, but the majority of freeway flows were generated from the FREQ model. Consequently, it is no surprise that an initial comparison of the INTEGRATION link flows to the observed link flows resulted in a link flow error that exceeded the day-to-day typical error. In an attempt to further understand the variability in the simulation results, a number of comparisons were conducted, as summarized in Table 2. The first comparison was to compare different 10-minute link volumes for the same simulation run. The results in Table 2 demonstrate that the variability in link volumes across 10-minute time intervals is larger than the variability in link volumes across seeds (Comparisons 1 and 2 versus Comparison 3). Furthermore, the variability in link volumes over a longer time interval is reduced (Comparison 3 versus Comparison 4). These results are consistent with the scatter plots of the link flows, however, due to the limited space available these plots are not included. Consequently, it was concluded that the existing link flow errors were sufficient to consider the network to be calibrated. Further statistical testing is recommended, however, it is beyond the scope of this paper.

Execution times on the order of 17 hours per single hour of peak demand may deem it impractical to do most types of sensitivity analyses for peak hour demands. Because UDOT envisioned using the INTEGRATION model for various types of sensitivity analyses, the INTCROP tool was developed to crop sub-networks of the INTEGRATION network (7). The logic and testing of the INTCROP tool is beyond the scope of this paper, and as such will be described separately.

The lessons learned from calibrating INTEGRATION to a large-scale network are:

- Start calibration with the off-peak periods in order to isolate problems with the node, link, and traffic signal coding.
- During calibration under congested conditions, screen output provides an ideal means to identify bottlenecks.
- Computer RAM can be the most effective means to speed up execution times.

CONCLUSIONS AND RECOMMENDATIONS

This study has demonstrated that it is feasible to construct and calibrate a large-scale network for use by a microscopic simulation model. The microscopic level of detail, as opposed to the macroscopic level of detail, is vital because it allows the model to capture the dynamics of vehicle-to-vehicle and vehicle-to-control interactions, which are present at complex intersections and interchanges. The study has demonstrated that a validated microscopic model can be a candidate for modeling large-scale networks if, and only if, it is capable of the following: (1) modeling O-D demand tables, (2) routing traffic dynamically, and (3) modeling the dynamic interaction of freeway/arterial facilities.

The data collection and coding effort for setting up microscopic models is more intensive than for macroscopic planning models. The calibration exercise for a microscopic model to a large-scale network, while feasible, is by no means a routine task and does require considerable expert assistance. The Salt Lake metropolitan region study has demonstrated that the data collection, coding, and calibration effort requires approximately 4-person-years.

Model execution times during peak periods are still quite high (up to 17 times the simulation time) for the PC platform (Pentium 200 with 64 Mbytes of RAM). Consequently, tools need to be applied that can extract portions of the large-scale network in order to allow the modeler to conduct various types of sensitivity analyses within a more practical time frame. The INTCROP tool can provide results that are consistent with the modeling of the entire network. Further investigation and testing is underway to ensure that findings for a sub-network are consistent with the findings for the full-scale network.

Based on this study, it is recommended that further work be conducted, as follows:

- Statistically verify, utilizing Analysis of Variance (ANOVA) techniques, that the variability in simulated link flow estimates are within the margin of error for day-to-day variability.
- Establish the sensitivity of results to O-D demands.
- Demonstrate the use of the cropping tool as a credible means to reduce execution time while producing realistic results.

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LIST OF FIGURES

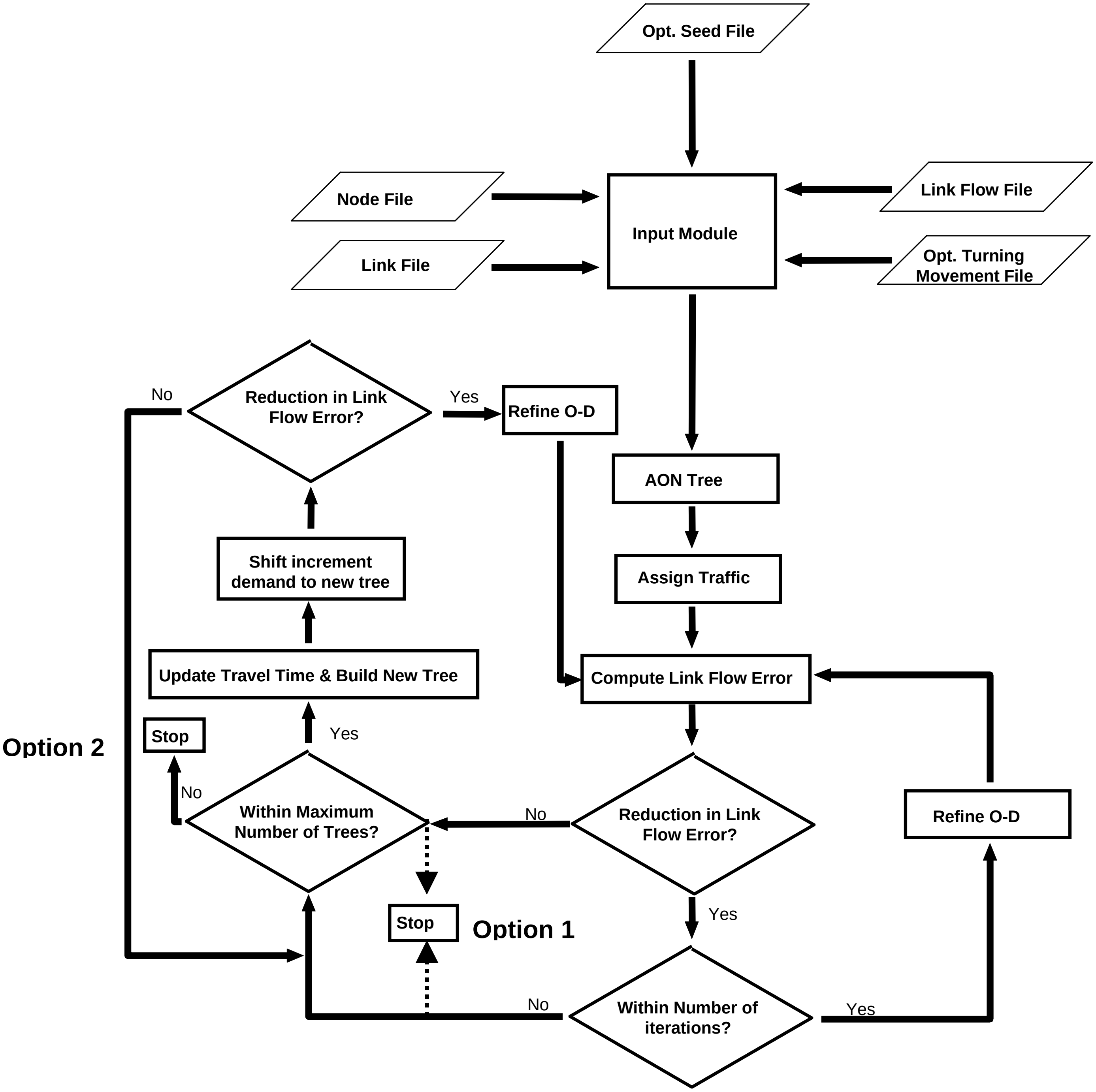


Figure 1. Option 1 and 2 for Computing O-D Demands

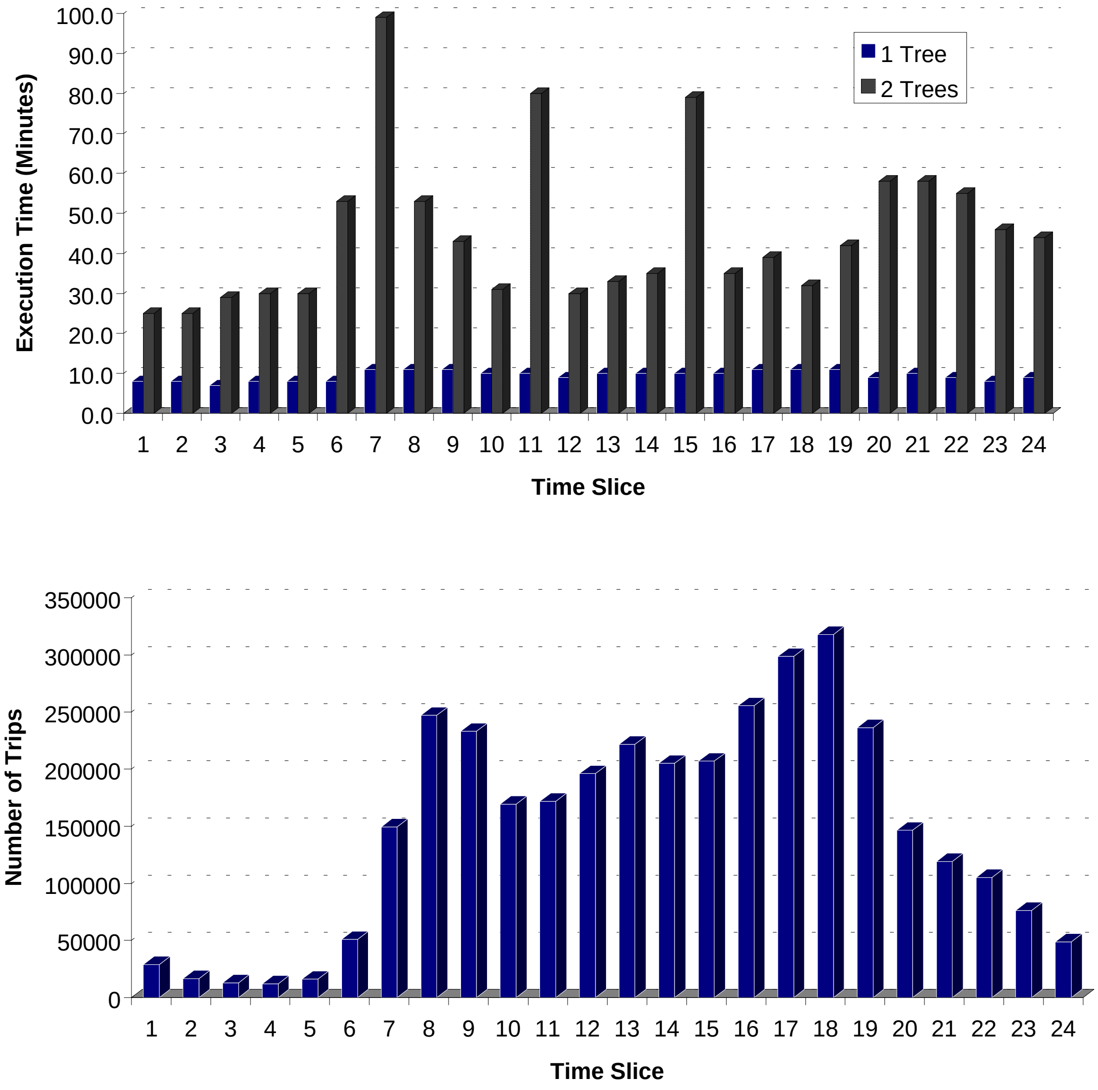


Figure 2. Variation in Execution time and Total Number of Trips as a Function of Time Slice (Pentium Pro2 266 MHz with 256 Mbytes of RAM)

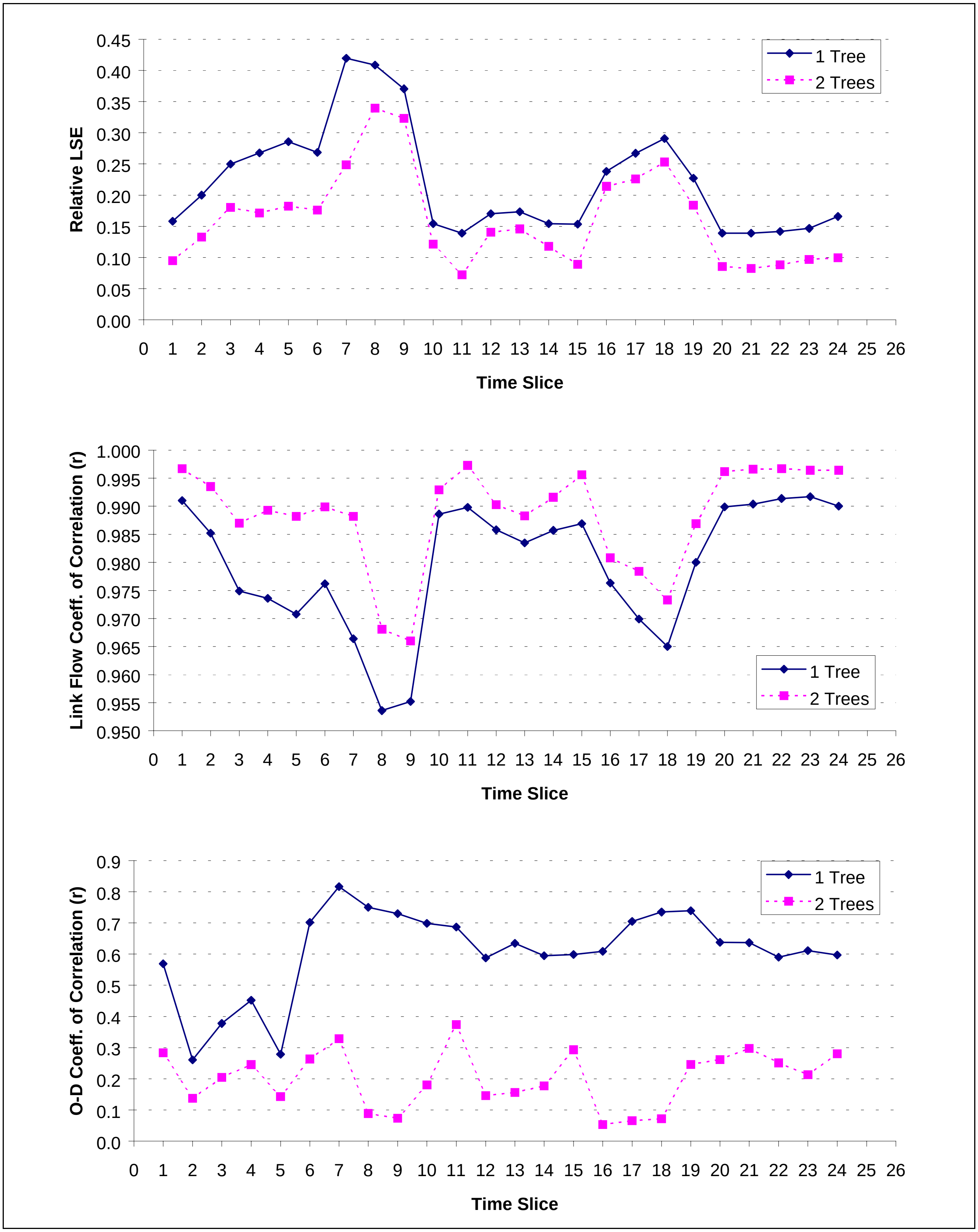
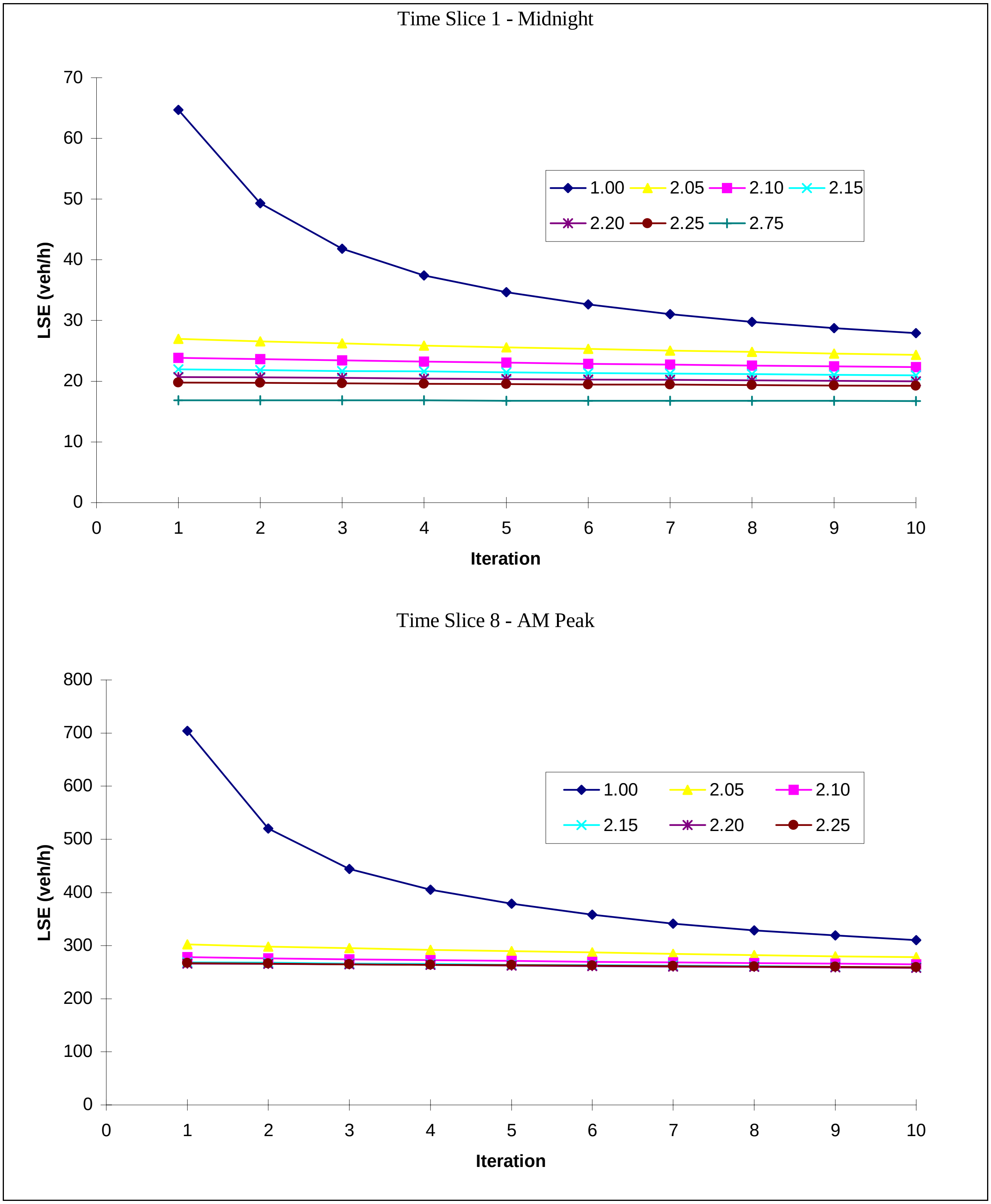


Figure 3. Variation in Estimated Link Flow Error Relative to Observed Link Flows, Link Flow Coefficient of Correlation and O-D Coefficient of Correlation



Time Slice 1 - Midnight

Time Slice 8 - AM Peak

Figure 4. Variation of LSE as a Function of Iteration for Time Slices 1 and 8

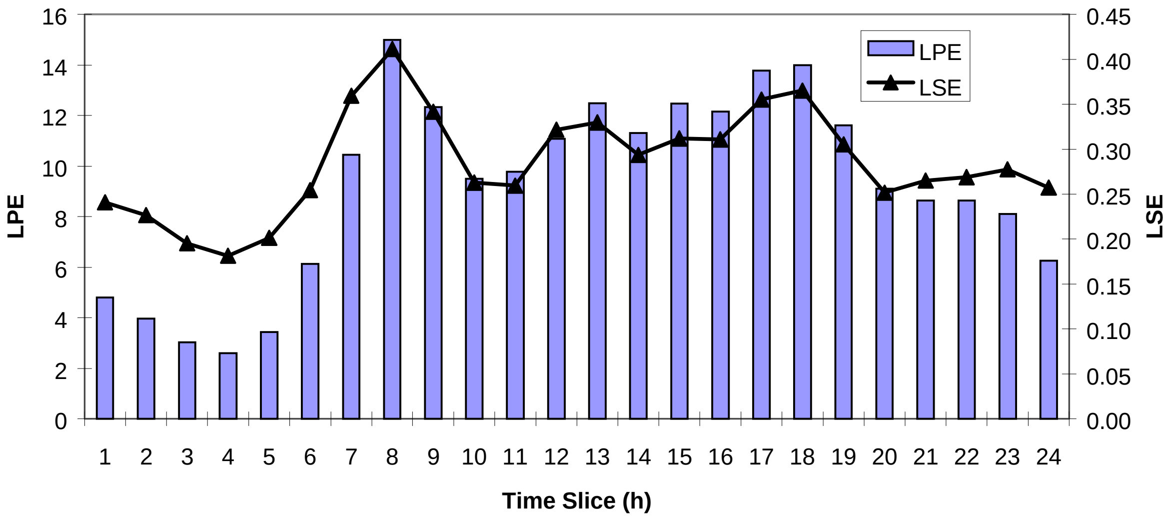


Figure 5. Variation of Link Flow Error as a Function of Time Slice

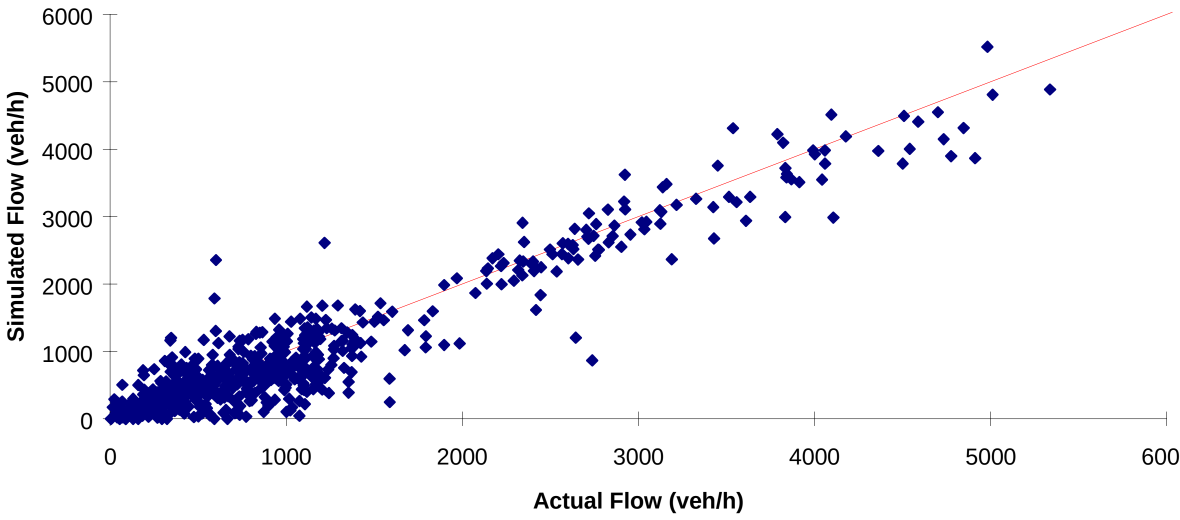


Figure 6. Actual Versus Simulated Flows (10-11 AM)

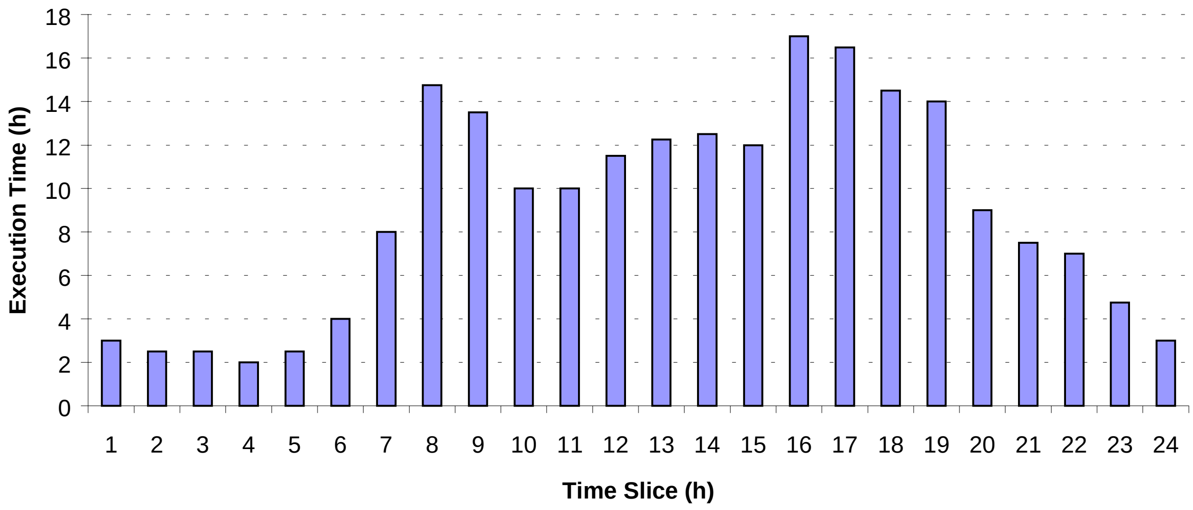


Figure 7. Variation in Typical Execution Time as a Function of Time Slice (Pentium 200MHz PC with 64 Mbytes of RAM)

LIST OF TABLES

Table 1. Summary Results for Day-to-Day Hourly Volume Comparison

	Tue. vs. Wed.	Wed. vs. Thu.	Thu. vs. Tue.
Number of Observations	353	206	189
Least Poisson Error (LPE)	3.15	4.75	5.18
Least Squared Error (LSE)	1.7 percent	2.4 percent	3.6 percent

Table 2. Summary Results for Seed Comparisons

	Number of Observations	Least Poisson Error (LPE)	Least Squared Error (LSE)
Comparison 1: Comparison of hourly link flow rates (30 to 40 minutes versus 40 to 50 minutes - Seed 1)	7945	12.20	27 percent
Comparison 2: Comparison of hourly link flow rates (30 to 40 minutes versus 40 to 50 minutes - Seed 2)	7945	11.98	31 percent
Comparison 3: Comparison of hourly link flow rates (Seed 1 versus Seed 2- 10-minute analysis period)	7945	7.72	22 percent
Comparison 4: Comparison of hourly link flow rates (Seed 1 versus Seed 2- 30-minute analysis period)	7945	4.08	12 percent