Abstract

WAN, BAOHONG. "Empirical Comparison of Simulation Models with Different Input Data Structures." (Under the direction of Dr. Nagui M. Rouphail.)

This thesis focuses on an empirical comparison of CORSIM and Paramics, two commonly used traffic simulation models with different input data structures.

The case comparison was executed between a field-validated CORSIM model and a fully calibrated Paramics network. These two models were constructed based on the same physical network dataset, which was originally created for the CORSIM simulation purposes. For those input data that were necessary for Paramics, but not available in this dataset, estimations were performed based on the known data and, sometimes, based on CORSIM default values. Of these the most important one was the Origin-Destination (OD) matrix.

To enter traffic demand in Paramics, an OD matrix was derived using two different methods, namely a statistical fitting method and a stochastic assignment method. The feedback results from a Paramics test network showed that the stochastic assignment method was more effective in deriving a good OD solution.

One straightforward finding of the comparison was that Paramics generated what appeared to be a larger percentage of unsuccessful runs than CORSIM. That was possibly because Paramics created more link flow fluctuations with the dynamic feedback traffic assignment algorithm; therefore, it had a higher chance of spillback or blockage for overloaded links or turn movements.

A comparison of link flows in the two simulation models was executed based on the sample replications after excluding outliers. It displayed that there were some apparent link flow discrepancies between these two models. To ensure a meaningful comparison of other selected traffic performance measures, two critical corridors with minor vehicle flow discrepancies were selected as the comparison sites.

By comparing the results on one corridor (NB LaSalle) , Paramics generated fewer vehicle trips and a higher vehicle travel speed, while on the other corridor (WB Ontario), the reverse occurred: although Paramics had fewer vehicle trips on that corridor, it still produced lower vehicle speeds than CORSIM.

The research suggests that empirical comparisons of simulation models with different input data structures are feasible and informative for model validation and selection. Further, for the same traffic demand, Paramics generated traffic performance that is at variance with CORSIM's when using dynamic feedback traffic assignment algorithm.

Empirical Comparison of Simulation Models with Different Input Data Structures

By

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Biography

Baohong Wan was born in Shandong Province, China. He finished his undergraduate study in transportation management engineering in Northern Jiaotong University in 1995.

After graduation, he was hired as technical lecturer in Jinan Railroad Mechanical School. In the following five years, he taught Freight Transportation Management and Professional English to hundreds of railroad transportation staff.

In 2000 he was admitted to North Carolina State University to pursue graduate study in transportation engineering in the Department of Civil Engineering. Under the direction of Dr. Nagui Rouphail, he got a Master of Science degree in 2002.

Baohong's major research interest is traffic capacity, delay and safety analysis using emerging technologies.

Acknowledgements

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Dr. Rouphail served as advisor for the author, for a candidate Master of Science degree in transportation engineering in North Carolina State University. During the past two academic years, his enthusiasm, valuable encouragement and indispensable guidance made the fulfillment of this work possible.

Dr. Hummer, with his excellent engineering knowledge, taught the author to study traffic problems from a practical perspective. Dr. John R. Stone presented the author his first transportation class in NC State University. His broad knowledge and humor made this class interesting and informative.

The ongoing research is under the direction of Dr. Jerome Sacks from Duke University. The author is so grateful to him for his continuous support, sincere advice and supervision during the work. It was Dr. Brian. B. Park who opened the door for the author to this research.

This thesis is dedicated to my family; special thanks are given to my wife, Qing Li, for her support and love during my life.

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Chapter 01: Introduction and Literature Review

1.1 Traffic Simulation and Simulation Models

Traffic Simulation

Traffic simulation refers to the process of designing and creating a computerized model of an existing or proposed transportation system, for the purpose of conducting numerical experiments to give users a better understanding of the behavior of that system for a given set of conditions (Kelton, 2001). Simulation is increasingly being used in the transportation and traffic engineering field, not only because of its strength in analyzing complex systems requiring a large number of calculations, but also because of its capabilities in providing users statistical measures of effectiveness and, more recently, visualized demonstration of target traffic scenarios.

The emergence of low-cost modern computers with higher computation speeds and larger storage capacity has extended the application of traffic simulation to small project analysis and routine traffic management. Rapid development in computer simulation software provides users various modeling choices to choose from.

Traffic Simulation Models

There are several ways to classify traffic simulation models, but one useful way is along three dimensions (Prevedouros, 2000):

- Microscopic, macroscopic or meso-scopic models. Microscopic simulation models include CORSIM (FHWA, 1997), PARAMICS (Quadstone, 1999), VISSIM (PTV, 1999), etc. Macroscopic simulation models include CORFLO (FHWA, 1997), FREFLO (Payne, 1979), and meso-scopic models include DYNASMART (FHWA, 2000) and TRANSIMS (LANL, 1998).
- Stochastic or deterministic models. CORSIM, VISSIM, INTEGRATION (Van Aerde, 1995), etc, are stochastic models, while DYNASMART, HCS (McTrans, 2000), and TRANSYT7F (McTrans, 1999), are deterministic models.
- Continuous or discrete models. Most traffic simulation models are discrete changing models running at fixed time steps (typically at 1 second interval or less).

From the perspective of traffic demand input data, traffic simulation models can be classified into flow-based simulation models (for example, CORSIM, SimTraffic), or path-based simulation models (for example, VISSIM, Paramics).

Flow-based traffic simulation models are designed mainly to reproduce link performance. Such models use entry volumes and turn percentages as the traffic input demand. Once inside the network, vehicles are assigned to downstream links according to prescribed turning probabilities.

By contrast, path-based simulation models concentrate on reproducing network trip making behavior. Therefore, Origin Destination (OD) matrices represent the input traffic demand. In this kind of models, traffic assignment is performed using specified routing algorithms based on minimizing total travel costs, or some variation thereof.

1.2 Model Selection and Comparison

Simulation model selection will affect not only the network modeling process and the required labor, but also the simulation results and, therefore, any user conclusions or recommendations. The selection of a simulation model should be based on its capability of producing accurate results as well as the feasibility of its use for specific applications.

Model comparison can assist users in making correct choices with regards to model selection. Performed at different levels, simulation model comparison entails both conceptual model comparison and empirical model comparison.

Besides assessing some general considerations, including modeling cost, speed, system needs, etc, a conceptual comparison evaluates the capabilities of each model. Material for this kind of comparison is mostly found in the user guides of the subject simulation models. The conceptual comparison is an efficient way to understand the modeling features and functionalities of different simulation models in a short time.

By contrast, the empirical comparison is targeted at answering higher-level questions such as “how” and “how well” these models function. To achieve this purpose, the selected traffic simulation models are separately applied to the same traffic network. A side-by-side visual comparison is regularly carried out as well as a statistical comparison of run outputs from different simulation networks.

The empirical comparison of simulation models with different input data structures, as for example, a flow-based simulation model versus a path-based simulation model, is complicated in that it requires traffic demand data in different structures. Traffic data in the form of entry volumes, as well as origin-destination matrices, are both required as inputs to the simulation models to be compared.

In the real world, OD matrix demands are usually very difficult to gather in the field because of technical and cost reasons. In a license-plate analysis, for example, missing vehicles will always degrade the accuracy of the survey. In addition, the large costs incurred in recording-station construction and car-plate data processing discourage many traffic researchers (Lu, 1998).

Since link flow and turn movement data are relatively cheaper and easier to acquire in the field, considerable research has been devoted to deriving OD matrices from these easily acquired traffic data. That literature is reviewed in section 1.5 of this chapter.

1.3 Subject Models: CORSIM and Paramics

The goal of this research is to develop a method to empirically compare traffic simulation models with different input structures. As an illustration, CORSIM and Paramics, two commonly used traffic simulation models that typify flow-based models and path-based models, respectively, are applied to a case network. A brief description of each traffic simulation model is given below.

CORSIM

The CORSIM (CORridor SIMulation) model was rooted in the development of DYNASIM in the 1970's. It is now the core part of the Traffic Software Integrated System (TSIS) package, which is sponsored by the Federal Highway Administration (FHWA). Version 1.0 of CORSIM was completed in1988. The most recent version of CORSIM, version 5.0, was released in 2001 as part of TSIS 5.0.

CORSIM uses entry volumes as the input form for traffic demand, and performs a stochastic-assignment at each intersection. Since the prescribed turning probabilities are taken to be independent of the network origins, vehicles from different origins have a similar likelihood of being assigned to a specified downstream link. The major objective of CORSIM is to reproduce link traffic performance, such as vehicle trips, vehicle speeds, etc, and not worry about trip or path based characteristics.

Nationwide applications illustrate that after careful calibration, CORSIM is able to reproduce link performance and therefore provide users with useful information for traffic scenario analysis. However, the stochastic assignment method (which is based on prescribed turning probabilities only) does prevent CORSIM from carrying out an evaluation of traffic scenarios with significant network changes (for example, adding or dropping links, or altering existing links, which will unavoidably result in different trip route patterns, and therefore changed turning probabilities). It also doesn't handle "trip-based" algorithms such as bottleneck avoidance.

Paramics

The Paramics (PARAllel MICroscopic traffic Simulator) is an advanced suite of software tools for microscopic traffic simulation. It has its root in the cooperate research of SIAS Limited and the University of Edinburgh's Parallel Computing Center (EPCC) in Scotland. In 1996 Quadstone Limited developed Paramics 1.0 for commercial use. Quadstone Paramics version 3 build 7 was released in 2001.

Paramics uses OD matrices as the input form for traffic demand. It provides a number of traffic assignment algorithms from which users can choose. To reproduce the network performance properly, users are required to choose the traffic assignment method that provides the best fit to observed data, and to calibrate the network assignment parameters to render the vehicle routing behavior as close to the "reality" as possible.

Since Paramics provides a dynamic feedback algorithm in the traffic assignment model, it can ostensibly be used to analyze traffic performance of the scenarios with drastic network changes, which could result in different traffic assignment patterns. This feature also enables Paramics to simulate Intelligent Transportation System (ITS) applications in some transportation networks. For example, Paramics 1.5 was recently used in the ITS study by the California Partners for Advanced Transit and Highways (PATH) program. (Abdulhai, et al, 1999)

As a simulation model originating in Europe, Paramics also has attracted interests from many U.S. researchers because of its powerful roundabout simulation tools. For example, an operational and functional design evaluation for Lane County, Oregon (www.paramics-oneline.com/projects/Kittelson) was carried out in Paramics. However, because of its emphasis on European design, the default vehicle and driver characteristics in Paramics had to be carefully recalibrated to U.S. conditions.

A summary comparison of the main feature of CORSIM and Paramics is shown in Table 1.1.

	CORSIM	Paramics
Vendor	McTrans Center, FL	Quadstone Limited, UK
System requirements	Microsoft Windows 95, Windows 98,Windows NT 4.0 or Windows 2000	Windows NT/95/98/2000, or Sun Microsystems/Solaris, or Silicon Graphics/IRIX
Classification	Microscopic, stochastic, flow-based	Microscopic, stochastic, path-based
Batch mode running	CORSIM script, runcor.exe	Paramics Processor, modeller-batch.exe
Graphical input editor	TRAFED (TRAF Editor)	Paramics Modeller
Animation Processor	TRAFVU (TRAF Visualization Utility)	Paramics Modeller, Analyser
Statistical Outputs	TRAFVU	Paramics Analyser
Input Demand	Entry volumes	OD Matrix
Traffic Assignment	Stochastic assignment based On turning probabilities	All-or-nothing (AON) assignment; Probabilistic AON assignment; Dynamic feedback algorithm
Traffic Control	Signal, stop/yield sign, ramp metering, roundabouts	Signal, priority control, roundabouts
Incident Simulation	Yes.	Yes.
Emission Analysis	Yes.	Paramics Monitor
Open Structure	No.	Paramics Programmer for API (Application Programming Interface)

Table 1.1: Summary comparison of Paramics and CORSIM

1.4 Problem Statement

Objectives and Scope

The objectives for this research are summarized as follows:

1. To develop a consistent input data structure for simulation model construction and comparison;
2. To identify similarities and differences between Paramics and CORSIM models; and
3. To validate the Paramics model.

To ensure a meaningful comparison, a Paramics network needs to be constructed based on the same network dataset as the CORSIM model. Although Paramics is very similar to CORSIM in most of its network input data, there are still some major differences between these two models' input structures, most noticeably, the specification of an OD matrix as the traffic input demand in Paramics. As the network dataset was originally constructed for the CORSIM model, no OD data were readily available. Therefore, some input data needed to be calculated or estimated from other known traffic data.

Consequently, because of the limitation of the original network dataset and the difficulty in collecting field OD data, the Paramics model was constructed based on: (a) available data from the network dataset used for the CORSIM modeling,

(b) calculated or estimated data from the CORSIM dataset, and (c) CORSIM default values which have been validated for the case study urban network.

Case Study

A medium-size urban network, which is located in the central part of the city of Chicago, served as the case study. This case network shown in Figure 1.1 includes 24 signalized intersections, 8 un-signalized intersections, 56 surface-street segments and 2 freeway segments. The target simulation time period is Thursday, May 27th, 2000, 17:00 to 18:00 PM, which is a typical evening peak hour period. About 13,000 vehicles travel through this network during the subject time period.

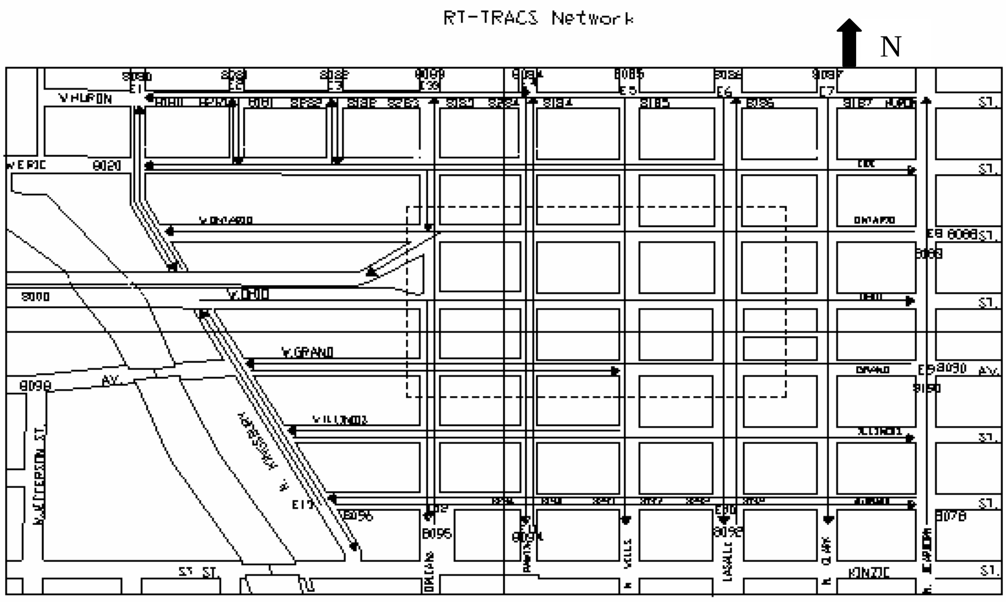

Figure1.1: Map of the case study network

As this research was a continuing part of a project aimed at optimizing traffic signal plans for the case network using CORSIM simulation (Sacks, et al, 2000), a network dataset for inputs to CORSIM had already been constructed, and a CORSIM network had already been constructed, calibrated and validated.

In order to perform the empirical comparison, Paramics was applied to this traffic network. An OD matrix was derived from known traffic data, such as entry volumes, turning percentages, link volumes, etc, to enter traffic demand in Paramics. Outputs from independent replications of the simulation networks in CORSIM and Paramics are gathered and compared in order to draw conclusions and make recommendations.

Thus, the following tasks were carried out:

1. Derive a Paramics OD matrix from known traffic information;
2. Construct and calibrate the Paramics simulation network; and
3. Design and carry out output comparisons between the two simulation networks.

1.5 Literature Review

The two key research problems of this thesis, application and evaluation of traffic simulation models and derivation of OD matrices from traffic count information, have been explored by many investigators. Some key findings are summarized below.

Application and Evaluation of Traffic Simulation Models

As a quasi-official traffic simulation model sponsored and used by FHWA, CORSIM has been widely used in many traffic-engineering studies. Daigle, et al (1998) used CORSIM for the simulation of two freeway reconstruction alternatives in Oklahoma City. The simulation was successful in identifying problem areas and in assisting transportation professionals in selecting a preferred alternative. Another application example was by Maze, et al (1998). CORSIM was used to simulate arterial traffic operations along US 61 corridor in Burlington, Iowa. The intersection-level performance measures from the simulation outputs enable researchers to compare five alternative models to the base model. A more recent application of CORSIM 5.0 by Luh (2001) to two projects in Florida included the modification of an existing interchange and the analysis of light rail running in the median of an existing surface street.

Sacks, et al, (2000) employed CORSIM to analyze different approaches to optimizing traffic signal plans. They described a general process of a statistical based validation of traffic simulation models, and concluded that CORSIM, though not perfect, was effective in evaluating signal plans of urban networks. Rouphail, et al, (2000) and Park, et al, (2000) proposed a stochastic signal optimization method based on a genetic algorithm (GA) that interfaced with CORSIM. They found that the solution from the method was superior to an optimum TRANSYT-7F (T7F) plan.

Although Paramics is relatively new simulation software, it is now used in more than twenty countries throughout the world. In the United States, one typical application of Paramics was for modeling Intelligent Transportation System (ITS) as part of the California Partners for the Advanced Transit and Highways (PATH) program. Abdulhai, B, et al (1999) reported the phase I, calibration and validation, of simulation of ITS on the Irvine Field Operational Test (FOT) area using Paramics 1.5 scalable microscopic traffic simulator. In this research Paramics was thoroughly evaluated for modeling ITS. It was concluded that Paramics is an excellent 'shell' or 'framework' for a comprehensive and extensive transportation simulation laboratory because of its high performance and scalability. In another ITS study, Liu, et al. (2000) reported some developments of Paramics Application Programming Interface (API) programs for actuated signals, signal coordination and ramp control through the Paramics Programmer.

Sahraoui, A. et al. (2002) proposed a methodology based on a hybrid simulation approach for microscopic simulation that was intended to explore two critical aspects, calibration/validation methodology and integration of path dynamics. The Paramics microscopic simulation was integrated with the DYNASMART macroscopic model to enhance the evaluation of traffic information-based routing behavior in the Advanced Traffic Management Information Systems (ATMIS).

An important exercise of simulation model comparison was recently performed In Europe. Entitled the Simulation Modeling Applied to Road Transport European Scheme Tests (SMARTEST) (1996-1999), thirty-two most commonly used traffic simulation suites were evaluated from different aspects, including the modeling functions available, objects and phenomena modeled, indicators provided, and other properties. In the United States, Boxill and Yu (2000) presented an evaluation of more than 80 traffic simulation models in an attempt to evaluate the potential application of ITS equipped networks. They found that CORSIM and INTEGRATION appeared to have the highest probability of success, whereas by adding more calibration and validation, the AIMSUN2 and Paramics would be brought to the forefront for use with ITS applications.

In an empirical comparison of simulation models, Wang and Prevendouros (1997) compared performance of Integration, CORSIM and WATSim by applying them to three small networks in Honolulu. They found that INTEGRATION was least able to model complex signal operations; CORSIM was best at replicating lane-changing behavior; WATSim needed the least calibration for producing good results, but its universal car-following parameters were undesirable. Bloomberg and Dale (2000) compared the VISSIM and CORSIM simulation models on a congested network. The consistency and reasonableness of the simulation results led them to believe that it might be practical to use more than one model for make the analysis more reliable, and the results more defensible.

OD Estimation

OD estimation is a well-established research topic in the field of transportation engineering as well as operation research. The OD estimation problem can be attacked from three different approaches, namely a traffic modeling approach, a statistical inference approach and a gradient approach (Abrahamsson, 1998).

The traffic modeling approach derives a ”minimum information” OD matrix to achieve entropy maximization. Zuylen and Willumsen (1980) initially explored this approach, based on a gravity trip distribution model. Fisk (1988) extended this model by introducing user-equilibrium conditions as constraints on congested transportation networks.

The statistical inference approach includes several different techniques, as different objective functions can be used. Spiess (1987) proposed an algorithm of maximizing the likelihood between the observed traffic counts of the target OD matrix and the estimated OD matrix. Cascetta (1984) and Bell (1991) duplicated their finding in estimating OD matrix using generalized least square (GLS) method with the assumption of proportional trip assignment. Maher (1983) also assumed proportional assignment in his Bayesian inference algorithm to estimate an OD matrix. Sherali (1997) explored this approach using a least norm estimator since it was intuitively more robust to outliers.

Among all different statistical objective functions, the generalized least square method was most frequently cited in recent research. For example, Dixon and Rilett (2002) examined a generalized least square method and a Kalman filtering method using automatic vehicle identification count data.

The gradient-based solution technique takes an OD matrix estimate as an initial solution, and then attempts to reproduce the traffic counts by iteratively adjusting OD pairs. It was separately explored by Spiess (1990), Yang, et al., (1992), and Chen (1994). This technique is proposed to solve the optimization problem for the traffic modeling and statistical inference approaches.

Chapter 02: Network Dataset and CORSIM Network

In this chapter, a network dataset containing different inputs to the simulation models is presented in Section 2.1. The CORSIM simulation network is described in Section 2.2, and outputs from the CORSIM network are summarized in Section 2.3.

2.1 Case Study Network Dataset

A case network dataset was prepared for the modeling using CORSIM and Paramics. This dataset contained field data, including network geometry, traffic control, traffic demand, vehicle and driver attributes, and some other attributes.

As mentioned in Chapter 1, since this research was the continuation of a project aimed at optimizing signal plans for this same case network using CORSIM simulation, most network data collection for the CORSIM inputs had already been done with the assistance of the Chicago Department of Transportation (DOT). Since this dataset would also be applied to the Paramics model, it is summarized from a general network modeling perspective and presented below.

Network Geometry Data

Network geometry data include street geometry data, intersection geometry data, and some other geometry data.

Key link geometric horizontal alignment data were gathered in details in the field. Stop-bar-to-stop-bar distances, and lengths of turning pockets were manually measured as important street lateral characteristics. The numbers of traveling lanes and pocket lanes were counted to determine street width.

For the geometry data that were difficult to gather in the field, some default values were assumed. These values included lane widths of 12 feet, and the link sections that were assumed to be straight. As the terrain was level, grades for all streets were assumed to be zero. Since none of the parking lots appeared to have a significant effect on this area, all streets were assumed not to have any driveway. These assumptions simplified the modeling process and did not significantly compromise the accuracy of the model.

Some intersection data, such as intersection length, width, turning radius, were assumed to have minor effect on the operation of the test network, although they were indeed used in some simulation studies as part of the control parameters. In this case study, no detailed intersection geometry data were gathered. No sight distance data were gathered in the field either.

Network Traffic Control Data

Network traffic control data include both intersectional traffic control data and sectional traffic control.

For the intersectional traffic control, the Chicago Department of Transportation (CDOT) provided the detailed signal plan for the signalized intersections, as well as sign types and locations for the un-signalized intersections. At the signalized intersections, right turn on red (RTOR) or left turn on red was allowed at most intersections in the target area, except for one turn movement from a surface street to a freeway section.

Sectional traffic control regulations including lane usage, lane changing and design speeds, were gathered for each street. Types and locations of warning signs for sectional traffic were not gathered since they are seldom being accounted for in most traffic simulation models.

On-street parking was not allowed throughout the case network, but during the target simulation time period, there were actually a few sections on some streets occupied by illegally parked vehicles. Since both simulation models don't have parking-lane simulating functions, lengths of actual parking lanes were recorded and corresponding parts of these lanes in the simulation networks were closed to traffic.

Network Traffic Input Data

As the traffic demand inputs to the simulation network, entry volumes and turning probabilities were manually gathered for the target time period. However, no OD traffic data were gathered in the field during that period.

In the network boundary area, entry volumes and turning movement counts were gathered manually, whereas inside the network, turning counts were gathered from videotapes, which were recorded from seven different angles covering most parts of the study area.

To enter the percentages of different vehicle types, heavy vehicle counts were done at the same time as the entry link counts. Buses were counted separately and the bus schedule was obtained from the Chicago Transit Authority.

Volumes of pedestrians were not counted in the field since almost all intersections had only low pedestrian traffic. Instead, two locations were estimated to have no pedestrian traffic, while others were estimated to have low pedestrian volumes. No bicycle data were gathered for the case network since the bicycle traffic was low throughout the network.

Network Vehicle Composition and Driver Attributes

In microscopic traffic simulation networks, vehicles are the simulation entities traveling through the network. As a major characteristic of the vehicles, the heavy vehicle percentage was gathered in the field. However, detailed vehicle composition data (for example, percentage of heavy vehicles that are single-unit trucks), were not gathered since they are too difficult to be measured. Therefore, when constructing the simulation model, default vehicle composition percentages were used.

Performance of an individual vehicle depends not only on the vehicle characteristics, but also on the driver attributes. Unfortunately, due to the same reasons as the vehicle composition data, no driver attribute data could be gathered in the field. The necessary driver attribute data for CORSIM and Paramics modeling include driver aggression, driver awareness, driver sensitivity factors in the car following, lane changing, and the gap acceptance model.

As a usual way to deal with driver studies, driver attributes were assumed to follow normal distributions, although in CORSIM some discrete distributions are used as simplified approximations.

Driver familiarity percentage is an important parameter to the traffic assignment algorithms in Paramics. Familiar drivers have different coefficients in the calculation of costs on minor streets. Moreover, familiar drivers are able to change their routes whenever they are experiencing extra delay, while unfamiliar drivers would remain on the preset routes, even when they are delayed by congestion for a long time.

The driver familiarity percentage for this case network could not be directly gathered in the field. The calibration of this percentage will be discussed in Chapter 5.

2.2 CORSIM Network

The CORSIM network was already constructed, calibrated and validated in a previous study for optimizing the signal plan using simulation. Details of the CORSIM network can be found in Sacks et al (2000).

Network Representation

The CORSIM simulation network is comprised of 166 network links, 56 network nodes, and 47 dummy entry nodes for the origins of vehicle inputs. The CORSIM network is shown in Figure 2.1.

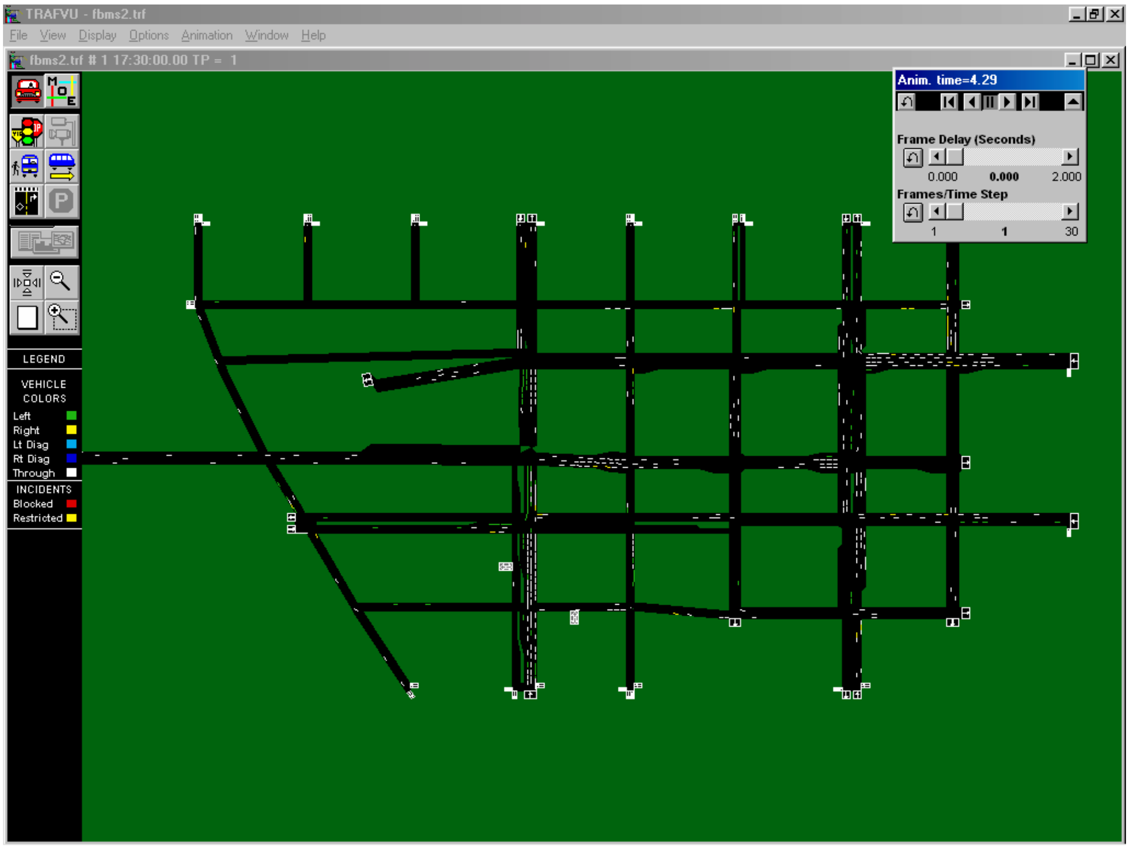

Figure 2.1: CORSIM simulation network

CORSIM default values were used for the vehicle and driver characteristics. Two noticeable calibration parameters having significant effect on capacity and delay are the mean start-up lost time and mean queue discharging headway. Default values in CORSIM, which were respectively 2.0 seconds and 1.8 seconds, were used; and the distribution forms of the individual vehicle attributes were approximately normal.

<u>Model Validation</u>

The validation was executed by comparing field data at several key links to CORSIM predictions. The criteria for selecting these links were 1) availability of field data, and 2) whether they were key to the overall performance of the network from a transportation standpoint.

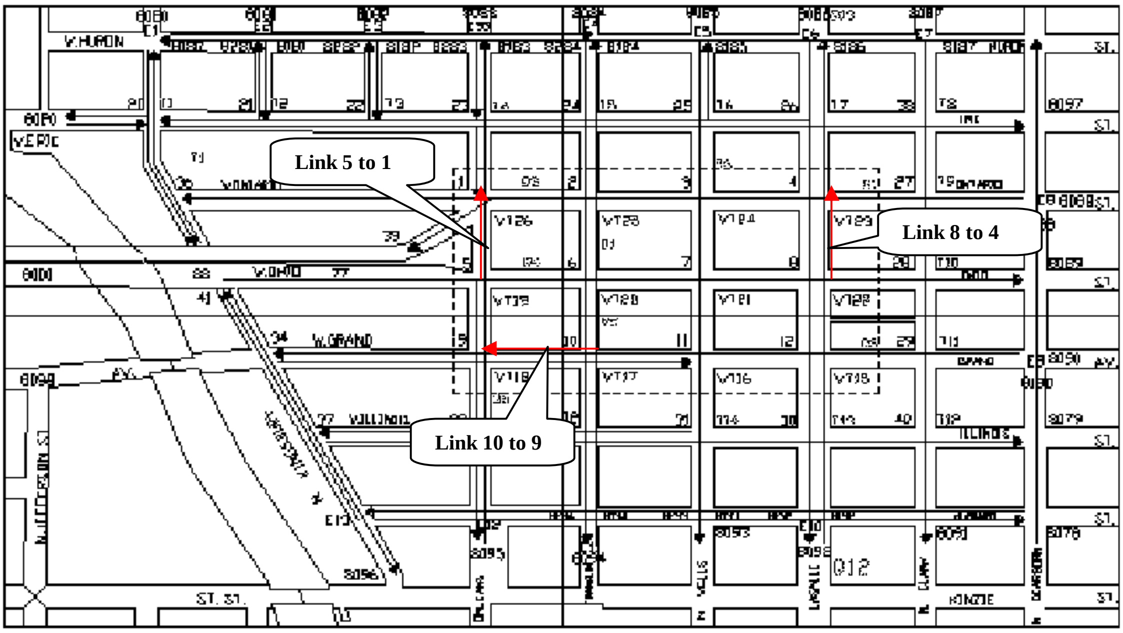

Figure 2.2: Selected CORSIM links for validation

The three selected links to perform validation are:

- Link 8 to 4, Northbound LaSalle Street from Ohio Street to Ontario Street,
- Link 5 to 1, Northbound Orleans Street from Ohio Street to Ontario Street; and
- Link 10 to 9, Westbound Grand Street from Franklin Street to Orleans Street.

The validation process was based on one hundred replications of CORSIM runs. The number of replication was statistically large enough to yield a relative short confidence interval around the mean.

The visual validation of individual simulation run showed that gridlock (network run failure because of vehicle spillback effect) appeared in some replications. These replications yielding apparent deviant outputs because of gridlock are referred to as outliers. Details about gridlock and outliers are discussed in Chapter 5. After excluding outliers, ninety-eight effective replications were summarized for statistical validation.

Mean link trips and mean stop time per vehicle were used as major measures of effectiveness (MOE) for validation. Summary results of these statistics are shown in Table 2.1.

CORSIM Link	Street Name	Link Trips				Link Stop Time per Vehicle			
		CORSIM Mean (1)	CORSIM STDEV (1)	Field Value	Ratio (2)	CORSIM Mean (1)	CORSIM STDEV (1)	Field Value	Ratio (2)
8 to 4	NB LaSalle	1616.8	23.4	1636.0	0.99	20.7	3.4	21.5	0.96
5 to 1	NB Orleans	1069.2	28.7	1078.0	0.99	9.8	1.5	9.1	1.08
10 to 9	WB Grand	1009.3	34.0	1117.0	0.90	22.5	7.4	24.4	0.92

Table 2.1: Validation results for the CORSIM simulation network

Note: 1) Based on 98 replications of CORSIM runs.
2) CORSIM mean (1) divided by field value.

As can be seen in Table 2, all CORSIM statistics are within 10 percent variance of the field values.

Student t-tests were not performed for the validation, since the mean values of the simulation outputs would not necessarily be the field observed values because of observation variability. Instead, direct plots of histograms for MOEs of interest were used and visual comparison with field observation was performed. Plots of link trips and link stop time for Link 8 to 4, Link 5 to 1, and Link 10 to 9, along with the observed field values, are shown in Figures 2.3 to 2.8, respectively.

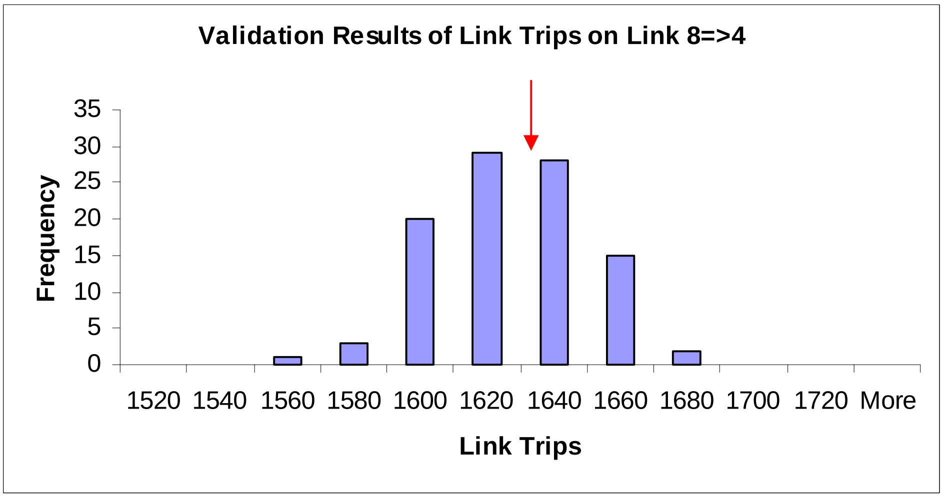

Figure 2.3: Link trips validation results on Link 8 to 4

Note: Arrow shows field value

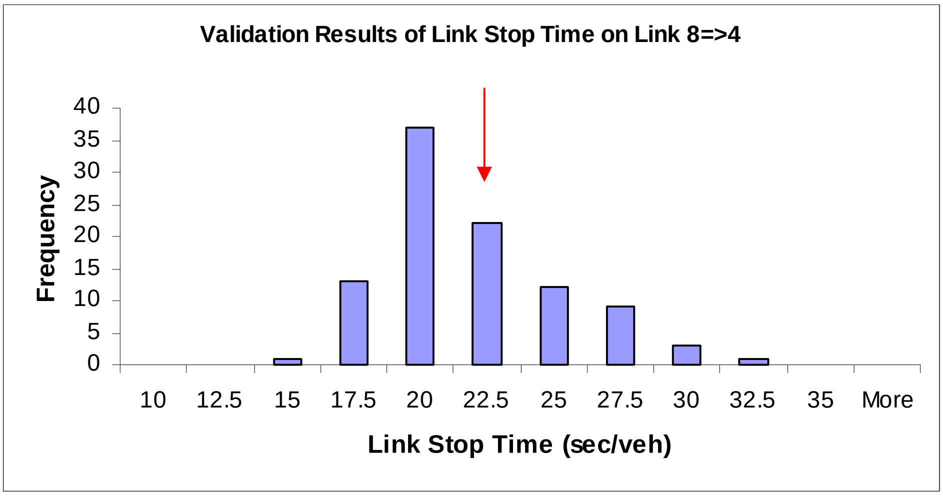

Figure 2.4: Link stop time validation results on link 8 to 4

Note: Arrow shows field value

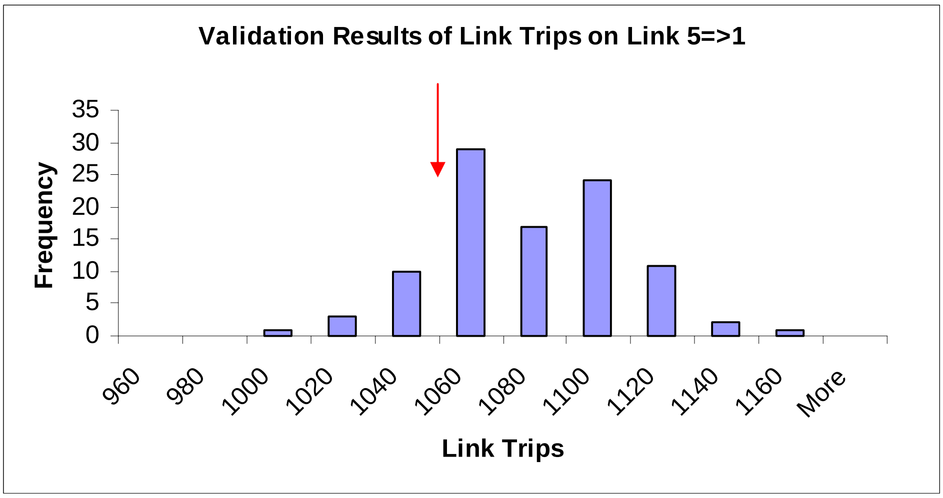

Figure 2.5: Link trips validation results on Link 5 to 1

Note: Arrow shows field value

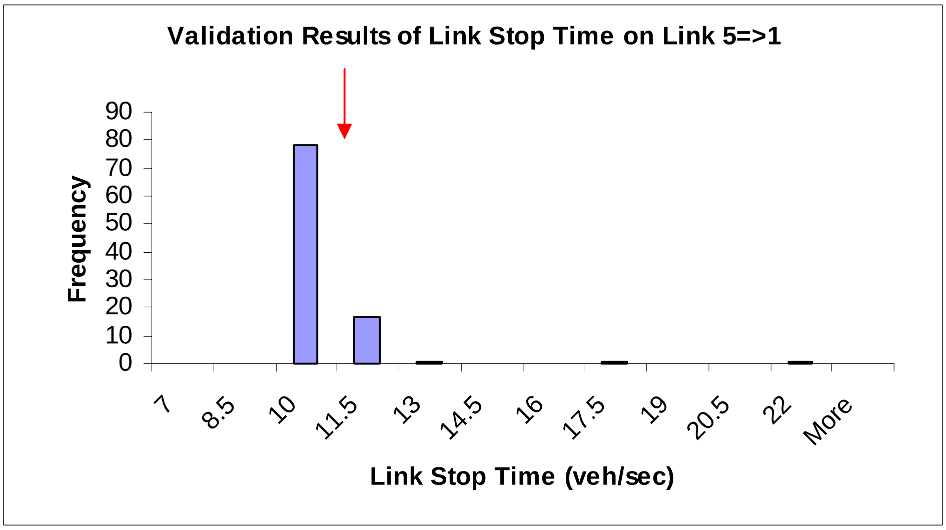

Figure 2.6: Link stop time validation results on link 5 to 1

Note: Arrow shows field value

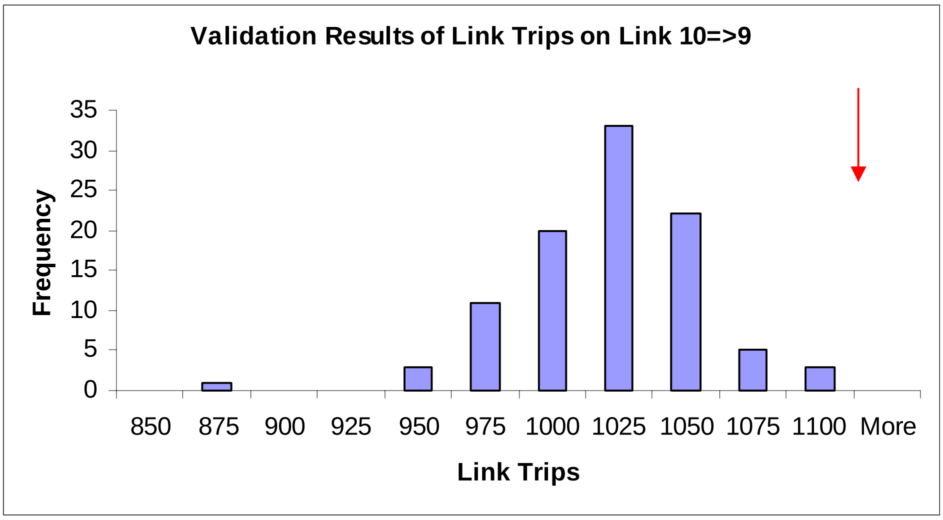

Figure 2.7: Link trips validation results on Link 10 to 9

Note: Arrow shows field value

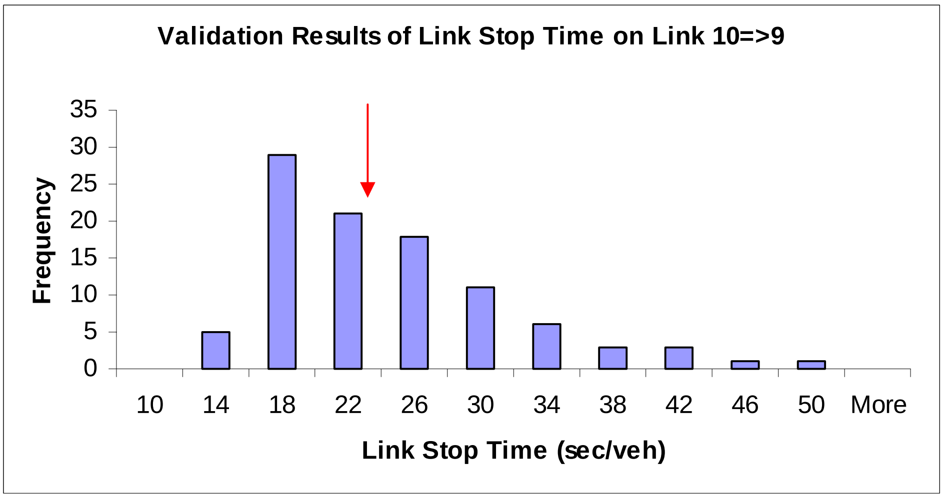

Figure 2.8: Link stop time validation results on link 10 to 9

Note: Arrow shows field value

The validation results demonstrated that the CORSIM network reproduced link trips and link stop times successfully, although in one link (Link 10 to 9) it produced link trips that were 10 percent higher than the field value.

2.3 CORSIM Network Outputs

The outputs from the CORSIM simulation network are briefly summarized below. The statistics of interest here are percentage of outliers and system queue time.

The percentage of outliers is frequently used to indicate network stability and model run effectiveness, assuming that the gridlocks are not caused by inadequate capacity or network coding errors. The criterion to judge outliers is if the system queue time exceeds a certain threshold, which are 300 vehicle hours in this research. Only two of the one hundred replications had system queue time more than 300 vehicle hours. This demonstrated that the CORSIM simulation network was a fairly stable model.

System queue time for the overall network was employed as the global measure of effectiveness (MOE) to characterize the system congestion level. The plot of system queue time is shown in Figure 2.9.

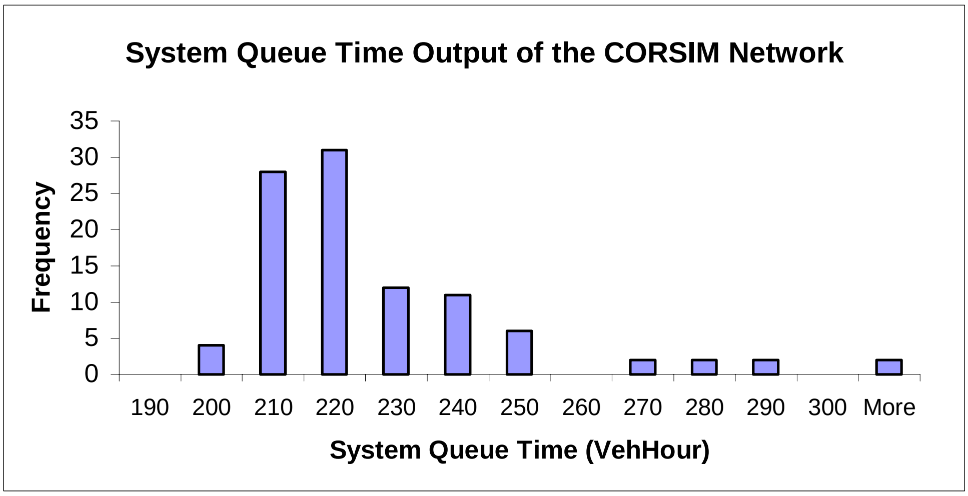

Figure 2.9: Plot of system queue time of the CORSIM simulation network

Note: 1) Based on one hundred replications of CORSIM runs
2) The right-most bar corresponds to data from 2 outliers

As shown in this histogram plot, the CORSIM network system queue time is right-skewed and the mode is between 210 and 220 vehicle-hours. The mean, median and standard deviation of system queue time are 225, 214 and 36 vehicle-hours, respectively.

Some other system-level statistics including network throughput, system stop time, system vehicle hours, etc, and local level statistics such as corridor or link trips, stop times, vehicle hours, were also gathered. These results will be discussed in Chapter 5.

Chapter 03: OD Matrix Derivation in Paramics

In this chapter, the OD matrix derivation methods and processes are described in detail. Section 3.1 provides criteria for evaluating OD solutions from different derivation methods. The statistical fitting method and stochastic assignment method are described in Sections 3.2 and 3.3. In Section 3.4 the adopted OD solution by manual adjustment is presented.

3.1 Target OD Matrix and Solution Constraints

OD derivation Methods and Evaluation

As mentioned in the literature review in Chapter 1, depending on different available data, the target OD matrix could be estimated using various methods. One criterion to evaluate the solutions from different derivation methods is the ability to reproduce link flows. If the OD matrix is fed to a well-tuned Paramics model, (a) the number of outliers (i.e., runs with gridlock) should be small (because it is small in CORSIM), and (b) the link flow discrepancies between Paramics and CORSIM should to be small too. Paramics was tuned to have a low mean driver reaction time (0.5 sec) and low mean car-following headway (0.7 sec) --- higher values caused an inordinate number of gridlocks.

In this research, based on the available data, two different OD matrix derivation methods were studied: a statistical fitting method and a stochastic assignment. The statistical fitting method was based on given (by CORSIM) link volumes and derived traffic assignment routes, while the stochastic assignment method was to determine the target OD matrix from given entry volumes and turning probabilities (the needed inputs to CORSIM). The number of outliers and the discrepancy between Paramics link flows and CORSIM flows were used to compare the two methods.

Constraints on the OD Solutions

Successful OD matrix solutions must satisfy feasibility constraints and entry-exit-volume constraints to achieve reasonable results.

- **Feasibility Constraint**

The feasibility constraint is to assign traffic demand only to those feasible OD pairs. For this case network, trips between some OD pairs are infeasible, so that for any solution matrix, the corresponding cell values should be 0. Summarizing the feasibilities for each OD pair leads to a feasibility OD matrix $\vec{F}$, in which each pair has values of 1 or 0 to stand for its feasibility status.

FROM\TO	1	2	3	4	…	20	21	22	23	*	SUM
1	0	0	0	0	…	0	0	0	0	*	**0**
2	0	0	0	1	…	1	1	0	1	*	**14**
3	1	0	0	0	…	1	1	0	1	*	**9**
4	1	1	0	0	…	1	1	0	1	*	**14**
…	**…**	**…**	**…**	**…**	**…**	**…**	**…**	**…**	**…**	**…**	**…**
20	0	1	1	1	…	0	1	0	1	*	**8**
21	0	1	1	1	…	1	0	0	1	*	**16**
22	1	1	0	1	…	1	0	0	0	*	**16**
23	0	0	0	0	…	0	0	0	0	*	**0**
*****	*	*	*	*	*	*	*	*	*	*	*****
SUM	**7**	**13**	**4**	**11**	**…**	**15**	**14**	**0**	**15**	*****	**219**

Table 3.1: Feasibility matrix $\vec{F}$ for the case network OD pairs

Table 3.1 shows part of the feasibility matrix $\vec{F}$ for the case network OD pairs. Therefore, vehicle trips will only be assigned to the 219 feasible OD pairs.

- **Entry-Exit-Volume Constraint**

This constraint requires a match between any OD solution and the known marginal entry and exit link volumes. Origin and destination volumes for all demand zones can be obtained from the field traffic counts at the entry and exit links. Thus, the rows and sum of columns of the target OD matrix solution should add up to the origin and destination vectors $\vec{O}$ and $\vec{D}$:

$$\sum_{j=1}^{n} od_{i,j} = O_i$$
$$\sum_{i=1}^{n} od_{i,j} = D_j$$

Where $od_{i,j}$ denotes the unknown OD traffic demand from zone i to zone j, O_i denotes traffic origin demand from zone i, D_j denotes traffic destination demand to zone j, and n denotes the number of demand zones in the case network.

The transpose of the origin vector $\vec{O}$ and the destination vector $\vec{D}$ for the case network are shown below.

$$O^T = (\ 0 \ \ 232 \ \ 43 \ \ 50 \ \ ... \ \ 47 \ \ 453 \ \ 1850 \ \ 0\ )$$
$$D^T = (\ 15 \ \ 126 \ \ 5 \ \ 88 \ \ ... \ 299 \ \ 712 \ \ 0 \ 3878\ )$$

3.2 Statistical Fitting Method

Approach

The statistical fitting method was based on given traffic link volumes and routes associated with each OD pair. Provided that an OD traffic routing algorithm is available, for each OD matrix solution, the corresponding “theoretical” link volumes could be solved. Since the target OD matrix always generates “theoretical” link volumes that match the known volumes, the solution that generates the least matching error, therefore, could be used as an approximation of the target OD matrix. Thus, the OD estimation problem can be solved as a constrained nonlinear programming problem.

- Step 1: Generate the traffic route matrix $\vec{R}$

A calibrated Paramics network using the static assignment option (where familiar drivers won't change their routes during the simulation) was used in the OD trip routing algorithm. As there were 219 feasible OD pairs and 111 effective network links, the routing algorithm was represented by a traffic route matrix $\vec{R}$, which was an 111×219 identity matrix where cell (i, j) was assigned a value of 1 if traffic between OD pair i traverses link j, 0 otherwise.

The Paramics network was run with a 0-1demand matrix, which was constructed by placing unit demand for all feasible cells. Since each unit trip stood for a different OD pair, the traffic route matrix $\vec{R}$ was constructed through recording all the resulting traffic routes in Paramics. Part of a generated route matrix $\vec{R}$ is shown below in Table 3.2.

Link		OD Pair								
Number	**Name**	**1**	**2**	**3**	**4**	**…**	**216**	**217**	**218**	**219**
1	**2=>1**	0	0	0	0	**…**	0	0	0	0
2	**5=>1**	0	0	0	0	**…**	0	0	0	0
3	**13=>1**	0	0	0	0	**…**	1	1	1	1
4	**23=>1**	0	0	0	0	**…**	0	0	0	0
…	**…**	**…**	**…**	**…**	**…**	**…**	**…**	**…**	**…**	**…**
108	**32=>94**	0	0	0	0	**…**	0	0	0	0
109	**33=>95**	0	0	0	0	**…**	0	0	0	0
110	**34=>96**	0	0	0	0	**…**	0	0	0	0
111	**10=>110**	0	0	0	0	**…**	0	0	0	0

Table 3.2: OD traffic route matrix generated from Paramics

- Step 2: Generate the theoretical link volume vector $\vec{T}$

For each possible OD matrix solution, a solution vector $\vec{S}$ is defined as the vector containing 219 corresponding feasible OD pair values. The “theoretical” link volume vector $\vec{T}$ is defined by:

$$t_j = \sum_{i=1}^{219} (R_{j,i} \times s_i)$$

- Step 3: Generate the empirical link traffic volume vector $\vec{E}$

An empirical link traffic volume vector $\vec{E}$, which was composed of 111 known link volumes, was gathered from the validated CORSIM network. To account for the randomness in CORSIM replications, ten runs were performed and the link counts were gathered from the replication having the median system queue time. One hundred and eleven link traffic volumes were collected as the empirical values to match.

- Step 4: Establish the objective function

The error between the theoretical and empirical link volumes,

$$SSE = \sum_{j=1}^{111} (t_j - E_j)^2$$

, where SSE stands for Sum Square Error of link volumes, is to be minimized by choice of $\vec{S}$. It is a nonlinear programming problem that requires the use of an optimization algorithm. The resulting problem included 219 adjustable variables that were subject to the origin/destination flow constraints. As a common tool for small linear or non-linear programming problems, Microsoft Excel Solver was used to solve for this problem.

- Step 5: Combine familiar driver and unfamiliar driver solutions

Since the static assignment option was used in Paramics, the OD routing matrix was actually solved based on an all-or-nothing traffic assignment method. Paramics generation was executed under two different assumptions, one using 100% familiar drivers and the other using 100% unfamiliar drivers, to account for the multiple-route behavior between some OD pairs. Thus, two routing matrices, $\vec{R}(F)$ for familiar drivers and $\vec{R}(U)$ for unfamiliar drivers**,** were created. These two routing matrices were applied to the entire derivation process separately and the solutions were ultimately combined with a 40/60 split for unfamiliar/familiar driver solutions to generate a final solution for application.

The combined solution is shown in Table 3.3.

FROM \TO	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	*	SUM
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	*	**0**
2	0	0	0	10	57	0	0	0	0	0	0	26	0	43	0	8	14	0	38	10	26	0	0	*	**232**
3	2	0	0	0	14	0	0	0	0	0	0	0	0	0	0	0	0	0	11	0	16	0	0	*	**43**
4	1	0	0	0	0	8	0	2	0	0	0	4	0	0	0	0	0	0	8	0	20	0	7	*	**50**
5	4	12	0	0	0	0	0	0	0	38	0	57	0	12	0	0	6	19	0	58	8	0	628	*	**841**
6	1	1	0	45	0	0	0	1	0	24	0	68	0	1	1	0	0	0	0	0	0	0	43	*	**186**
7	0	0	0	0	49	0	0	0	0	135	0	89	0	13	1	5	206	1	0	0	0	0	50	*	**549**
8	4	0	0	0	0	8	0	0	0	0	0	32	0	125	35	527	29	1	1	8	9	0	192	*	**970**
9	0	0	0	0	22	87	0	0	0	0	0	0	0	174	640	11	1	1	6	2	16	0	453	*	**1413**
10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	*	**0**
11	0	0	0	0	5	25	1	242	0	0	0	0	0	38	84	52	12	1	1	0	0	0	1482	*	**1943**
12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	*	**0**
13	1	109	2	0	0	0	1	18	0	5	0	0	0	0	265	73	214	5	30	0	446	0	107	*	**1275**
14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	*	**0**
15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	*	**0**
16	0	0	0	0	7	2	7	962	0	39	0	50	0	99	0	0	0	1	0	24	154	0	62	*	**1406**
17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	*	**0**
18	0	2	0	0	5	120	0	51	0	16	0	19	0	124	0	24	0	0	0	28	4	0	0	*	**394**
19	0	0	1	0	489	0	28	11	0	20	0	41	0	83	9	37	0	0	0	169	13	0	691	*	**1593**
20	0	1	1	28	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	13	*	**47**
21	0	1	1	0	52	0	0	50	0	0	0	128	0	29	0	0	41	0	0	0	0	0	150	*	**453**
22	2	0	0	5	431	69	2	65	0	0	0	866	0	40	82	46	205	37	0	0	0	0	0	*	**1850**
23	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	*	**0**
*****	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*****
SUM	**15**	**126**	**5**	**88**	**1133**	**318**	**39**	**1402**	**0**	**278**	**0**	**1381**	**0**	**783**	**1117**	**784**	**728**	**65**	**94**	**299**	**712**	**0**	**3878**	*****	**13245**

Table 3.3: OD solution matrix from the statistical fitting method

Solution Evaluation through Feedback

The solution OD was fed to the calibrated Paramics model. The results were very disappointing since all the Paramics runs using the proposed OD resulted in network gridlock (See for example, Figure 3.1).

Since it was possible that the SSE solution would treat high-volume links differently than low-volume ones, another objective function attempting to place the links on more equal footing, was tried. The use of

$$SCSE = \sum_{i=1}^{l} \left(\frac{t_i - E_i}{E_i}\right)^2$$

, where SCSE denotes Sum Chi-Square Error, however, did not succeed in reducing the level of gridlock.

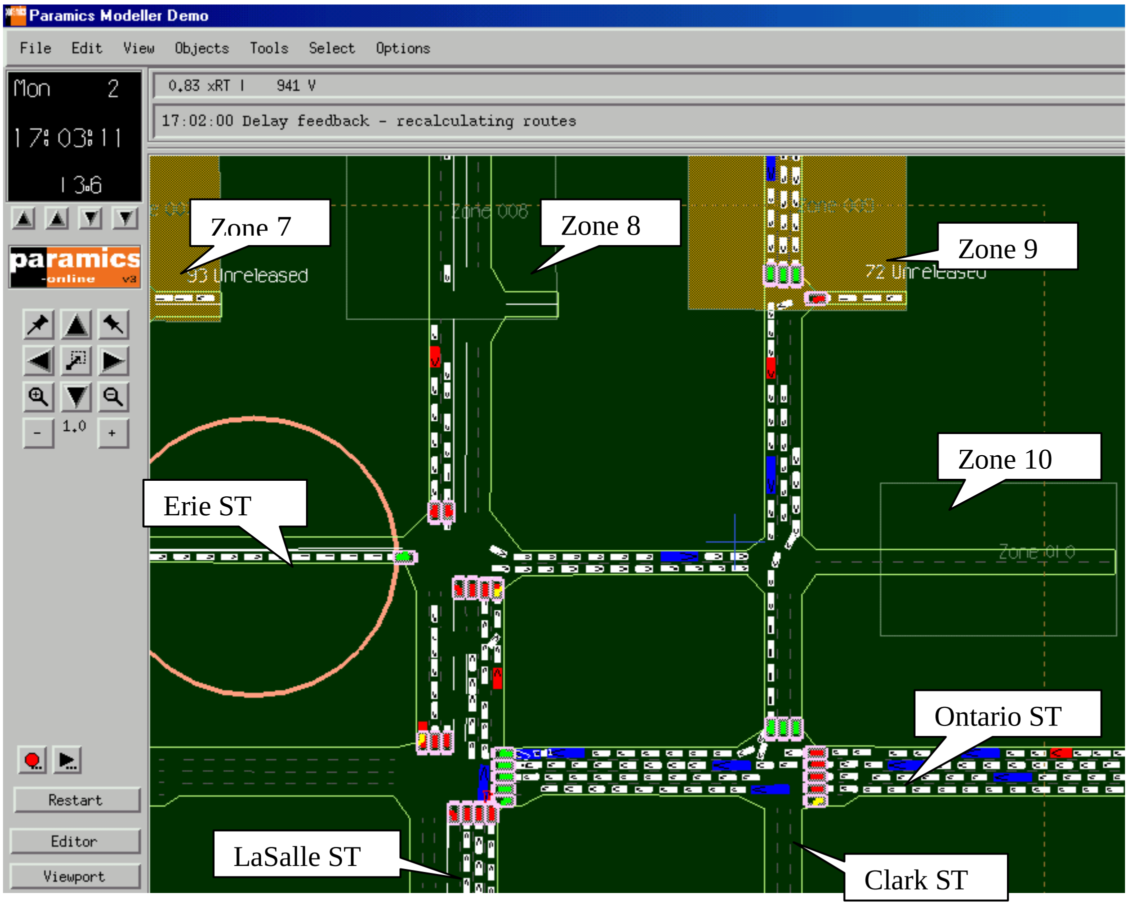

Figure 3.1 Gridlock cause with the Solver OD

Further probing of the results indicated that the statistical fitting method generated unrealistic traffic demand in the Clark Street at Erie Street area (see Figure 3.1). Field observations had shown that southbound Clark at Erie had a left turn percentage of around 8%, which was about 100 vehicles turning left during the subject time period. However, the solutions generated by statistical fitting method had a much lower traffic demand from zone 9 to zone 10, which was balanced by a greater demand from zone 9 to zones located west of LaSalle and from those zones to zone 10. As a result, these solutions had put more through vehicles on eastbound Erie Street at Clark and more right turns on SB Clark Street at Ontario.

EB Erie Street is stop-controlled and has a small capacity. Also, the heavy usage of the right-turn lane from SB Clark to WB Ontario caused spillback that further aggravated the situation. It was observed that just about all gridlocks were initiated at that location.

It is hypothesized that the statistical fitting method gives preference to long trips. Obviously, with the same amount of adjustment, changing to longer trips would enable faster fitting to the empirical data since longer trips would include more links that can be adjusted at the same time.

As a result, shorter OD trips were decreased or even eliminated in the solution process and longer OD trips were increased. This resulted in difficult turning movements at some sensitive intersections, thus leading to a high risk of breakdown on the whole network. To avoid this problem, turn movement volume fitting error could be used as the objective function. However, these data are too expensive to gather in the field, and it would explode the dimensions of the optimization problem.

A modification of the statistical method was to constrain the true traffic demand from zone 9 (Southbound Clark Street) to be empirical values, and optimize other feasible OD pairs. The constrained solutions from different objective functions were satisfactory in generating successful Paramics runs and yielded lower SSE or SCSE. The results are shown in Table 3.4.

Statistical Fitting Method	Theoretical Calculation				Paramics Run Results Using the Proposed OD					
	Unfamiliar Driver Routes		Familiar Driver Routes		Static Assignment			Dynamic Assignment		
	SSE	SCSE	SSE	SCSE	# of Outliers	SSE	SCSE	# of Outliers	SSE	SCSE
1	3.7E+05	1,336	1.8E+06	4,543	100	N/A	N/A	100	N/A	N/A
2	4.7E+05	1,168	2.1E+06	4,091	100	N/A	N/A	100	N/A	N/A
3	5.4E+05	1,513	2.1E+06	4,797	23	1.8E+06	3,751	4	9.3E+05	2,705
4	6.7E+05	1,337	2.3E+06	4,327	63	3.1E+06	4,600	6	1.0E+06	2,663

Table 3.4 Summary of statistical fitting method solutions

Note: fitting method 1 is calculated to minimize link volume SSE (sum square error) by adjusting all feasible OD pairs, method 2 is calculated to minimize SCSE (sum chi-square method) by adjusting all feasible OD pairs, method 3 is to minimize SSE by keeping SB Clark OD pairs to be derived values from the stochastic assignment method and adjusting other feasible OD pairs, and method 4 is subject to the same conditions as method 3, but to minimize SCSE.

3.3 Stochastic Assignment Method

Approach

The stochastic assignment method is based on the entry volumes and turning probabilities that were gathered in the field and used in CORSIM. It is assumed that vehicle routing is based on a stochastic traffic assignment method, where vehicles are assigned to downstream links stochastically, and independent of their network origins.

Since vehicles between origin zone *i* and destination zone *j* are assigned to downstream links according to prescribed turning probabilities, then, for a particular route *r* containing n links (link *0* corresponds an entry link, link *n* corresponds an exit link) with an entry volume of E_r,

$$od_{ij}{}^{r} = E_r \prod_{k=1}^{n} P_{k-1,k}$$

Where $P_{k-1,k}$ denotes turning probability from link *k-1* to link *k*.

For one particular OD pair, vehicle demand would equal the aggregation of vehicle trips traveling through all possible routes between the origin and the destination zone.

$$od_{ij} = \sum_{r} od_{ij}{}^{r}$$

The OD matrix solution could be solved pair-by-pair using the same method as above.

Manual calculation or even computer programming for this method is laborious. Therefore the solution could be achieved by simulating CORSIM.

A series of single-source CORSIM runs were carried out, each having a single entry volume as traffic demand.

For each single-source run, the traffic volumes at all exit links were gathered as the pair values for one corresponding row of the OD matrix. The solution OD matrix was solved through running the single source network for each origin input separately.

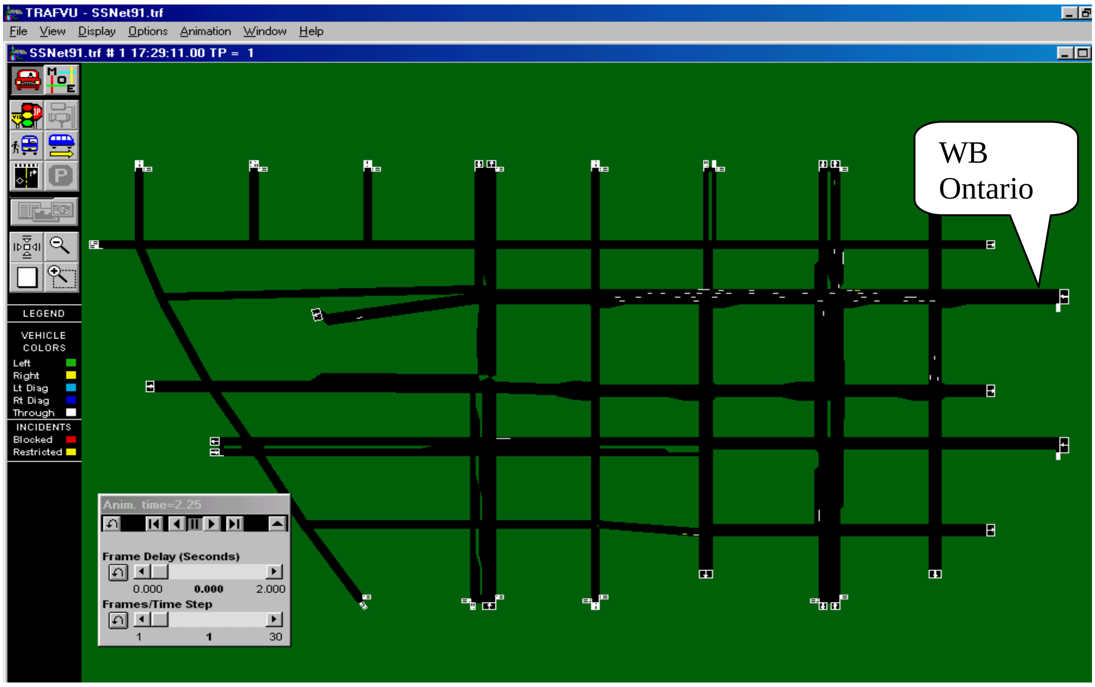

Figure 3.2 Single-source CORSIM network (WB Ontario)

To avoid extreme randomness, the median values from multiple CORSIM runs were collected as the OD pair values. The derived solution is shown in Table 3.2:

FROM \TO	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	*****	**SUM**
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	*	**0**
2	0	0	1	18	11	3	0	2	0	0	0	6	0	24	2	3	37	1	6	66	24	0	32	*	**236**
3	2	3	0	14	4	1	0	0	0	0	0	0	0	0	0	1	3	0	1	4	4	0	7	*	**44**
4	1	5	0	0	2	1	0	4	0	1	0	2	0	2	1	1	5	0	1	3	5	0	12	*	**46**
5	4	8	0	9	0	22	0	22	0	27	0	8	0	17	8	9	31	8	0	20	13	0	625	*	**831**
6	1	2	0	3	5	0	0	5	0	4	0	15	0	24	4	6	12	19	1	3	11	0	71	*	**186**
7	0	5	0	7	21	8	0	23	0	10	0	54	0	90	18	17	183	1	0	3	21	0	84	*	**545**
8	4	2	0	0	15	12	17	0	0	25	0	99	0	55	17	471	11	1	2	2	39	0	198	*	**970**
9	0	1	0	0	18	13	0	41	0	106	0	154	0	119	621	17	8	1	1	6	25	0	282	*	**1413**
10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	*	**0**
11	0	2	0	4	56	44	1	136	0	15	0	31	0	38	102	79	29	1	2	2	11	0	1379	*	**1932**
12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	*	**0**
13	1	12	2	8	93	31	1	137	0	10	0	33	0	57	176	56	51	9	10	24	383	0	169	*	**1263**
14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	*	**0**
15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	*	**0**
16	0	0	0	4	18	14	7	806	0	41	0	103	0	99	38	0	7	3	0	3	43	0	209	*	**1395**
17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	*	**0**
18	0	1	0	1	17	110	0	10	0	10	0	23	0	51	10	16	49	0	1	2	33	0	80	*	**414**
19	0	38	1	15	448	13	1	16	0	4	0	51	0	64	18	15	61	10	0	124	86	0	610	*	**1575**
20	0	16	1	2	1	0	0	0	0	0	0	0	0	4	0	0	4	0	0	0	14	0	5	*	**47**
21	0	31	1	9	48	18	0	7	0	3	0	7	0	65	12	8	131	3	9	28	0	0	78	*	**458**
22	2	8	0	6	364	28	2	148	0	22	0	795	0	74	90	51	106	9	72	9	47	0	57	*	**1890**
23	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	*	**0**
*****	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*****
SUM	**15**	**134**	**6**	**100**	**1121**	**318**	**29**	**1357**	**0**	**278**	**0**	**1381**	**0**	**783**	**1117**	**750**	**728**	**66**	**106**	**299**	**759**	**0**	**3898**	*****	**13245**

Table 3.5: OD solution matrix from stochastic assignment method

The solution OD matrix was run in Paramics. The results were encouraging in that a small number of gridlocks were generated and traffic volumes on most links were close to the known link volumes.

3.4 Adopted OD Matrix after Manual Adjustment

<u>Roundtrips in the Stochastic Assignment Method Solution</u>

Further observations of Paramics running with the solution OD from the stochastic assignment method showed that some inner links had lower traffic than expected, whereas the boundary links had better fitting results to the known traffic volumes.

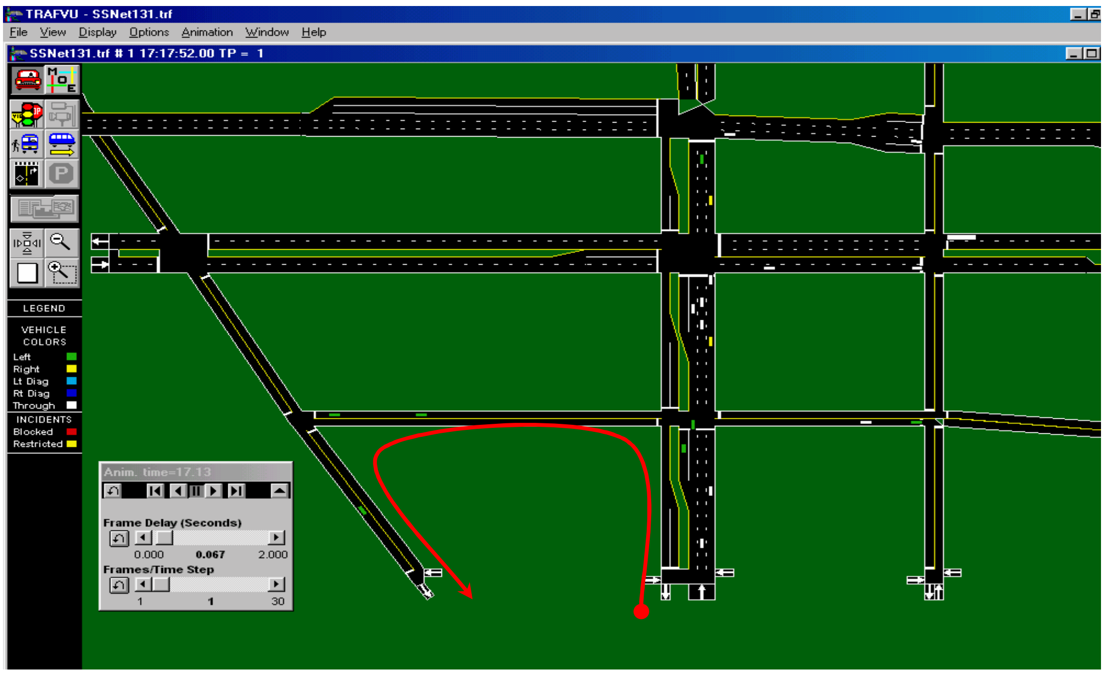

Figure 3.3 Round trips in CORSIM network runs

This occurred because the stochastic assignment method could yield round trips between OD pairs (See Figure 3.3). In flow-based simulation models, vehicles could be assigned stochastically, so that some round trips would be generated in a series of consecutive left turns or right turns; in the real world and in route-based simulation models, vehicles would not enter the inside network and circle around if they could go though boundary areas to reach their destinations directly. Therefore these round trips should be transferred to other reasonable OD pairs.

OD Solution after Manual Adjustment

To zero out these round trips and keep the marginal values of rows and columns fixed at the same time, a rectangular adjustment method was used.

For any OD pair *(i, j)* to be adjusted to 0, another corresponding OD pair *(l, m)* is found. Assume the adjustment amount is *A*, the pairs *(i, j) and (l, m)* would be decreased by *A,* and at the same time pairs *(l, j)* and *(i, m)* would be increased by *A.*

Performing this adjustment requires network-specific knowledge in order to decide which corresponding pairs to assign the adjusted traffic to. In this case, a transportation expert performed that operation manually. Around 600 vehicle trips, or about 5% of total network demand, were manually adjusted using this method.

The solution after manual adjustment is shown in Table 3.6.

FROM \TO	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	*	SUM
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	*	**0**
2	0	0	0	15	11	3	0	2	0	0	0	6	0	24	2	3	37	1	6	96	24	0	2	*	**232**
3	2	0	0	0	4	1	0	0	0	0	0	0	0	0	0	1	3	0	1	6	4	0	21	*	**43**
4	1	5	0	0	0	1	0	8	0	1	0	2	0	2	1	1	5	0	1	3	5	0	14	*	**50**
5	4	8	0	0	0	0	0	32	0	34	0	23	0	17	8	9	31	8	0	29	13	0	625	*	**841**
6	1	2	0	3	0	0	0	5	0	4	0	15	0	14	4	6	12	29	1	3	11	0	76	*	**186**
7	0	5	0	7	21	0	0	0	0	33	0	54	0	41	18	21	232	1	0	3	21	0	92	*	**549**
8	4	2	0	0	15	12	0	0	0	25	0	130	0	72	17	423	11	1	2	2	39	0	215	*	**970**
9	0	1	0	0	18	13	0	0	0	106	0	154	0	121	619	17	8	1	1	6	25	0	323	*	**1413**
10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	*	**0**
11	0	2	0	4	56	44	1	162	0	0	0	0	0	38	102	110	29	1	2	2	11	0	1379	*	**1943**
12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	*	**0**
13	1	12	2	8	93	31	1	159	0	10	0	0	0	0	216	78	58	8	18	24	376	0	180	*	**1275**
14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	*	**0**
15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	*	**0**
16	0	0	0	4	18	14	7	844	0	33	0	136	0	137	0	0	0	3	0	3	50	0	157	*	**1406**
17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	*	**0**
18	0	1	0	1	17	141	0	10	0	3	0	8	0	100	10	16	0	0	0	2	33	0	52	*	**394**
19	0	39	1	30	425	13	28	37	0	4	0	71	0	94	18	20	0	0	0	68	86	0	659	*	**1593**
20	0	16	1	2	1	0	0	0	0	0	0	0	0	4	0	0	4	0	0	0	14	0	5	*	**47**
21	0	25	1	8	33	17	0	9	0	3	0	7	0	65	12	8	131	3	10	43	0	0	78	*	**453**
22	2	8	0	6	421	28	2	134	0	22	0	775	0	54	90	71	167	9	52	9	0	0	0	*	**1850**
23	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	*	**0**
*****	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*****
SUM	**15**	**126**	**5**	**88**	**1133**	**318**	**39**	**1402**	**0**	**278**	**0**	**1381**	**0**	**783**	**1117**	**784**	**728**	**65**	**94**	**299**	**712**	**0**	**3878**	*****	**13245**

Table 3.6: OD solution matrix after manual adjustment

The final solution OD was fed back to the Paramics network. The run results proved to be stable in generating few numbers of outliers. As shown in Table 3.7, the fitting SSE was better than the best solution in the statistical fitting method.

Solutions from Different Derivation Methods	Paramics Results Using the Proposed OD					
	Static Assignment			Dynamic Assignment		
	# of Outliers	SSE	SCSE	# of Outliers	SSE	SCSE
Best Statistical Fitting Solution	23	1.8E+06	3,751	4	9.3E+05	2,705
Stochastic Assignment Adjusted Solution	79	2.5E+07	19,412	7	7.5E+05	1,429

Table 3.7 Summary of feedback results with the adjusted OD

Note: Best statistical fitting solution is option 3 in table 3.4, to minimize SSE by keeping SB Clark OD pairs constant and adjusting other feasible OD pairs

This adjusted OD matrix was adopted as the traffic demand input to the Paramics simulation network.

Chapter 04: Paramics Network Construction, Calibration and Link Flow Comparison

In this chapter, the Paramics network modeling process, including model construction and calibration, is discussed in sections 4.1 and 4.2. For evaluation, link flows of Paramics are compared with those of CORSIM in section 4.3.

4.1 Paramics Network Construction

The Paramics network was constructed with the OD matrix derived from the stochastic assignment method with some manual adjustment, as the input traffic demand. Heavy vehicles were assumed to have the same OD pattern as cars. In general, the Paramics network construction process was comprised of modeling the (a) network geometry, (b) traffic control data, (c) traffic and driver attributes, and (d) input traffic demand.

To ensure an unbiased model comparison, the Paramics network was modeled using the same network dataset that was used for the CORSIM network. For those inputs that were not available in the field, the CORSIM default values, which represent a typical urban traffic environment, were used for Paramics as well.

Network Geometry

The network geometry in Paramics is represented through nodes, links, stop-bars, curbs, and curves. As the basic layout of the study network, the relative coordinates of the Paramics nodes were calculated using link lengths that were originally measured from stop-bar-to-stop-bar distances for CORSIM link inputs.

Further geometric details, including locations of curbs, locations of stop bars, turning radii at intersections, were unavailable from the field dataset. Therefore, these characteristics were modeled and matched against CORSIM's using both models' visualization tools.

Since Paramics doesn't have a function to simulate turning-pockets, a network link with a turning pocket was modeled by connecting two adjoining sections that had different numbers of lanes, within which lane-changing regulations were defined.

Network Traffic Control

The Paramics default traffic control methods are based on a British urban traffic environment. Although most traffic control concepts in the U.K. are similar to those in the United States, the traffic control regulations for un-signalized intersections are different. Thus, at un-signalized intersections, the actual stop and yield signs were modeled using priority controls. In detail, the movements controlled by stop signs were assigned a “minor” priority, while the movements controlled by yield signs were assigned a “medium” priority. In order to force vehicles on those links with minor priority to make complete stops before they progress through the intersection again, the end-speeds on those minor links were set to zero.

The lane changing regulations were modeled according to the United States conditions, which match the default values in the CORSIM simulation model.

Vehicle Composition and Driver Attributes

The default design vehicles in Paramics are different from those in CORSIM; however, Paramics allows users to override any of the vehicle’s physical characteristics of each vehicle type. Since CORSIM had been properly calibrated, the same variety of design vehicles was applied to the Paramics network as well. Thus, the vehicle geometric and mechanical attributes of design vehicles in Paramics were modeled according to the CORSIM default values.

Since driver attribute data were not available in the field, the Paramics driver attributes should have been modeled according to the CORSIM default data as well. However, the driver attributes parameters are different between Paramics and CORSIM. CORSIM defines variability of driver types using different coefficients in the car following model, lane changing model, free-flow-speed selection model, amber response model, etc. However, based on research results from the UK, Paramics uses driver aggression and awareness distributions to describe the general driver attributes (Paramics-online, 2000).

Since the CORSIM default driver attribute data approximately follow normal distributions, normal distributions were used to describe both the driver awareness and aggression in Paramics. The resultant Paramics network is shown in Figure 4.1.

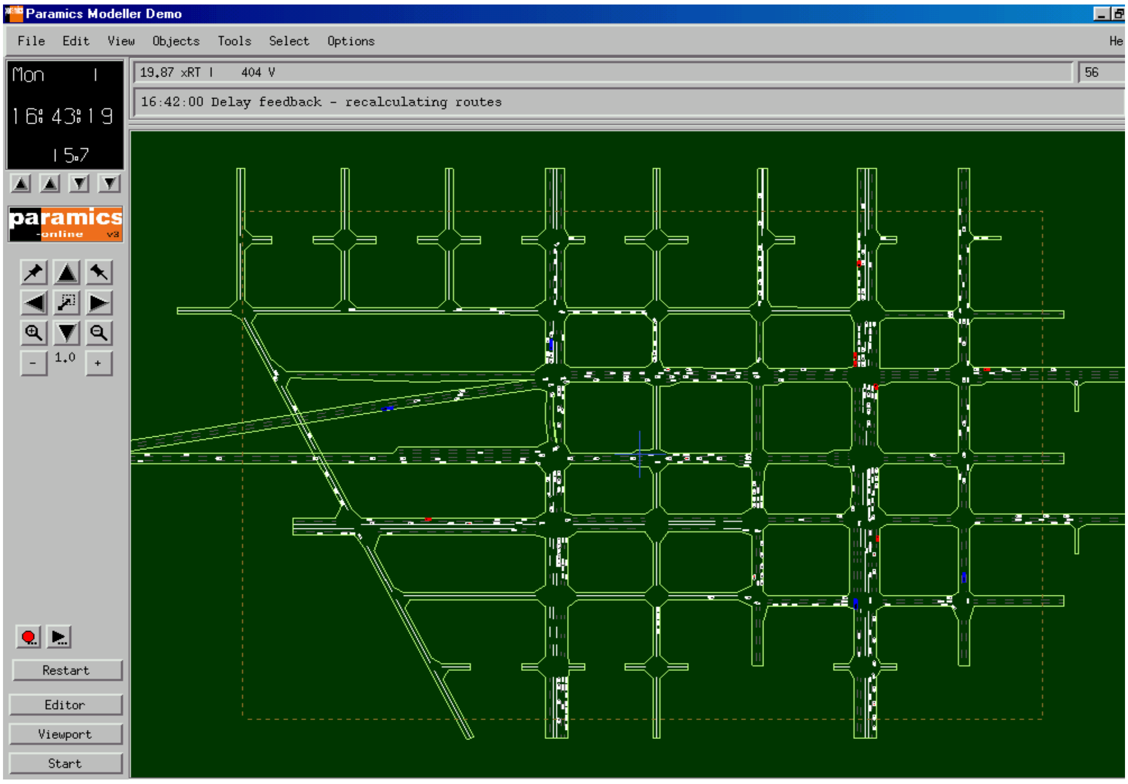

Figure 4.1: Paramics simulation case network

4.2 Paramics Network Calibration

The Paramics network was calibrated for the key control parameters. These parameters include mean target headway (MTH), mean driver reaction time (MDRT), traffic assignment algorithm, driver familiarity percentage, major/minor link classification and link cost factors. Each of these parameters is discussed next.

Mean Target Headway and Mean Driver Reaction Time

Traffic performance in Paramics was found to be highly sensitive to the mean target headway and mean driver reaction time. In Paramics, the mean target headway stands for the average headway time that is targeted in the car-following model; while the mean driver reaction time stands for the mean reaction time during the car following, gap acceptance, and lane changing process.

From a perspective of traffic flow theory, the driver reaction time should be less than the car following headway to maintain a safe following distance. However, the default values in the Paramics model are 1.0 seconds for both MTH and MDRT. Through repeated calibration runs, the best performance was achieved when 0.8 seconds was used for the mean driver reaction time and 1.2 seconds for the mean target headway. They are used as the calibration results for the two parameters.

Traffic Assignment Algorithm

Paramics provides users three options of traffic assignment algorithms: all-or-nothing, stochastic all-or-nothing, and dynamic assignment methods. The all-or-nothing method assumes that drivers will always follow minimum travel cost routes under free flow conditions, while the stochastic all-or-nothing method incorporates driver perception errors into the route cost calculations. As a result, although drivers still prefer a shortest-path, they may not choose it because of random perception errors. The dynamic assignment method assumes that some drivers have the ability to know the actual path delay along all alternate travel routes. Therefore, they will select the least costly routes according to real time delay, then have the potential to adjust their routes based on the dynamic route costs.

It was surprising to discover that in Paramics the travel cost under free-flow conditions accounts only for link travel cost, which is calculated as link distances divided by free-flow-speeds. Since the intersection delay comprised a large part of the travel delay for most vehicles in this urban network, the all-or-nothing method and stochastic all-or-nothing method are apparently inappropriate since they both ignore intersection delay. Thus, the dynamic traffic assignment algorithm was used in the Paramics simulation of the case network.

Driver Familiarity

In the dynamic feedback method, driver familiarity percentage is one key parameter, since in this method it is assumed that only familiar drivers have the ability to perceive actual delay and enable rerouting. A sensitivity test was performed on the case network with 100 replications, and the number of successful runs (i.e., no gridlock) was used as the response to indicate the network stability. As illustrated in Figure 4.2, the sensitivity test showed that for this case network, the Paramics network was most stable when it was modeled with sixty percent familiar drivers. Thus, 60% was adopted as the driver familiarity percentage in the Paramics simulation network.

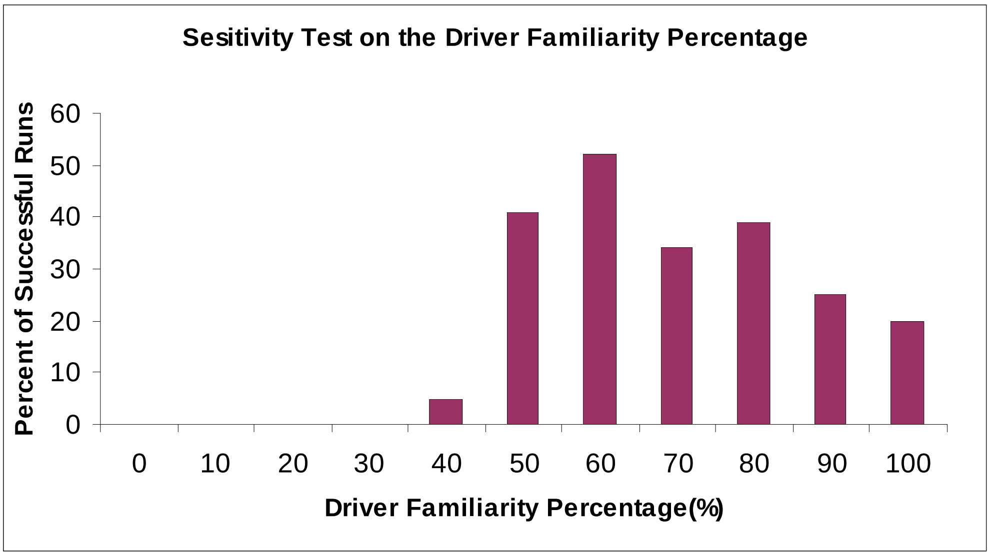

Figure 4.2 Sensitivity test results on driver familiarity percentage

Major/Minor Link Classification

In the Paramics routing algorithms, the designation of major and minor links impacts the route cost calculation. On major links, familiar drivers experience the same cost as unfamiliar drivers, whereas on minor links, the unfamiliar drivers experience twice the cost compared to the familiar drivers. This function is designed to model the attractiveness of some network links to unfamiliar drivers.

For the case study network, two minor streets, Erie Street and Kingsbury Street, and part of one major street, Illinois Street, were defined as minor links (Figure 4.3). All others streets were defined as major links.

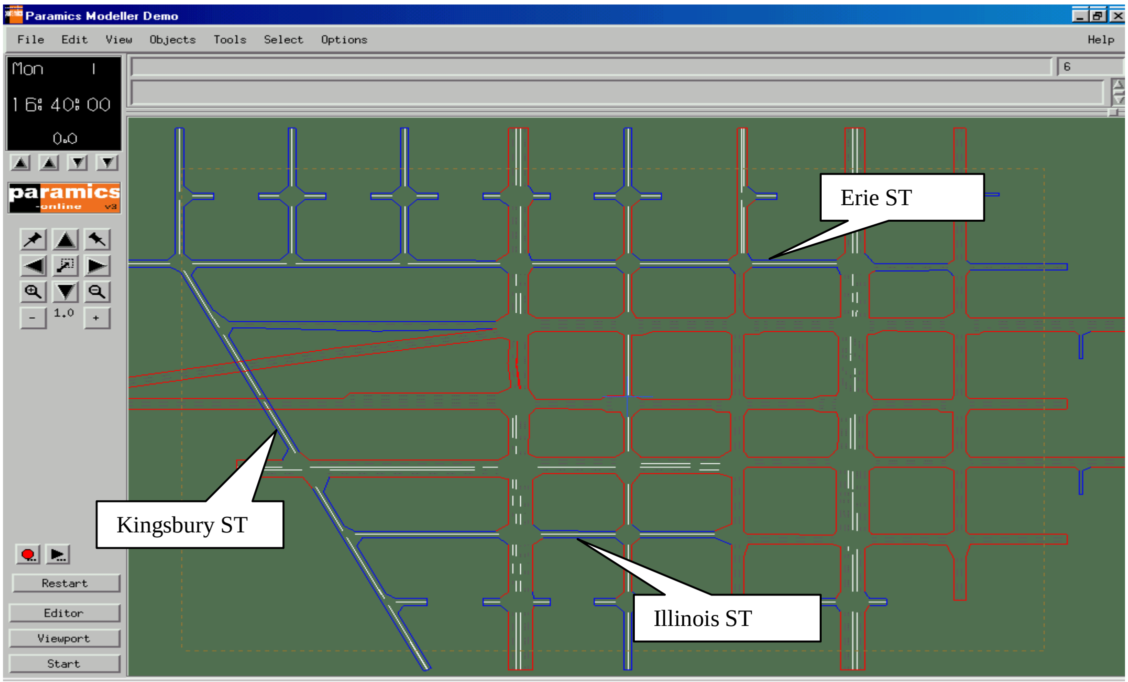

Figure 4.3 Major/Minor link classifications in Paramics network

Note: links shown with blue edge are minor links.

Link Cost Factors

Beside link distances and link free-flow-speeds, users can define link cost factors for each link to simulate realistic link costs. The link cost factors work like coefficients for the travel route cost calculation. The Paramics default value for link cost factors is 1.0. Changing the links cost factors affects the route selections of both familiar drivers and unfamiliar drivers.

Bigger cost factors may be added to those links attracting higher traffic flows than expected (in this case, by comparison to the CORSIM flows). As shown in Figure 4.4, it was noticed that part of the EB Ohio traffic was unrealistically assigned to EB Grand and EB Illinois Street as opposed to proceeding directly on Ohio. To address this problem, cost factors along part of Orleans Street on links 5 to 9 and 9 to 33 were increased to 1.5 to constrict right turn from Ohio Street. Also, as Franklin Street had far more traffic than expected, the links along this street were defined to have a cost factor of 2.0.

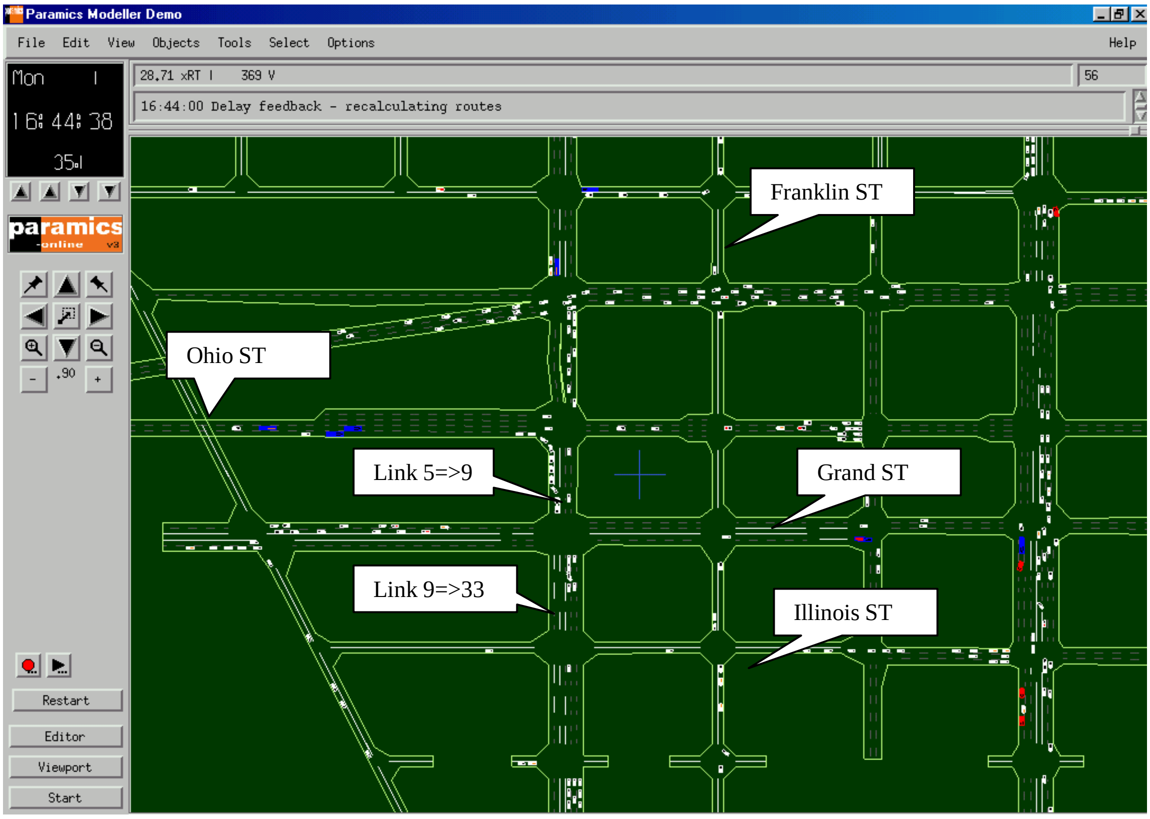

Figure 4.4 link cost factors added to some undesirable links

4.3 Paramics Link Flow Matching

The link traffic performance measures, including the link flow, vehicle miles, vehicle hours, etc, were gathered from CORSIM and Paramics runs for one hundred and eleven network links. In order to perform an effective comparison, the Paramics network is required to generate comparable link flows as CORSIM. Table 4.1 summarized characteristics of the link flow distributions based on ninety-eight successful CORSIM runs and sixty-six successful Paramics runs. It is important to note that even after an extensive calibration exercise and the selection of a good OD matrix, a full 1/3 of the Paramics runs resulted in gridlocks, compared with only 2% for CORSIM.

Links	**CORSIM (1)**	**Paramics (2)**	**Ratio (2)/(1)**
Number	111	111	1
Mean Flow Rate (VPH)	758.4	708.6	0.93
STDEV	695.3	677.4	0.97
Skewness	1.285	1.45	1.13
Minimum	3.7	6	1.62
Maximum	3846.9	3815.7	0.99

Table 4.1: Comparison of link flows between CORSIM and Paramics

Thus, in the comparison of the distributions of 111 link flows, Paramics has a 1.7% lower mean link flow value than CORSIM. The standard deviation of both is about the same. The range of Paramics link flow distribution is (6, 3815.7), which is about the same as the CORSIM range of (3.7, 3846.9).

To compare the paired observations of link flows, plots of the corresponding link flows ordered by the CORSIM values are shown in Figures 4.5. This is shown only for those links having flow rate exceeding 500 VPH.

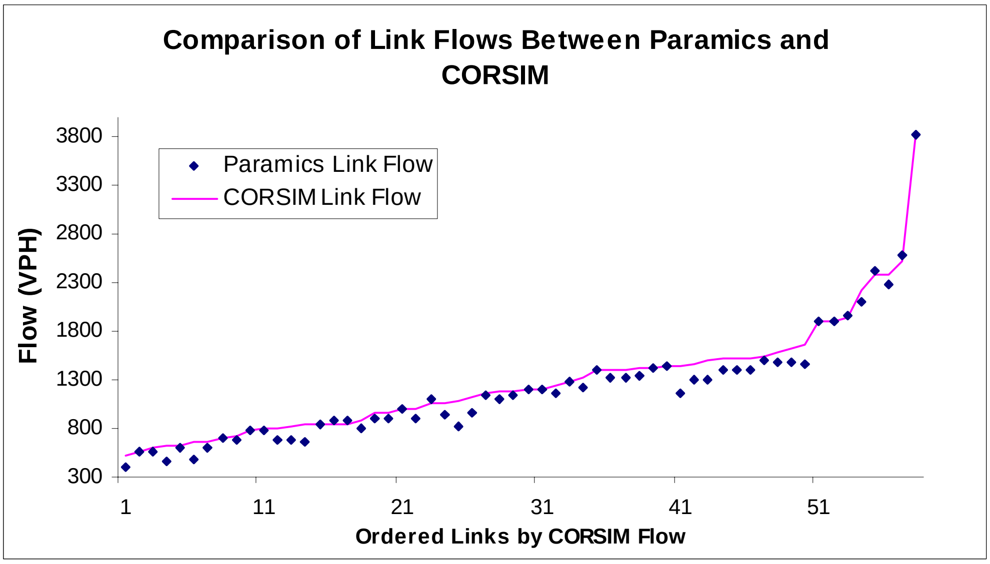

Figure 4.5: Comparison of link flows between CORSIM and Paramics

As shown in this figure, in general, Paramics links flows show the same increasing pattern as CORSIM. To verify that, an x-y plot is performed on the paired Paramics-CORSIM link flow observations as depicted in Figure 4.6. It shows that there is an obvious linear relationship between the Paramics and CORSIM link flows.

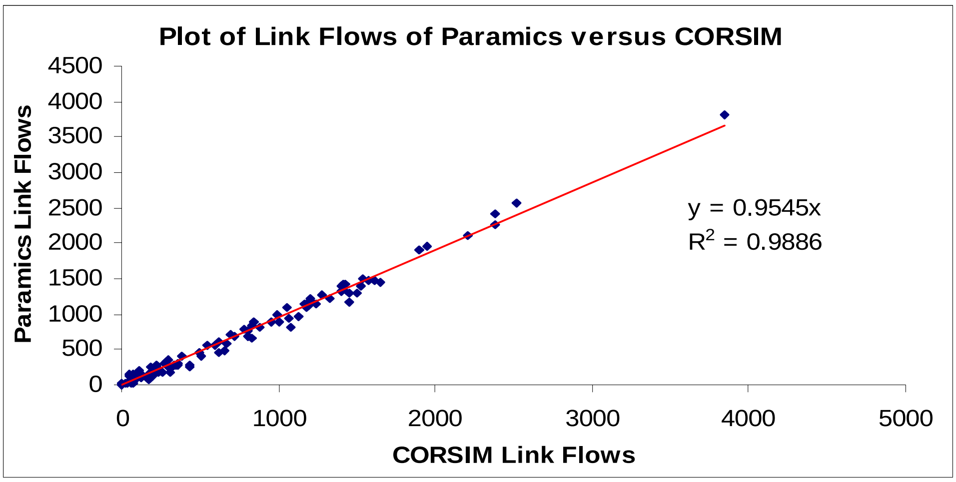

Figure 4.6: Linear relationship between the CORSIM and Paramics link flows

It is also noticed that the regression line has a slope of 0.9545 with a R^2 of 0.9886, which is a bit smaller than 1. That indicates that Paramics is generating slightly lower link flows than CORSIM. The cumulative density function curve of link flow ratios is shown in Figure 4.7. Again, this figure confirms the same findings. In it 70% of the links have a Paramics to CORSIM link flow ratio under 1.0.

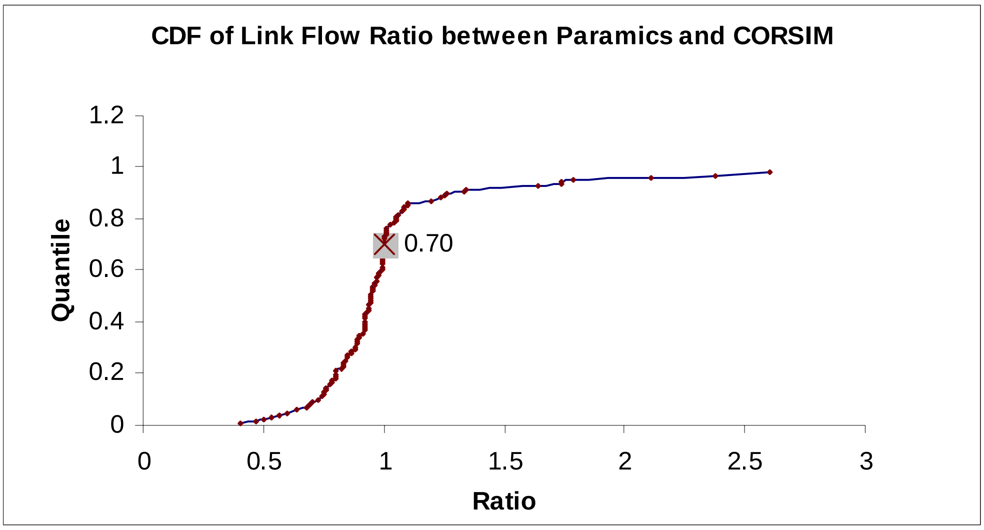

Figure 4.7: Cumulative density function curve of link flow ratios

Prior to comparing link performance between the two models, it is important to ensure that these links carry comparable traffic flows. Thus, it is important to isolate those links that meet this criterion first. It was decided that (a) only those links that carry significant flows should be considered and that (b) allowance should be made for random errors in link flow estimation.

In this study, only 58 links with flows that exceeded 500 VPH (in CORSIM) were considered. Of them, those links that had a Paramics to CORSIM flow ratio of 0.95 to 1.05 were selected for output comparison. Criterion (a) above resulted in the elimination of 53 links (see Figure 4.5), while criterion (b) eliminated another 31 links (see Figure 4.8). This left 27 links that met both criteria available for comparison.

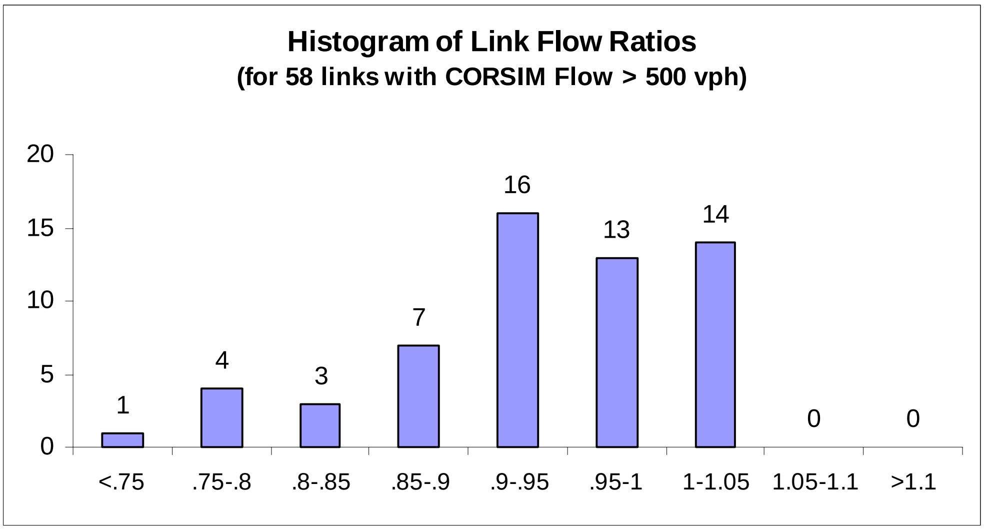

Figure 4.8: Histograms of link flow ratios for the heavy loaded links

These selected links are shown graphically in Figure 4.9. It is shown that these links cover the WB Ontario Corridor, the NB LaSalle Corridor, and other miscellaneous links scattered in different part of the network.

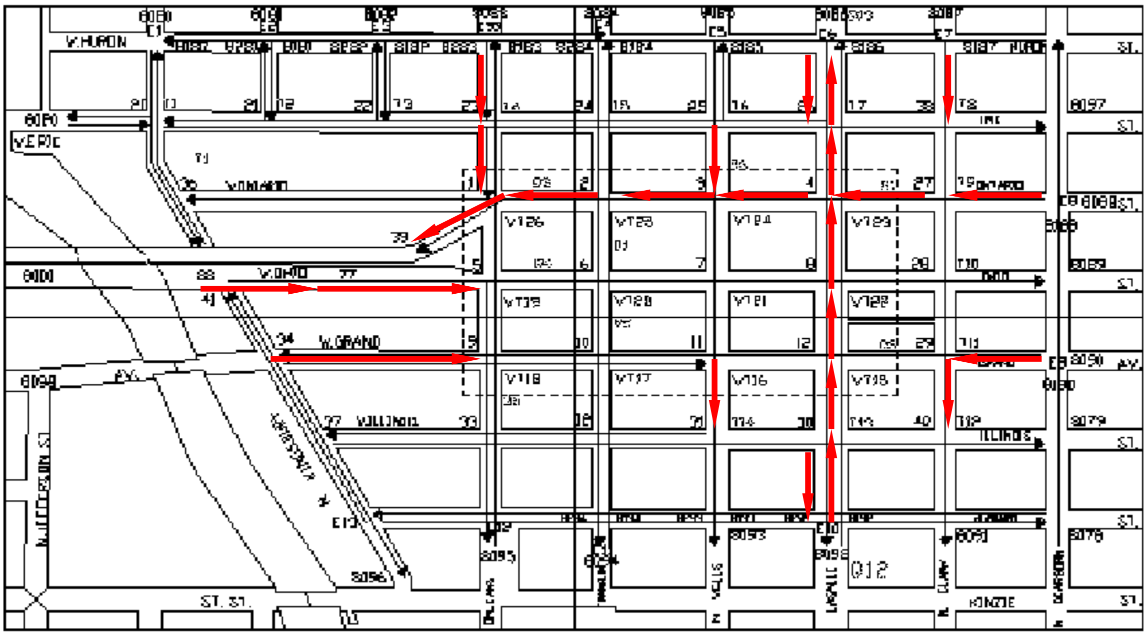

Figure 4.9: Plot of important network links with link flow ratios within (0.95,1)

Chapter 05: Simulation Output Comparison and Analysis

In this chapter, outputs from the two simulation models are summarized and compared to each other. In Section 5.1, the percentage of outliers is discussed. Some comparison factors: corridor selection, MOE selection, sample size determination, and comparison methods, are described in Section 5.2. The comparison results on the two selected corridors, the Northbound LaSalle corridor and WB Ontario corridor, are discussed in detail in Section 5.3 and 5.4, respectively. Section 5.5 gives an overall discussion of the findings.

5.1 Outliers in CORSIM and Paramics Models

Outliers are those simulation runs that have traffic gridlock caused by some unrealistic driver/vehicle behavior (for example, turning vehicles that block each other). They, therefore, generate abnormal traffic behavior leading to deviant performance measure values in the simulation outputs. Figure 5.1 is a snapshot of a Paramics animation with traffic gridlock.

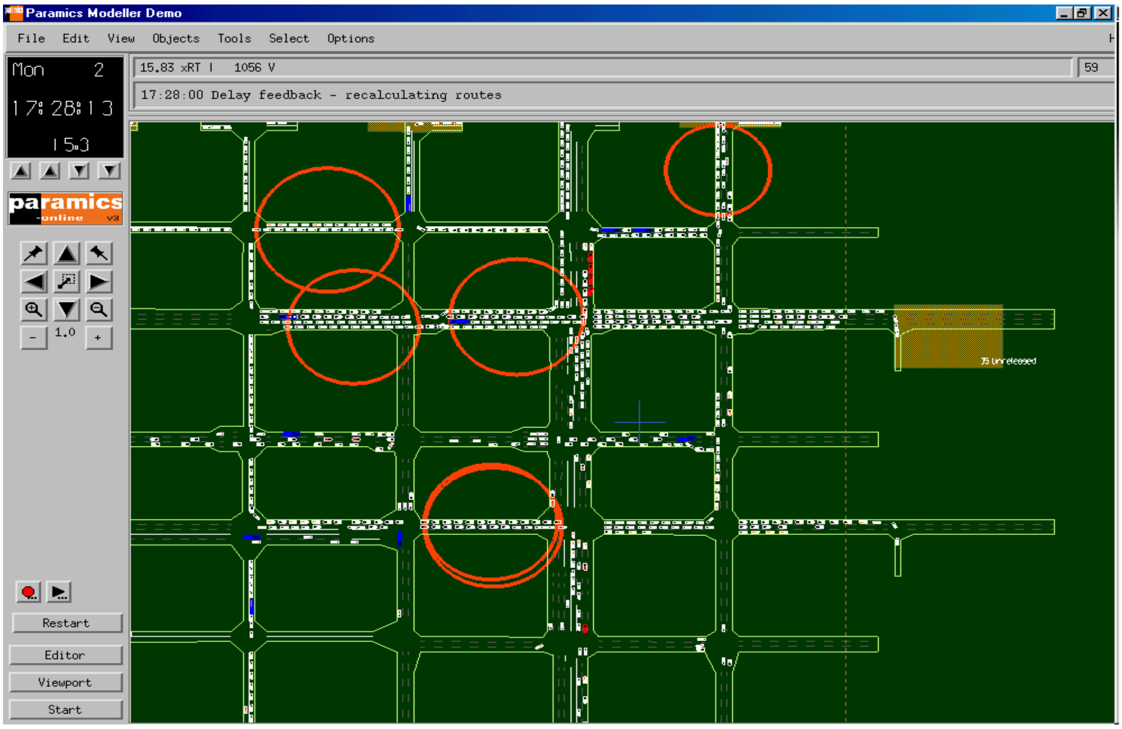

Figure 5.1: Animation of an outlier replication with traffic gridlock

The percentage of outliers reflects the simulation network stability and efficiency. Since the causes of outliers themselves do not occur in reality, the occurrence of outliers indicates that the simulator fails to emulate reality. In the analysis of traffic performance measures, the outliers are excluded from further statistical analysis in order to make meaningful comparisons.

The likelihood of generating outliers in a traffic simulation model is related to the model logic and network congestion level. In this study, since CORSIM and Paramics have been applied to the same traffic network with the same congestion level, the percentage of outliers can be used to compare the two models' stabilities.

In our experiment, in one hundred replications, the CORSIM simulation yielded two outliers, while Paramics produced thirty-four of them. Thus, CORSIM is apparently more stable than Paramics. A possible explanation is that Paramics allows periodic rerouting in the dynamic traffic assignment algorithm, creating larger link-flow fluctuations and, therefore, having a greater chance of spillback and blockage on overloaded links or turn movements.

5.2 Comparison Design

Corridor Selection

The comparison is performed at a corridor level. Since in this case network there are eleven corridors in total, the attention is restricted to only two of them.

The comparison corridors are selected from two criteria: relevance to the overall network performance, and similarity in link flows across models (as shown in Chapter 4).

Based on these criteria, the NB LaSalle corridor (Northbound LaSalle Street from Illinois to Erie) and WB Ontario corridor (Westbound Ontario Street from Clark Street to Orleans Street) were selected (Figure 5.2).

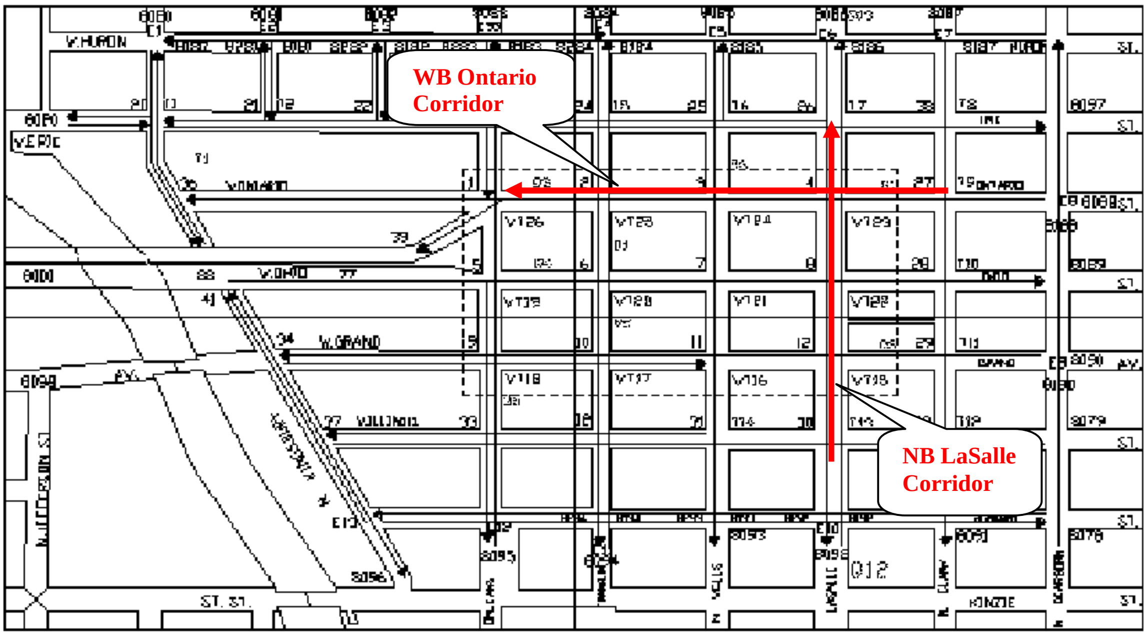

Figure 5.2: Two selected corridors for the comparison between Paramics and CORSIM

Both selected corridors include four consecutive links. Since traffic performance on these links are not independent of each other, two single links, Link 12 to 8 on NB LaSalle corridor and Link 2 to 1 on WB Ontario corridor, were selected to analyze the difference between the mean traffic flow rates.

A statistical test is performed on the difference between the mean traffic flow rates. Suppose that n_1, $\overline{Y}_1$, S_1 and n_2, $\overline{Y}_2$, S_2 are respectively the sample size, sample mean and sample standard deviation of CORSIM and Paramics runs, confidence intervals for $\theta = \mu_1 - \mu_2$ can be constructed as follows. In the following, we let:

$\hat{\theta} = \overline{Y}_1 - \overline{Y}_2$ and $\hat{\sigma}_{\hat{\theta}} = \sqrt{\frac{s_1^{\ 2}}{n_1} + \frac{s_2^{\ 2}}{n_2}}$

The 100(1-α)% CI is

$$\hat{\theta} - Z(\alpha/2)\hat{\sigma}_{\hat{\theta}} \le \theta \le \hat{\theta} + Z(\alpha/2)\hat{\sigma}_{\hat{\theta}}$$

95% confidence intervals for the difference between the mean flow rates of CORSIM and Paramics are constructed on links 12 to 8 and 2 to 1(see Table 5.1).

Links	CORSIM		Paramics		Z(0.025)	95% CI for (CORSIM-Paramics)	
	Mean Flow Rate (VPH)	**STDEV**	**Mean Flow Rate (VPH)**	**STDEV**		**Lower Boundary**	**Upper Boundary**
Link 12=>8	1538.80	21.42	1495.55	35.88	1.96	33.61	52.89
Link 2=>1	2513.69	30.81	2580.08	54.76	1.96	-80.93	-51.83

Table 5.1: 95% confidence intervals for the difference of mean flow rates

Although the differences between the mean flow rates are statistically significant, the actual differences are small and well within 5% of the flow rate (even after allowing for statistical fluctuation).

MOE Selection

Since Paramics and CORSIM were developed under different traffic environments, they produce different performance measures. To ensure an unbiased comparison, the MOEs used for comparison are the most similarly defined ones.

- **Queue Time and Stop Time**

Vehicle stop time and vehicle queue time are direct measures that reflect the vehicle delay level in a traffic network. But these definitions are different in CORSIM than in Paramics; therefore, we do not use them.

In CORSIM, the vehicle queue time is defined as the time when vehicles travel at speeds less than 9 feet per second and at acceleration rates less than 2 feet per second per second. The vehicle stop time is defined as the time when vehicle speeds are less than 3 feet per second. (TSIS User Support, 2001)

In Paramics, the vehicle stop time is defined as the time when vehicles have a speed less than the queue speed, and vehicle distance less than the queue distance (Paramics User's Guide, 2000). Users can define the queue speed and queue distance as the thresholds in the configuration of simulation. There is no separate queue time definition in Paramics.

Therefore, for the stop time definition in Paramics, even though the queue speed can be set to 9 feet per second to match CORSIM, it still lacks an acceleration rate threshold.

Furthermore, it is difficult to gather link queue time or link stop time information in Paramics without resorting to the application programming interface (API) development, as Paramics doesn't provide output files containing such data directly.

- **Vehicle Flow, Vehicle Hours, Vehicle Miles**

Vehicle flow and vehicle miles are two measures that reflect network traffic production, while vehicle hours is a measure of traffic congestion.

At the corridor level traffic performance, corridor flow, vehicle miles, and vehicle hours are computed as functions of link flow, vehicle miles and vehicle hours of the links comprising that corridor. Thus, for a corridor comprised of *n* links,

$$Mean\ Corridor\ Flow\ Rate = \frac{1}{n}\sum_{i=1}^{n} Link\ Flow\ Rate(i)$$

$$Total\ Corridor\ Vehicle\ Miles = \sum_{i=1}^{n} Link\ Vehicle\ Miles(i)$$

$$Tatal\ Corridor\ Vehicle\ Hours = \sum_{i=1}^{n} Link\ Vehicle\ Hours(i)$$

- **Average Vehicle Speed, Average Vehicle Time**

The derivative performance measures, including average vehicle speed and average trip time, can be calculated as:

$$Average\,Vehicle\ Speed = \frac{Total\ Corridor\ Vehicle\ Miles}{Total\ Corridor\ Vehicle\ Hours}$$

$$Average\ Travel\ Time = \frac{Total\ Corridor\ Vehicle\ Hours}{Mean\ Corridor\ Flow\ Rate}$$

Sample Size Determination

In stochastic traffic simulation models, performance measures are random variables. In order to estimate the stochastic properties of MOEs (mean, median, percentile, variance, etc), replicate runs of the simulators are necessary. One hundred such replicate runs were made on each simulator in order to get sufficient estimates of these quantities.

As CORSIM and Paramics are both text-in-and-text-out simulation models (i.e., model inputs and outputs are stored in text files accessible to users), a small personal REXX (IBM, 2000) program was coded to gather the statistics from the replication output files and summarize them for analysis.

Comparison Methods

The outputs from ninety-eight CORSIM runs and sixty-six Paramics runs (those that were not gridlocked) were compared in several ways. Formal statistical tests are not performed here because the assumptions for such may not be met in dealing with the restricted samples. Histograms are suggestive, however, and lend themselves to interpretations that can be later pursued.

5.3 Comparison Results on the Northbound LaSalle Corridor

The corridor is composed of four links, all controlled by pre-timed traffic signals. A summary comparison for the two models for the northbound LaSalle Corridor is shown in Table 5.2.

MOE	**Unit**	**CORSIM**		**Paramics**		**Ratio (Par/COR)**	
		Mean (1)	**STDEV (2)**	**Mean (3)**	**STDEV (4)**	**(3) / (1)**	**(4) / (2)**
Corridor Flow	VPH	1502	18	1409	34	0.94	1.90
Veh Miles	VMT	280.3	3.3	262.8	6.2	0.94	1.85
Veh Hours	VH	39.2	4.2	29.1	3.9	0.74	0.93
Avg Travel Time	Sec	93.9	9.9	74.3	9.9	0.79	1.00
Avg Veh Speed	MPH	7.2	0.7	9.2	1.1	1.27	1.59

Table 5.2: MOE comparison results on the Northbound LaSalle Corridor

Note: Results are based on 98 successful CORSIM and 66 Paramics runs

For this corridor, Paramics generates 6% fewer vehicle trips and vehicle miles than CORSIM. During the simulation time period, since NB LaSalle Street was experiencing high delay in reality, it appears that the Paramics model rerouted trips onto other corridors in its dynamic feedback traffic assignment algorithm. The higher vehicle speed in Paramics is therefore reflective of the fact that the Paramics network has lower vehicle trips and lower congestion levels, although the relationship of these changes is highly non-linear.

Plots of the distributions of vehicle miles, vehicle hours, and vehicle speed on the NB LaSalle Corridor in the two simulation models are shown in Figure 5.3, 5.4, and 5.5, respectively.

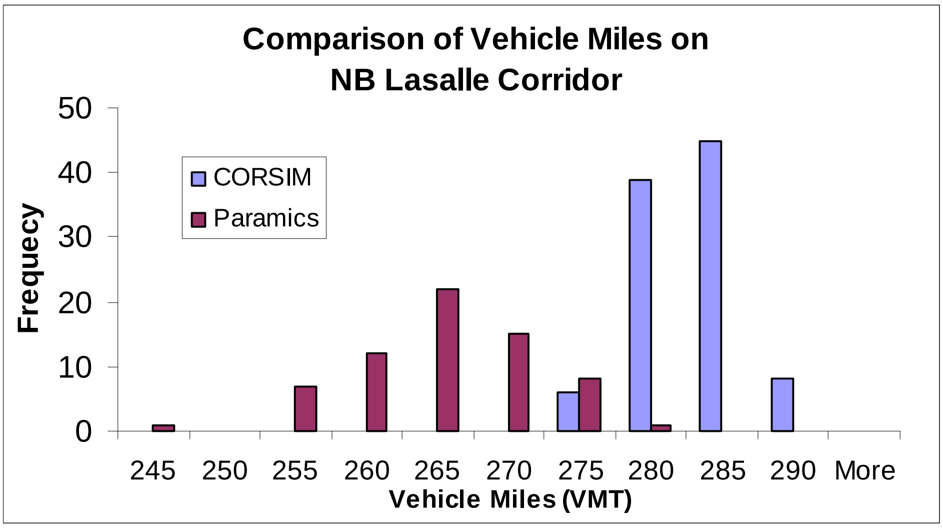

Figure 5.3: Plot of vehicle miles comparison on the NB LaSalle Corridor

When comparing vehicle miles on this corridor, Paramics has a lower mode than CORSIM (265 vs. 285). Moreover, Paramics shows a much larger dispersed distribution with a range from 245 to 280 VMT, while that for CORSIM is only from 270 to 290 VMT.

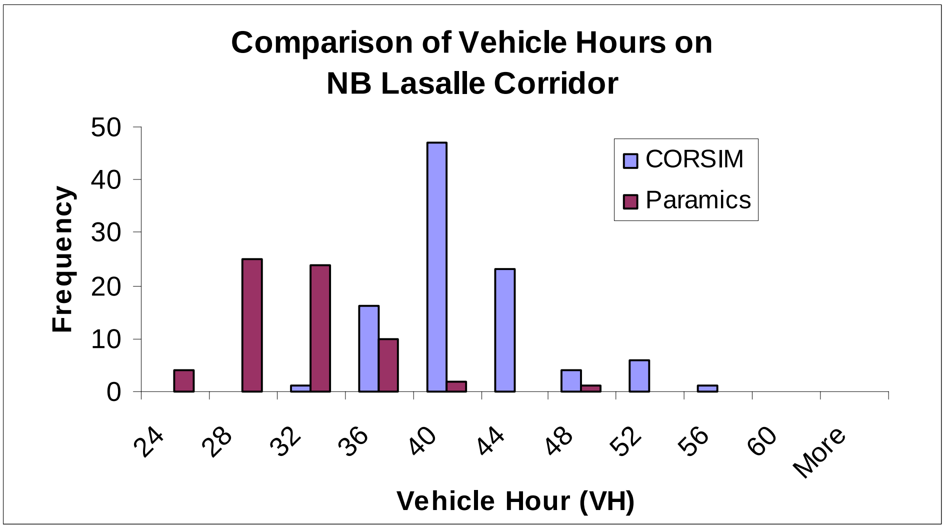

Figure 5.4: Plot of vehicle hours comparison on the NB LaSalle Corridor

Regarding the vehicle hours, figure 5.4 shows that Paramics has a lower mode than CORSIM (32 vs. 42). The range of the CORSIM distribution varies between 32 and 60 VH, while that of Paramics is between 24 and 52 VH.

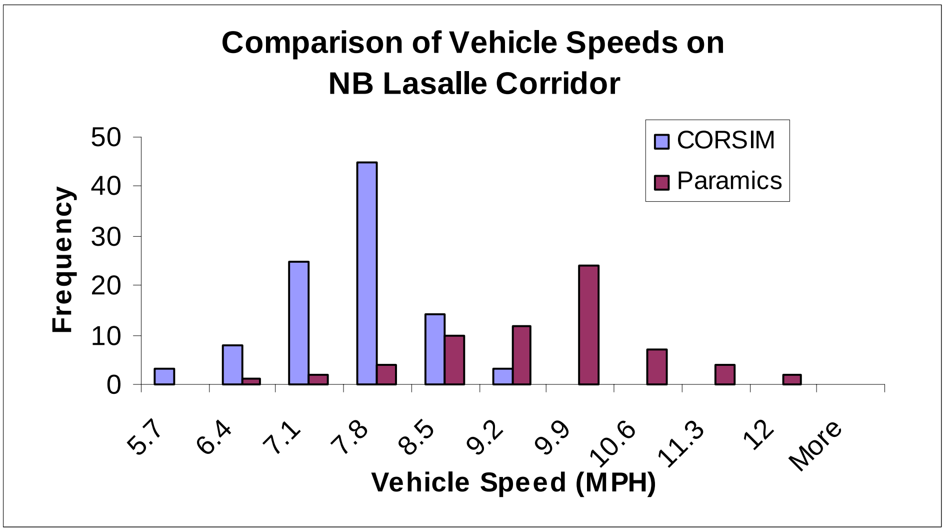

Figure 5.5: Plot of vehicle speeds comparison on the NB LaSalle Corridor

Because of the smaller vehicle hours and vehicle miles in CORSIM, Figure 5.5 confirms that Paramics generates higher vehicle speeds than CORSIM. The mode values are about 8 MPH for CORSIM, compared to 10.3 MPH in Paramics. It is noticeable that the speed range in Paramics is 5.6 MPH (6.4 to 12 MPH), which is much higher than the CORSIM range of 3.5 MPH (5.7 to 9.2 MPH). Paramics consistently produced a higher variability in the average vehicle speed.

5.4 Comparison Results on WB Ontario Corridor

WB Ontario corridor is a one-way street containing four traffic links, with three pre-timed traffic signals between them. A summary of comparison results on that corridor is given in Table 5.3.

MOE	Unit	CORSIM		Paramics		Ratio (Par/COR)	
		Mean (1)	STDEV (2)	Mean (3)	STDEV (4)	(3) / (1)	(4) / (2)
Corridor Flow	VPH	2373	23	2308	39	0.97	1.71
Veh Miles	VMT	589.9	5.7	589.9	10.1	1.00	1.76
Veh Hours	VH	38.5	2.8	44.9	2.8	1.17	1.01
Avg Travel Time	Sec	58.4	4.0	70.0	3.7	1.20	0.92
Avg Veh Speed	MPH	15.4	0.8	13.2	0.7	0.86	0.86

Table 5.3: MOE comparison results on Westbound Ontario Corridor

Note: Results are based on 98 successful CORSIM and 66 Paramics runs

It is shown in that table that Paramics has a 3% lower average corridor flow than CORSIM. Although the vehicle miles for both simulation models are equal, Paramics has 17% higher vehicle hours, which leads to a 14% less average vehicle speed and a 20% higher average trip travel time than CORSIM. It is possibly because the compositions of link flows and movement flows are different between the two simulation models. Also, as a major corridor for westbound traffic, the traffic flow fluctuations resulting from the dynamic feedback assignment method could lead to a low efficiency in the Paramics network.

The plots of the vehicle miles, vehicle hours and vehicle speed comparisons on this corridor are shown in Figure 5.6 to 5.8.

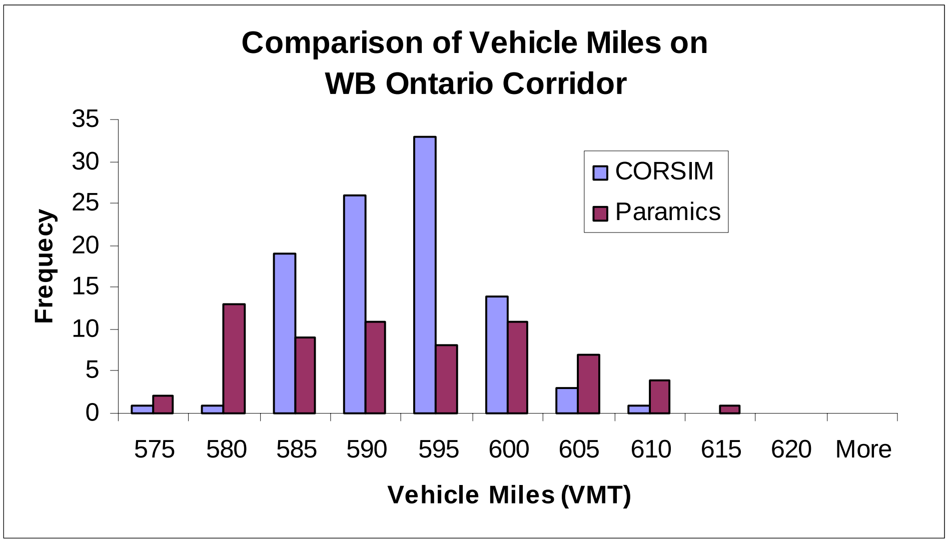

Figure 5.6: Plot of vehicle miles comparison on WB Ontario Corridor

It shows that even though both distributions have almost the same range (575 to 614 VMT), the Paramics distribution is apparently flatter than CORSIM. Therefore, Paramics has a higher variation in the vehicle miles on this corridor.

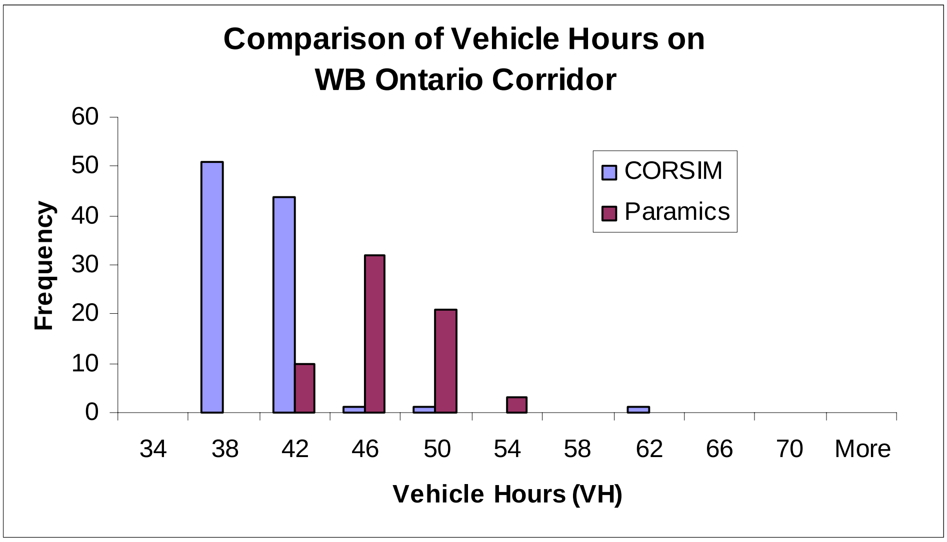

Figure 5.7: Plot of vehicle hours comparison on WB Ontario Corridor

Figure 5.7 shows that the CORSIM distribution is apparently skewed right, with higher frequencies on the two left most bins, while Paramics looks symmetric. Also, the CORSIM distribution has a lower mode and a bigger range than Paramics.

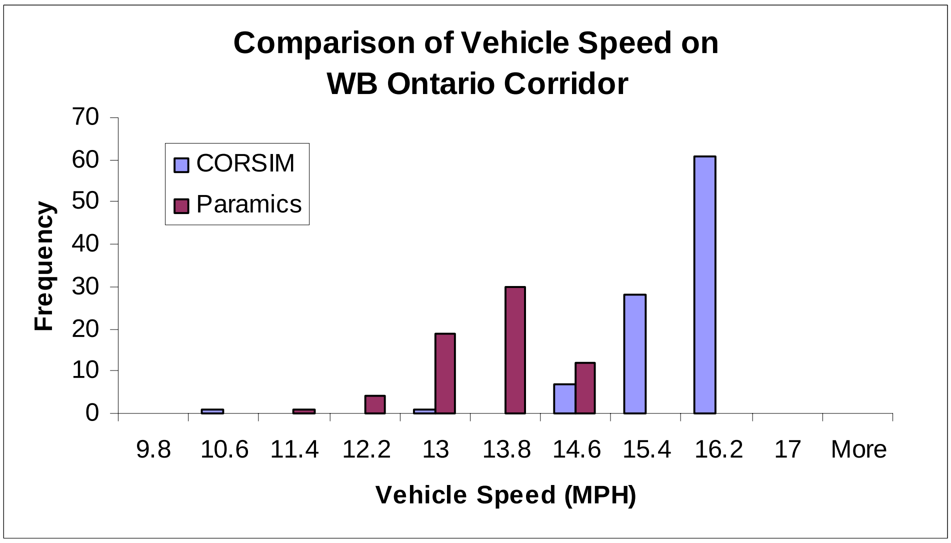

Figure 5.8: Plot of vehicle speeds comparison on WB Ontario Corridor

It is shown in Figure 5.8 that CORSIM has a left-skewed distribution with a bigger mode than Paramics, while the Paramics distribution is approximately symmetric.

5.5 Summary and Discussion

To ensure an effective comparison, two corridors, NB LaSalle corridor and WB Ontario corridor, with a similarity in traffic flow rates are selected for comparison of traffic MOEs.

It is found that even with the almost the same flow level, the traffic MOEs in Paramics might not be the same as CORSIM. From a traffic engineering perspective, the comparison results of one corridor (NB LaSalle corridor) showed an expected pattern with Paramics producing less vehicle trips and a higher vehicle travel speed, while on the other corridor (WB Ontario corridor), it was surprising that an adverse pattern was demonstrated: even though Paramics had less vehicle trips, it generated an apparently lower vehicle speed.

As WB Ontario is comprised of four consecutive links, namely link 27 to 4, 4 to 3, 3 to 2, and 2 to1, the average through movement proportions on these four links and the upstream link 188 to 27 are summarized in Table 5.4.

Anode	Bnode	CORSIM			Paramics		
		Flow	Upsteam TH Flow	TH (%)	Flow	Upsteam TH Flow	TH
188	**27**	1950	N/A	94	1950	N/A	89
27	**4**	2213	1833	87	2107	1732	87
4	**3**	2382	1925	97	2270	1824	100
3	**2**	2382	2311	96	2411	2270	96
2	**1**	2514	2287	96	2580	2320	92
Overall		2373	1426	60	2342	1326	57

Table 5.4: Comparison of through movement compositions on WB Ontario Corridor

It is noticed that although Paramics had fewer vehicle trips on that corridor, it also had a lower straight-through percentage than CORSIM. Therefore, since the signal plan on that corridor puts more stress on the progression of westbound straight through vehicles, Paramics experienced a larger average travel delay.

Chapter 06: Summary, Conclusions and Recommendations

6.1 Summary

The principal objectives of this research were to (a) develop a consistent input data structure for flow and path-based simulation programs as exemplified by the CORSIM and Paramics models, respectively, (b) to identify similarities and differences between the CORSIM and Paramics models, and (c) to validate the Paramics model.

The case comparison was executed between a field validated CORSIM model and a fully calibrated Paramics network. These two models were constructed based on the same physical network dataset, which was originally established for CORSIM modeling purposes. For those Paramics input data that were not available in the dataset, some calculations/estimations were performed based on the known data and, sometimes, based on CORSIM default values. Of them the most important one was the Origin-Destination (OD) matrix.

To enter traffic demand in Paramics, an OD matrix was derived using two different methods, namely a statistical fitting method and a stochastic assignment method. The feedback results from the Paramics test network showed that the stochastic assignment method was more effective in deriving a good OD solution.

One straightforward finding of the comparison was that Paramics generated apparently a larger percentage of unsuccessful (i.e. gridlock) runs than CORSIM (34% in Paramics compared to 2% in CORSIM). Therefore, the CORSIM simulation was deemed to be more stable than Paramics. That was possibly because Paramics created more link flow fluctuations with the dynamic feedback traffic assignment algorithm; therefore, it had a higher chance of spillback or blockage on overloaded links or turn movements.

The comparison of link flows in the two simulation models was based on the sample replications after excluding the unsuccessful runs. It showed that there were some apparent link flow discrepancies between the two models. To ensure a meaningful comparison of other selected traffic performance measures, two critical corridors with minor vehicle flow discrepancies between the two models were selected as the comparison sites.

The comparison results on one corridor (NB LaSalle corridor) showed an expected trend with Paramics having 6% fewer vehicle trips and a 27% higher vehicle travel speed, while on the other corridor (WB Ontario corridor), the reverse occurred. Although Paramics had 3% fewer vehicle trips on that corridor, it still produced a 14% lower vehicle speed than CORSIM.

Further checks showed that the incoming and outgoing movement proportions on that corridor were different between the two models. Although Paramics had fewer vehicle trips, it had lower straight-through traffic volume than CORSIM. Since the signal plan on that corridor emphasize progression of westbound straight through vehicles, the Paramics model yielded a larger average travel delay.

6.2 Conclusions

The stated conclusions associated with each objective are described next.

With regards to Objective (a), the research conclusions are:

- Empirical comparisons of simulation models with different input data structures are feasible and informative for model validation and selection;
- Paramics has a different input data structure from CORSIM; therefore, data acquisition that enables the application of the two simulation models independently is cost prohibitive. This gives rise to the need for transforming the field data from one model input structure to the other;
- Of the two methods that were tried to develop a synthetic OD matrix that matched the observed link flows, the stochastic assignment method, which is based on known entry volumes and turning probabilities, proved to be effective in deriving a good OD matrix estimator.

With regards to Objective (b), the following conclusions are offered:

- As Paramics was developed in different traffic environments than the U.S., it lacks some important functions such as modeling of turning bays and sign controls, and its vehicle and driver attributes needed to be carefully tuned to achieve reasonable performance;
- Even for the same network demand, Paramics generated individual link flows that were at variance from CORSIM's since it had the tendency to redistribute flows on routes periodically when using the dynamic feedback algorithm;
- Even when carrying the same link flows, Paramics traffic performance was found to be different from CORSIM's as a result of discrepancies in incoming and outgoing turning movement proportions.

With regards to Objective (c), the following conclusions are offered:

- Both the deterministic and stochastic versions of the all-or-nothing assignment method ignore signal delay. Therefore, they are not appropriate for modeling a signalized urban network;
- Although the dynamic feedback assignment method is meant to avoid overloading congested links in Paramics, it tended to create large fluctuations in demand over certain links as the simulation progressed.

6.3 Recommendations

The research recommendations for the simulation model selection are:

- Using CORSIM when
  - Having turning counts available
  - To simulate large complex networks, and
  - No major changes in network geometry are contemplated.
- Use Paramics when
  - Having OD data available
  - To simulate networks have fewer route options, and
  - To analyze scenarios which are going to significantly change a network, such as adding links or significantly upgrading one or more link.

This study was founded on a network dataset consistent with the CORSIM modeling requirement. Because of field data constraints, the comparison experiment was performed in one direction only. In other words, we used the CORSIM input dataset and other CORSIM-based data to construct a Paramics model, and then compared the resulting traffic performance of the two models. This kind of comparison might cause some bias in the modeling process.

The adopted OD matrix for the Paramics modeling was based on the stochastic assignment method. Although the OD has been manually adjusted to exclude short round trips, the assumption that the traffic assignment is independent of the vehicle origin is a notable weakness of this procedure.

During the model output comparison process, the same network dataset was used for both the network calibration purposes and for output comparison. This gives rise to statistical concerns regarding the dual use of the data.

Research is underway to develop an effective method to carry out empirical comparisons of two traffic simulation models with different input data structures, and to automatically detect flaws in the simulation runs and their origins in time and space.

Some additional tasks that will be explored:

- Use a dataset (gathered on a different day) as the input demand for both Paramics and CORSIM simulation models, and compare the new performance measures to avoid the dual use problem;
- Explore an automatic diagnosis feedback method to improve the estimation of OD matrix and calibration of traffic assignment parameters;
- Carry out a reverse comparison effort by coding a valid Paramics network (which includes flows and turning movements), back into CORSIM and compare the resulting performance across models.

Since this research was based on only one case study of a grid-type urban network with medium to high traffic volumes, extending the empirical comparison to other traffic networks, and to other simulation models, will help verify and strengthen this research's findings and conclusions.

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