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교통 미시 시뮬레이션 결과에 영향을 미치는 요소의 민감도 분석

Sensitivity Analysis of the Factors Affecting Traffic Micro-simulation Results

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요 약

미시적 시뮬레이션 모델은 차량과 차량, 차량과 교통제어와의 개별차량 상호작용을 분석할 수 있어 교통공학 분야에 광범위하게 사용되고 있다. 미시 교통 시뮬레이션 모형을 이용하여 교통시스템을 분석 및 평가할 때 많은 고려요소가 있다. 이 요소들은 현장의 분석 대상지, 시뮬레이션 소프트웨어, 분석 시간, 평가 척도, 패러미터, OD 자료, 랜덤 넘버 등을 포함한다. 이러한 요소들이 미시적 시뮬레이션 결과에 어떠한 영향을 미치는 지 평가하기 위해 CORSIM과 TRANSIMS 결과를 토대로 민감도 분석이 실시되었다. 휴스톤에 위치한 I-10과 US290, 샌안토니오에 위치한 I-37 고속도로가 분석에 이용되었다. 오전 첨두, 오후 첨두, 비첨두 시간이 분석되었고, 세 개의 OD 자료가 이용되었다. 분석결과 모델의 패러메터와 OD 자료가 가장 큰 영향을 주었다. 또한 분석대상지와 분석 시간에 따라 민감도가 달라졌다.

Abstract

Microscopic simulation models, which focus on individual vehicles, are used extensively in the transportation operations in order to capture vehicle to vehicle and vehicle to traffic controls. There are many important factors involved when a micro simulation model is applied as an evaluation tool for the traffic system. They typically include test bed, software, simulation time period, measure of effectiveness, parameter for a software, OD matrix, and random seed number. To evaluate the effects of those factors, sensitivity analysis was performed to identify the effects of those factors based on CORSIM and TRANSIMS results. Three freeway corridors, two in Houston (I-10 and US 290) and one in San Antonio (I-37), were chosen as test beds. Three time periods (AM, PM, Off-peak) and three OD matrix estimates were used for the analysis. It was found that the micro-simulation results were highly sensitive to the model parameter sets and the OD information. The degree of sensitivity was a function of the test bed and time period.

Key Words : Microscopic simulation model, sensitivity analysis

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Ⅰ. Introduction

Microscopic simulation models, which focus on individual vehicles, are used extensively in the transportation operations in order to capture vehicle to vehicle and vehicle to traffic controls. More than fifty-seven microscopic simulation models have been introduced as evaluation tools in transportation fields [1]. These models include CORSIM, INTEGERATION, PARAMICS, and VISSIM. In addition, microscopic simulation approaches have been adopted in the transportation planning field as evidenced by the development of TRANSIMS at Los Alamos National Laboratory [2]. A critical component to successful use of micro simulation models is that they be calibrated successfully to represent real traffic systems.

Each micro-simulation model requires a parameter set to be defined, a priori, and this set allows the modeler to model the supply characteristics, demand characteristics, and their interaction. The proper selection of the parameters is important because they control the interaction among the drivers, vehicles, and the roadway environment systems. The recent developments in ITS have resulted in the deployment of a number of data collection systems. The archived data from these systems provide more opportunities to calibrate the micro-simulation models more accurately. Parameter calibration including software parameters and OD parameters has been recognized as a very important procedure and has been studied recently for CORSIM, TRANSISMS and PARAMICS [3-7].

There are many important factors involved when a micro simulation model is applied as an evaluation tool for the traffic system. They typically include i) identification of test bed, ii) selection of a software, iii) determination of analysis time period, iv) selection of a measure of effectiveness, v) parameters for software, vi) OD matrix, and vii) random seed numbers of simulation runs. In a simulation study, the determinations of test bed and traffic software are key elements to be considered. Availability of reliable supply and demand data is very important to develop a simulation model. Model capability and easiness of use are considered when selecting a software. Because of various traffic patterns according to traffic congestion, time period for an analysis may be a factor for a simulation study. Generally, a peak period has been studied extensively for many applications. In order to compare the simulation results with observed data, counted volume for each link, travel time, and speed have been employed.

The analyses of simulation results rely on the type of data collected. Empirical data that have been used include 24-hour volume and speed data, five-minute volume, speed and headway data, aerial photogrammatic information, global positioning systems(GPS) data, etc. The goodness of fit metrics that have been used in calibration include least squared error, analysis of variance (ANOVA), and mean absolute percentage error [5]. With the recent growth in computational resources and ITS data there is an opportunity for developing an automatic calibration methodology for traffic microsimulation models that is based on optimization theory. Genetic algorithms were used to identify the parameters values for CORSIM, PARAMICS, VISSIM, and TRANSIMS [3-7]. A simplex algorithm was used to find the best parameter values for the CORSIM and TRANSIMS [8]. Evolutionary optimization algorithms have been studied for the automatic calibration methodology.

This paper was motivated from the lack of fundamental studies and investigations on which factors are more important with respects to the calibration procedure. This paper focuses on identifying the effects of the factors for two typical micro traffic simulation CORSIM and TRANSIMS models. The CORSIM and TRANSIMS were selected because CORSIM has been widely used in traffic operation fields and TRANSIMS has been developed especially for the use in planning fields. More importantly to the study, they are implemented with different traffic flow theories, i.e. CORSIM uses a nonlinear car-following theory and TRANSISMS uses a cellular automata theory.

This paper is organized with four sections. In following sections, the methodology for the study is presented and the factors for the sensitivity analysis are introduced. The second section discusses calibration results briefly. The third section presents the sensitivity analysis results. Finally the conclusions are drawn.

II. METHODOLOGY

An automatic calibration methodology for micro-simulation models was developed in order to select the "best" parameter set based on observed ITS data and optimization algorithms [5, 6]. The automatic calibration methodology was implemented using the PERL language for the PC platform (CORSIM) and the AWK language for the Unix platform (TRANSIMS). A genetic algorithm and a simplex algorithm were examined for use in the optimization component of the calibration methodology because they do not require derivatives of the objective function, unlike traditional optimization algorithms. While both algorithms were successful in that they identified similar parameter sets in approximately the same number of iterations, the calibration results from a genetic algorithm were presented for the sensitivity analyses. A full description for the calibration methodology may be found elsewhere [5].

After identifying the "best parameter set", a sensitivity analysis was performed to identify the effect of five factors on CORSIM and TRANSIMS:

- Parameter sets for the two models,
- Time periods,
- Test beds,
- OD matrices, and
- Random seed numbers.

For each case, the results from the calibrated CORSIM and TRANSIMS models were presented and compared to the observed baseline data. The I-10 corridor, AM peak period, and AVI_OD matrix were used to illustrate the analysis of the effects of the CORSIM and TRANSIMS parameters. For the analysis of time period, three time periods for the I-10 corridor were examined and these were the AM peak, PM peak, and off-peak periods. The AM peak period for three test beds were tested for the effects of test beds. Three OD matrices were used for the analyses of the effects of OD demand. Random seed numbers were selected randomly and were used to run simulations for CORSIMS and TRANSIMS. For the purpose of comparison, the simulation results for the default parameter set were presented. The simulation time was one hour.

1. Micro-simulation Models and Parameters

Transportation Analysis and Simulation System (TRANSIMS)

The highway traffic simulation module of TRANSIMS is based on particle hopping or cellular automata (CA) theory. It may be considered large scale because it is capable of modeling the entire transportation network from highways to individual local roads and driveways. It can be classified as low fidelity because it uses a minimal representation of road traffic. Because there are few update rules the model can run quickly as compared to most micro-simulation models. The goal was not to represent small-scale dynamics accurately but rather to model the large-scale dynamics that are important from a planning perspective [9].

The most interesting fact about the TRANSIMS micro-simulation from a traffic modeling perspective is that acceleration, deceleration, and constant speed decisions are all controlled by a single parameter PT1, deceleration probability. The deceleration probability (PT1) ranges from 0 to 1.0 and the default value if 0.2. The lane change probability (PT2) ranges from 0 to 1.0 with a default value of 0.99. Basically, the lower the value of PT2 the more likely a vehicle is to change lanes. Lastly, the third parameter, PT3, is the plan look ahead distance. This parameter controls how many cells ahead each vehicle examines when looking for its next link change. The range is from 0 to any positive integer value and the default is seventy cells. A full description of the underlying logic of the CA model, including such issues as passing and conflicting movements at intersections, may be found elsewhere [2,10].

CORSIM Micro-Simulation Model

The highway micro-simulation module of CORSIM is based on the FRESIM model which is in turn derived from the INTRAS model developed in the late 1970's [11]. In contrast to TRANSIMS, CORSIM may be considered medium scale because it is designed to model primarily freeway and arterial networks but not local streets. More importantly it can be classified as high fidelity because it attempts to represent the spatial interaction of drivers on a continuous, rather than a discrete, basis and because it attempts to model the car-following logic of the drivers in detail. Because the overall goal is to mimic both the small scale and large scale dynamics of traffic the modeler has control over a large number of parameters including grade, percentage of trucks, driver aggressiveness, free flow speed, etc. It has been adopted in this paper for comparison purposes because it is used extensively for traffic operations analyses. Nineteen CORSIM parameters were selected for calibration and evaluated for sensitivity analysis. These parameters may be categorized into three groups: car-following sensitivity factors (11), acceleration /deceleration factors (2), and lane change factors (6). It was found from the preliminary study that the car-following sensitivity factors affected the simulation results greatly while other factors had a minor impact on the results. It should be noted that version 4.32 was used in this study. A full description of CORSIM car-following logic and parameters may be found elsewhere [5,11].

2. Test Beds, Time Periods, and Traffic Data

I-10 and US290 Corridors in Houston, Texas

A 22.4 km section of I-10 and a 23.0 km section of US 290 were chosen for the Houston test beds as shown in Figure 1(a). Two corridors are divided freeways with full grade separation, AVI stations in the main lanes, high occupancy vehicle (HOV) facilities in the median, and on-ramps/off-ramps connected to the main lanes. The I-10 corridor tested consists of 14 on-ramps and 13 off-ramps. It is monitored as part of the

Houston TranStar advanced traffic management system and has five AVI readers, which correspond to four AVI links, along its length. The section of US 290 network has 12 on-ramps, 12 off-ramps, and six AVI stations. The 23km corridor begins east of FM 1960 and extends to west of I-610.

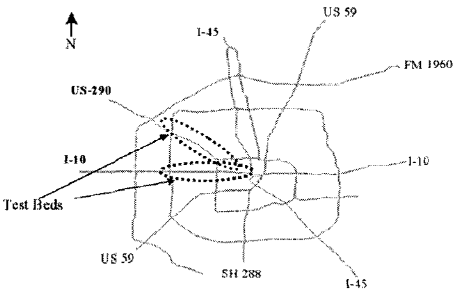
Volume data were collected using pneumatic tubes in May and June of 1996 as part of an annual average daily traffic (AADT) estimation effort. These counts were then aggregated into hourly volumes and subsequently adjusted so as to ensure consistency across the network. These values form the baseline volume counts for the analyses. In addition, the AVI data were used to calculate the average space mean travel time and standard deviation for each AVI link by time of day during the time period when volume data were collected. Three time periods were identified for the I-10 corridor, and they were the AM peak, PM peak, and off-peak, which corresponded to the periods from 7:00 AM. to 8:00 AM, from 5:00 PM to 6:00 PM, and from 2:00 PM to 3:00 PM, respectively. The AM peak period, between 7:00 AM and 8:00 AM, was selected for the US 290 corridor.

I-37 Corridors in Houston, Texas

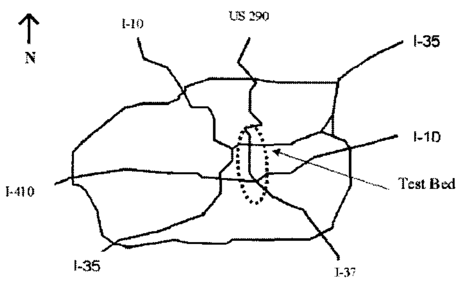
Figure 1(b) shows the map of northbound I-37 in San Antonio, Texas. A 9.8km section of I-37 has 9 on-ramps and 7 off-ramps, and has inductance loop detectors installed on the main freeway lanes at approximately 0.8 kilometers spacing. Speed and volume data collected by the TransGuide traffic management center from 7:00 AM to 8:00 AM from May 10 through May 14, 2000, were obtained for this research. The data collected May 11 were used in this research because the highest congestion was experienced on that day.

3. Origin-Destination Matrix Estimates

For both the I-10 and the US 290 corridors, synthetic OD estimates were obtained using a technique developed by Dixon and Rilett which is based on AVI data collected at each AVI station [12,13]. OD matrices estimated using AVI data are referred to as AVI_OD matrices. For the I-37 corridor, loop volume counts from the on- ramps and off-ramps were used to create OD volumes based on using a robust OD methodology [14]. OD matrices estimated using inductance loop detector are referred to as ILD_OD matrices. In addition for all the freeway test corridors, CORSIM OD estimates were obtained and these are referred to as C_OD



(a) Map of the Freeway System in Houston, Texas.



(b) Map of the Freeway System in San Antonio, Texas.

<Fig. 1> Study Urban Freeway Corridors in Houston and San Antonio, Texas

matrices. CORSIM estimates OD matrices with a modified gravity model [15].

The mean absolute error (MAE) and the average mean absolute error (AMAE), shown in Equations 1 and 2, were used to compare the two matrices on each of the highway test beds [16].

$$MAE = \frac{1}{N}\sum_{ij}\left|ITS\_OD_{ij} - C\_OD_{ij}\right| \tag{1}$$

Where N = Number of cell entries in OD matrix

ITS_ODij = Row i and column j entry for AVI_ OD matrix or ILD_OD matrix

C_ODij = Row i and column j entry for C_OD matrix.

$$AMAE = \frac{1}{N}\frac{\sum_{ij}\left|ITS\_OD_{ij} - C\_OD_{ij}\right|}{\overline{ITS\_OD_{ij}}} \times 100 \tag{2}$$

Where

$\overline{ITS\_OD_{ij}}$ = Average trips of all cell entries in the OD matrix based on ITS data (i.e., either AVI_OD matrix or ILD_OD matrix.)

Table 1 summarizes the comparison results of OD matrices for the three test beds. While there were few differences between the AVI_OD and C_OD matrices with respect to the number of trips, the AVI_OD matrix trip lengths of the I-10 corridor for the AM peak, the PM peak, and the off-peak periods were 7, 5, and 2 percent higher than trip lengths for C_OD matrix. In the US 290 corridor, the trip length for the AVI_OD matrix was 6 percent higher than that for the C_OD matrix. Compared to the I-10 and US 290 corridors, there was little difference found between the C_OD matrix and the ILD_OD in the number of trips and trip length for the I-37 corridor.

Table. 1 Comparisons of OD Matrices

Test Bed	Time Period	OD Types	Number of Trips	Trip Length (km)	MAE[1] (trips)	AMAE[2] (%)
I-10	AM peak	AVI_OD	19,072	139,327.8	71	45
		C_OD	19,079	130,668.4		
	PM peak	AVI_OD	16,471	122,578.7	86	61
		C_OD	16,469	117,332.7		
	Off-peak	AVI_OD	14,828	101,898.3	79	67
		C_OD	14,833	99,766.6		
US 290	AM peak	AVI_OD	16,240	123,098.1	128	80
		C_OD	16,237	116,558.5		
I-37	AM peak	ILD_OD	10,817	50,110.2	149	3
		C_OD	10,816	50,473.8		

[1] MAE: Mean Absolute Error
[2] AMAE: Average Mean Absolute Error

The MAE of the I-10 corridor for the AM peak, the PM peak, and the off-peak periods were 71, 86, and 79 trips, respectively. These correspond to an average error between the individual cells of the AVI_OD matrix and the C_OD matrix of 45, 61, and 67 percent, respectively. In addition, the MAE for the US 290 and I-37 corridors were 128 and 149 trips, respectively, while the AMAE between the two matrices (the AVI_OD and C_OD matrices for the US 290 corridor, and the ILD_OD and C_OD matrices the for the I-37 corridor) were 80 and3 percent, respectively. Compared to the I-10 and US 290 corridors, there was little difference found between the C_OD matrix and the ILD_OD for the I-37 corridor. This result could be expected because of the lower congestion and corresponding volume experienced in San Antonio. However, for the Houston test beds the OD estimates were considerably different as shown in Table 1. For example, the AVI_OD matrix for the I-10 test bed had about 10 percent fewer trips than the C_OD matrix, but the average travel time of these trips was about 40 percent longer.

It should be noted that when the OD matrix is provided as an input the CORSIM model uses the turning rate at each destination that is internally computed based on the input OD matrix. It was found that the turning rates for the AVI_OD matrix were approximately 22 percent lower than those for the C_OD matrix. Consequently, it was found that the C_OD matrix has shorter trips but higher turning rates than the AVI_OD matrix.

4. Measures of Effectiveness

Volume

Volume is essential traffic data to model and calibrate the traffic network. The mean absolute error ratio (MAER) is used as MOE shown in Equation 3.

$$MAER = \frac{\sum_{j=1}^{N}\left(\frac{\left|V_j^O - V_{ij}^E\right|}{V_j^O}\right)}{N} \quad (3)$$

VjO = Observed volume for link j

VijE = Estimated volume (from simulation run i) on link j

N = Number of links in network Individual or chromosome

TRANSIMS Travel Time

Equation 4 was used to evaluate the TRANSIMS results with respect to the travel time on the AVI links. Values of mean and standard deviation for each AVI link were calculated from the snapshot file of TRANSIMS and compared to the those of baseline that were obtained from AVI stations. For the comparison purposes, values of 0, 0.5, 1 were tested, indicating that the effects of mean and standard deviation are considered as evenly important.

$$MOE = \frac{1}{N}\left[\alpha\sum_{i=1}^{N}\left(\frac{\left|A_i{}^M - A_i{}^B\right|}{A_i{}^B}\right) + (1-\alpha)\sum_{i=1}^{N}\left(\frac{\left|S_i{}^M - S_i{}^B\right|}{S_i{}^B}\right)\right] \quad (4)$$

Where

AiM = Mean travel time from Model M for link AVI link i

AiB = Baseline mean travel time for link AVI link i

SiM = Standard Deviation of travel time from Model M for link AVI link i

SiB = Baseline standard deviation of travel time for link AVI link i

N = Constant for standard deviation term Number of AVI link

CORSIM Travel Time

Equation 5 was used to evaluate the CORSIM travel time with respect to the travel time on the AVI links. Aggregated travel time within each AVI link was obtained and compared. Note that CORSIM travel time presented in this paper is not an individual travel time traveled in AVI link.

$$MOE = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{\left|\sum_{j=1}^{M} t_{ij} - T_i\right|}{T_i}\right) \quad (5)$$

Where

tij = Average travel time at link j within AVI link i

Ti = Mean travel time for AVI link i

N = Number of AVI link

M = Number of link within AVI link

III. CALIBRATION RESULTS

A genetic algorithm and a simplex algorithm were used for calibrating traffic micro-simulation parameters automatically. The calibration was carried out with respect to volume, travel time, and a combination of volume and travel time. It was found that the volume MAER results tended to fluctuate when the calibration was carried out with respect to the travel time. This indicates that the parameter sets are identified differently according to the defined fitness function and selected traffic data types, resulting in different micro-simulation results. For example, when the TRANSIMS model was calibrated with respect to travel time, the fitness value for volume was not equal to the fitness value for the travel time identified during simulation runs. It should be noted that for the travel time analysis the weights for mean and standard deviation on link travel time had a significant effect on the calibration results. Because space is limited and this paper is focused on the factor sensitivity, the whole calibration results were not presented in this paper. They may be found elsewhere [6]. The best model parameter sets were identified and the results were used for the sensitivity analysis. For the comparison purposes, volume MAERs were mainly presented for the analysis.

IV. SENSITIVITY ANALYSIS

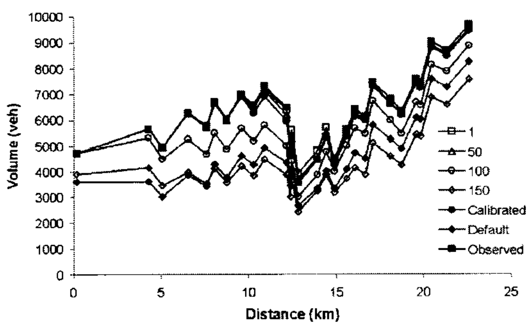
1. CORSIM and TRANSIMS Parameters

CORSIM Parameter

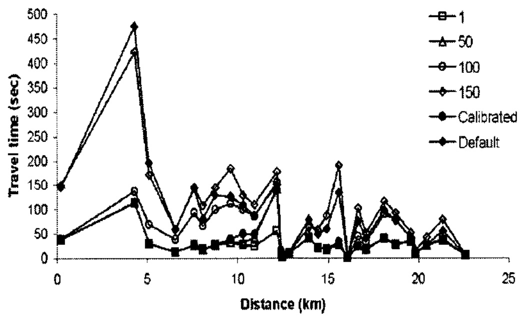
Figures 2(a) and 2(b) present the CORSIM simulation results in term of volume and travel time for each tested parameter set as a function of corridor location. Note that 150 cases were tested from 1 to 150 by the increment of 10 allowing 10 drivers to have the different car-following headways. While all nineteen parameters were evaluated, the car-following sensitivity parameters had a big impact on the simulated traffic flows. For the comparison purposes, the results from four car-following headway values were presented.

In Figure 2(a), as headway values increased the simulated volume decreased. The volume MAER for the default and calibrated parameter set were 27.3 percent and 2.2 percent, respectively. Figure 2(b) presents the travel time as a function of car-following headway. As would be expected, as the headway increased up to the value of 50 the AVI link travel time increased. It was hypothesized that this occurred because the simulated drivers attempt to have more space headway. These results indicate that travel time, in addition to volume, should be considered as a major MOE in calibrating micro-simulation models. It was also found that speed was changed in a wide range indicating that it was more sensitive to the parameters.

Compared to the calibrated results, the simulation results using default values yielded considerably different traffic characteristics with

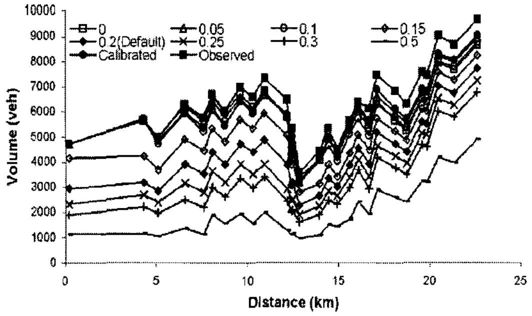


(a) CORSIM Volume

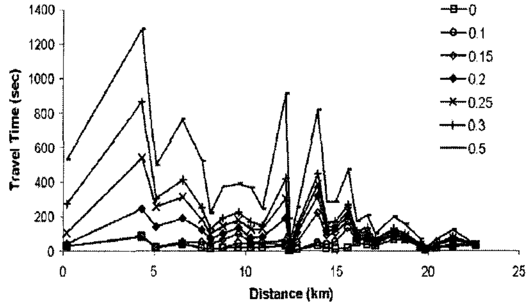


(b) CORSIM Travel Time.

<Fig. 2> CORSIM Volume and Travel Time Results



(a) TRANSIMS Volume



(b) TRANSIMS Travel Time

<Fig. 3> TRANSIMS Volume and Travel Time Results

respect to volume, travel time, and speed. The default average link travel times were about 170 percent higher than the calibrated link travel time, while the volume for default was about 25 percent lower than the calibrated volume. The average simulated speed over the corridor was 25 miles/hour and 51 miles/hour for the default parameter set and the calibrated parameter set, respectively. Consequently, it was found that while there were small differences in the parameter set the traffic flow characteristics were changed very much.

TRANSIMS Parameter

Figure 3 presents the TRANSIMS micro-simulation results in terms of volume and travel time for the deceleration parameter (PT1). Figure 3(a) shows the AM peak volumes that were output from the TRANSIMS module for the AVI_OD matrix. Similar tothe effects of car-following factors for CORSIM, the PT1 parameter was critical for the TRANSIMS modeling. As the value of PT1 increased, the volume MAER was increased dramatically, as evidenced by the MAER values of 7.6 percent and 69.2 percent for the PT1 value of 0.0 and 0.5, respectively. The lowest MAER were 7.1 percent and 9.4 percent and occurred when PT1 was set to 0.05 and 0.1, respectively.

Figure 3(b) presents the link travel time as a function of PT1 parameter value. It can be seen that the link travel times increased dramatically as the value of PT1 increased. This is attributed to the fact that as the value of PT1 increases there is a higher probability of decelerations, resulting in longer travel times.

2. Time Period

The test bed was the I-10 corridor in Houston, Texas, and the time periods analyzed were the AM peak (7:00 AM to 8:00 AM), the PM peak (5:00 PM to 6:00 PM), and the off-peak (2:00 PM to 3:00 PM). When comparing the default values, both CORSIM and TRANSIMS had the largest MAER values for the AM peak as shown in Table 2. It can be seen that the default CORSIM MAER was 27.3 percent for the AM peak, 11.9 percent for the PM peak, and 2.8 percent for the off-peak periods. Similar to the CORSIM trend, the default TRANSIMS MAERs were 18.9, 13.7, and 3.3 percent for the AM peak, the PM peak, and the off-peak periods, respectively. As would be expected given the under-congested conditions, the off-peak period had the lowest volume MAER. These results indicate that the peak period can have higher

Table. 2 Time Periods Sensitivity Analysis

Time Period	Parameter Set	Observed Volume		Volume MAER (%)		Travel Time MAER (%)	
		On-ramp Total Volume	Off-ramp Total Volume	CORSIM	TRANSIMS	CORSIM	TRANSIMS
AM Peak	Default	98,689	87,785	27.33	18.86	188.3	261.8
	Calibrated			2.17	5.48	116.5	41.5
PM Peak	Default	88,142	71,658	11.9	13.72	80.5	35.2
	Calibrated			3.12	4.38	38.4	7.6
Off Peak	Default	74,596	63,144	2.86	3.34	41.3	21.2
	Calibrated			1.37	0.86	26.8	4.3

Table. 3 Test Beds Sensitivity Analysis

Test Bed	Parameter Set	Observed Volume		CORSIM	TRANSIMS
		On-ramp Total Volume	Off-ramp Total Volume	Volume MAER (%)	Volume MAER (%)
I-10	Default	98,689	87,785	27.33	18.86
	Calibrated			2.17	5.48
US 290	Default	69,215	62,344	13.83	8.9
	Calibrated			10.68	0.72
	Calibrated on I-10			13.70	1.50
I-37	Default	6,623	6,805	14.39	33.36
	Calibrated			10.75	5.48
	Calibrated on I-10			22.20	11.70

calibration errors if the default values are used. It should be noted that both CORSIM and TRANSIMS for all time periods could replicate the baseline volume data within 5 percent.

3. Test Bed

In a simulation study, the determination of the test beds is the very first and fundamental step. The purpose of the sensitivity analysis of the test bed is to identify whether the simulation results are found in other locations. The I-10, US 290, and I-37 corridors were used as the test beds in this analysis. Only the AM peak period was used for comparison purposes. Table 3 shows the results. For CORSIM and the default parameter set, the MAER from I-10 test bed was 27.3 percent while the MAER from US 290 and I-37 were 14 percent. While TRANSIMS had higher MAER than CORSIM for I-10, its MAER from US 290 and I-37 were 93 percent and 49 percent lower than CORSIM, respectively. The results show that geographic transferability of the parameter set may be low not only for different cities in the same state but also for different corridors in the same metropolitan area. Interestingly, when the calibrated values were transferred, they did marginally better than the default parameters. The fact that the results are different is not unexpected because the geometric and traffic conditions are different for each site. In addition, the more congested the corridor, the tougher it was to calibrate and the higher the MAER. It should be noted that the low-fidelity TRANSIMS model could replicate the baseline data more accurately when the parameter sets are calibrated using the proposed calibration methodology.

4. OD Matrix

Both the C_OD and ITS_OD matrices were tested on the three test beds, and the results are shown in Table 4. In the majority of the scenarios the simulations that used ITS_OD matrices were better able to replicate the baseline data as evidenced by the improvement in the volume MAER. The percent improvement ranged from 6.3 to 53.3 percent for CORSIM and from 14.1 to 59.5 percent for TRANSIMS. The only exception was the TRANSIMS analysis for I-37 using the default parameter set. However, the ITS_OD matrix was superior to the C_OD matrix when the calibrated parameter sets were used. The percent improvement for calibrated values ranged from 46.8 to 94.1 for TRANSIMS. It is very important to notice that the TRANSIMS scenarios were more sensitive to the OD information and consequently received greater benefit from the calibrated values.

5. Random Seed Number

It is a known property of stochastic simulation

<Table. 4> OD Matrix Sensitivity Analysis

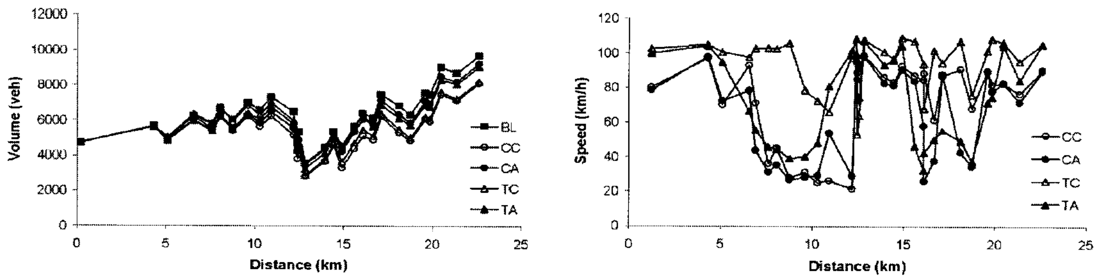
Test Bed	Parameter Set	CORSIM Volume MAER			TRANSIMS Volume MAER		
		ITS_OD[1]	C_OD	Percent[2] Improvement	ITS_OD[1]	C_OD	Percent[2] Improvement
I-10	Default	27.33	29.18	6.3	18.86	21.95	14.1
	Calibrated	2.17	4.65	53.3	5.48	10.31	46.8
US 290	Default	13.83	18.82	26.5	8.90	21.95	59.5
	Calibrated	10.68	12.16	12.2	0.72	12.16	94.1
I-37	Default	14.39	16.09	10.6	33.36	21.70	-53.7
	Calibrated	10.75	10.76	0.09	5.48	10.31	46.8

[1]ITS_OD = AVI_OD for I-10 and US 290 test beds, and ITS_OD = ILD_OD for I-37 test bed; [2]Percent Improvement = (CORSIM MAER - ITS MAER)/CORSIM MAER

models that the results are a function of the initial seed number. Consequently, Monte Carlo techniques are often used where a number of simulation runs, with different randomly selected seed numbers, are performed in order to ensure that the simulation results are stable. The purpose of this analysis was to identify the sensitivity of TRANSIMS and CORSIM, which are both stochastic models, to the random seed number while holding the parameter set constant. The CORSIM scenario involved 20 runs, and the mean and standard deviation of the volume MAER were 0.0802 and 0.0094, respectively. The TRANSIMS model was run with 64 random seed numbers and the manual calibration parameter set. It was found that the mean of MAER was 0.1073 and that the standard deviation was 0.0041. It should be noted that in both scenarios the standard deviation was small and the maximum difference among the obtained MAER was within 2.7 percent for both models. Consequently, CORSIM and TRANSIMS were not sensitive to the chosen random seed numbers.

6. CORSIM / TRANSIMS Comparison

To further investigate the differences in CORSIM and TRANSIMS, the speed and volume results were compared for the two OD matrices at the individual link level. Figure 4(a) shows the volume versus distance relationships for the AM peak. Five scenarios are shown for each period: i) the CORSIM results with the C_OD matrix (CC), ii) the CORSIM results with the AVI_OD matrix (CA), iii) the TRANSIMS results and the C_OD matrix (TC), iv) the TRANSIMS results and the AVI_OD matrix (TA), and v) the baseline volumes (BL). Figure 4(b) shows the speed versus distance graphs for the AM peak. The best parameter set for each model and each OD matrix was identified and used for the analysis. In general, the results from all four analyses are similar and roughly track the baseline volumes although the upstream sections of freeway have a better fit than later downstream sections. There was very little difference between the calibrated models in terms of replicating the baseline volumes. Given the inherent uncertainty in the baseline volumes, either model appears acceptable for replicating



(a) Volume versus Distance – AM Peak Period

(b) Speed versus Distance – AM Peak Period

<Fig. 4> Volume and Speed for CORSIM and TRANSIMS on I-10 Test Bed

the volume data on the test bed. The difference was that CORSIM tended to have lower speeds than TRANSIMS. The high travel time MAER in Table 2 helps explains the wide range of speed profiles.

V. CONCLUDING REMARKS

The sensitivity analysis was performed on two simulation models, TRANSIMS and CORSIM. Two highway corridors in Houston, Texas, I-10 and US 290, which have been instrumented with AVI technology were used as test beds. Another highway corridor in San Antonio, Texas, I-37 was used as a test bed because it has been instrumented with inductance loop detectors.

The calibrated parameter values for both CORSIM and TRANSIMS were not only different from the default parameter values but also different for each corridor. This illustrates the importance of calibrating micro-simulation models to local conditions before using them. This is particularly true for CORSIM, which had less geographic transferability than TRANSIMS. The TRANSIMS analysis showed that the most critical parameter was the deceleration probability PT1 because it controls the vehicle's acceleration and deceleration characteristics. Interestingly, neither the lane change probability nor plan following distance affected the results as much. The CORSIM simulation results were highly dependant on the car-following sensitivity parameters because they control the vehicle's speed, and space headway between vehicles. It was found that the biggest differences in parameter sets were observed during congested conditions. This is not unexpected because these conditions are considerably and therefore more difficult to model. In contrast it was found that many different parameter sets gave similar results for uncongested conditions.

It should be noted that the ITS_OD matrix gave considerably better results than the C_OD matrix, indicating that the demand estimate is also an important parameter to be calibrated. The superior performance of the ITS_OD matrix was attributed to the fact that a subset of the actual OD was used in the estimation process. In addition, the ITS_OD matrix gave better results as compared to the C_OD matrix independent of which parameter set was used. While the OD information is important for the CORSIM model, it is more important for the TRANSIMS model. It is an important finding that the TRANSIMS model was more sensitive to the OD information and could get more benefit from the use of calibrated parameter sets.

In summary, it was found that the micro-simulation results were highly sensitive to the parameter set and the OD information. The degree of sensitivity was a function of the test bed and time period. It was found that the volume MAERs for I-10 were 2.17 and 5.48 for the CORSIM and TRANSIMS models, respectively, when the calibrated parameter set and ITS_OD matrix were used. Surprisingly, for the US 290 and I-37 test beds the TRANSIMS model had an approximately 5 percent MAER while the CORSIM model had an approximately 11 percent MAER when the calibrated parameter set and ITS_OD matrix were used. That is the low-fidelity TRANSIMS gave better results than the high-fidelity CORSIM. It was found that while both models could replicate the baseline volumes to the same level of accuracy, the low-fidelity TRANSIMS model was observed to have higher emergent speeds as compared to the high-fidelity CORSIM model, indicating that the emergent fundamental flow relationships are different.

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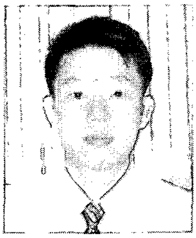
〈저자소개〉



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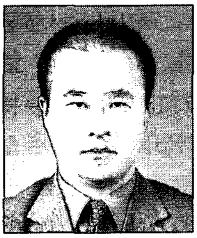

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