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A Calibration Procedure for Microscopic Traffic Simulation

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ABSTRACT

Simulation modeling is an increasingly popular and effective tool for analyzing transportation problems that are not amendable to study by other means. For any simulation study, model calibration is a crucial step to obtaining any results from analysis. This paper presents a systematic, multi-stage procedure for the calibration and validation of PARAMCIS simulation models. The procedure is demonstrated in a calibration study with a corridor network in the southern California. The model validation results for the study network are also summarized.

1. INTRODUCTION

Simulation modeling is an increasingly popular and effective tool for analyzing transportation problems that are not amendable to study by other means. In the transportation simulation field, there is general agreement that microscopic simulation, i.e., a computational resolution down to the level of individual travelers, is now a viable alternative and may be the only answer to questions arising from a wide variety of problems. Recent advancements in computer technology have led to the development of high fidelity microscopic simulation models. Examples of widely used microscopic traffic simulation models are AIMSUN, MITSIM, PARAMICS, and VISSIM.

A microscopic traffic simulation model generally includes physical components, such as the roadway network, traffic control systems, and driver-vehicle units, etc., and associated behavioral models, such as driving behavior models and route choice models. These components and models have complex data requirements and numerous model parameters. Although most simulators provide data input guidelines and default model parameters, these models nevertheless need to be calibrated for the specific study network and the intended applications [1].

In the traditional process of model calibration, model parameters are adjusted until reasonable (qualitative and quantitative) correspondence between the model and field-observed data is achieved. Such adjustments with multiple parameters are a time-consuming and tedious process. The trial-and-error method based on engineering judgment or experience is usually employed for model calibration. More systematic approaches include the gradient approach and Genetic Algorithms (GA) [2, 3]. These approaches regard the model calibration procedure as an optimization problem in which a combination of parameter values that best satisfies an objective function is searched. Most calibration efforts reported in the literatures have focused on either the calibration of driving behavior models [3, 4, 5, 6], or the calibration of a simple linear freeway network [2, 7, 8, 9]. However, these studies represent only an incomplete process of model calibration and validation. In order to analyze network-wide transportation problems, it is necessary to include not only driving behavior model calibration but also dynamic Origin and Destination (OD) demand estimation and route choice in the calibration process. This paper describes a systematic procedure to calibrate a network-level simulation model, consisting of both freeways and their adjacent parallel streets, using a widely used microscopic simulation package, PARAMICS, developed by Quadstone in Scotland.

This paper is organized as follows. Section 2 briefly describes the study network and data used in the calibration study. In Section 3, the overall calibration procedure is introduced first and then we explains the details on how the study network is calibrated using the proposed procedure. The model validation results are given in Section 4. Discussion and conclusions are presented in the last section.

2. STUDY SITE AND CALIBRATION DATA ACQUISITION

2.1 Study Site

The study network is a highly congested corridor network in the city of Irvine, Orange County, California, as shown in Figure 1. The network includes a 6-mile section of freeway I-405, a 3-mile section of freeway I-5, a 3-mile section of freeway SR-133 and the adjacent surface streets. This network is calibrated to investigate the effectiveness of various Intelligent Transportation Systems (ITS) strategies on relieving traffic congestion happened along the northbound I-405 in the morning peak periods.

Microscopic simulation models have complicated data input requirements and many model parameters. To build a PARAMICS simulation model for this network, two types of data are required. The first type is the basic input data used for network coding of the simulation model. The second type is the observation data employed for the calibration of model parameters and the simulation model.

2.2 Basic Input Data

Basic input data include data of network geometry, driver behavior, vehicle characteristics, transportation analysis zones, travel demands, and traffic control systems and traffic detection systems.

We built the study network in PARAMICS based on aerial photos and the road geometry and infrastructure maps, obtained from Caltrans and the city of Irvine. Since PARAMICS regards each vehicle in the simulation as a Driver Vehicle Unit (DVU), driver behavior data, vehicle mix by type, vehicle characteristics data are basic inputs of the established PARAMICS simulation model. The vehicle mix by type data were determined by the statistical analysis of traffic flow data observed from surveillance videos at two freeway locations (i.e. I-405N at Irvine Center Drive junction and I-5N at Alton Drive junction) in the network. The vehicle characteristics and performance data included vehicle length, maximum speed, maximum acceleration and deceleration rates, etc., which were obtained from California Department of Transportation (Caltrans). The driver behavior data, represented by aggressiveness and awareness factors in PARAMICS, were assumed to be the default normal in this study.

Based on data of traffic control systems and traffic detection systems from Caltrans and City of Irvine, the established simulation network had the same loop detector stations as those in the real world and the same traffic control operations, including actuated signal control and time-based ramp metering, modeled by full-actuated signal and ramp metering plug-ins, respectively [11].

Based on the transportation analysis zones in the regional planning model, Orange County Transportation Authority Model (OCTAM), we defined the transportation analysis zones of the PARAMICS simulation model.

2.3 Data for Model Calibration

The coded PARAMICS simulation network needs to be further calibrated. The calibration involves checking the model results against observed data and adjusting parameters until the model results fall within an acceptable range of error. The collected data included freeway traffic volume and travel time data, and arterial traffic volume data.

2.3.1 Freeway traffic data

For the freeway traffic volume data, including mainline, on-ramp and off-ramp loop detector data, they can be obtained from an on-line database at the University of California, Irvine. For the travel time data, we obtained probe-vehicle based travel time data for the northbound and southbound freeway I-405, collected at Oct. 17 and Oct. 18 of 2001 by Caltrans.

The traffic congestion in the study network happened mainly on the freeway. The freeway was the major concern of the calibration. Obviously, we had too many freeway data available to be potentially used. Because field observations vary from day to day due to the stochastic nature of traffic, our calibration objective is to re-construct the typical real-world traffic variation in simulation. The typical traffic variation can be represented by the traffic condition of a typical day, whose traffic data are the target of the calibration process. The selection of a typical day can be implemented based on the comparison of the peak-hour (i.e. 7-8 AM) volume of a candidate day at any selected loop station with the average peak-hour volume of all candidate days using the GEH statistic, used by British engineers [10]:

$$GEH = \sqrt{\frac{(Vol(i) - ave\_Vol)^2}{(Vol(i) + ave\_Vol)/2}} \tag{1}$$

If the GEH values for more than 85% of the selected loop stations are less than 5, the traffic condition and the demand pattern of the candidate day is typical. There are 35 selected loop stations, placed at the upstream end of each freeway, all on-ramps and all off-ramps.

In our study, the selection of a typical day was restricted by another factor, the availability of the travel time data, which were also required for the calibration process.

Because we only had two days of freeway travel time data (i.e. Oct. 17 and Oct. 18 of 2001), we had to pick one of them as the typical day. Based on the above method, we found the traffic condition on Oct. 17, 2001 was typical with respect to all weekdays' data in October. Therefore, the travel time and loop data of Oct. 17 were chosen for the calibration study.

2.3.2 Arterial traffic data

The traffic volume data at all arterial cordon points and some important measurement links of the network were required for the calibration. Theoretically, these data should be collected at the same day and thus there were more than one hundred data collection points for the study network. Because we did not have resources to perform this kind of comprehensive data collection, we had to use some available data.

We obtained 15-minute interval traffic counts at some cordon points and important links of the network from the City of Irvine, collected in June 2001 and January 2002. For those missing data collection points, their data were derived based on the surveillance video data, video-taped between March 27th and April 19th of 2002. Since the arterial data were collected at different days, an assumption we made in order to use these arterial data for calibration was that the traffic patterns of those data collection days were the same.

3. CALIBRATION

3.1 Overall Calibration Procedure

We calibrated the PARAMICS simulation model according to the procedure shown in Figure 2. The calibration process starts from an un-calibrated PARAMICS simulation network (see Section 2.2). In order to calibrate the simulation network, the following four steps of calibration efforts are required:

(1) Calibration of driving behavior models;
(2) Calibration of route choice model;
(3) OD estimation;
(4) Model fine-tuning.

It also should be noted that the network coding errors are major source of abnormal vehicular movements. Such errors can be found at any time during the process of the calibration from some. Accordingly, fixing network coding errors is an important task throughout the whole calibration process.

3.2 Determination of Number of Simulation Runs

PARAMICS is a stochastic simulation model, which rely upon random numbers to release vehicles, assign vehicle type, select their destination and their route, and to determine their behaviors as the vehicles move through the network. Therefore, multiple simulation runs using different seed numbers are required and the median simulation run (based on a user-specified measure) or the average results of several simulation runs can reflect the average traffic condition of a specific scenario.

In order to determine the number of simulation runs, we need to know the variance of a number of performance measures from simulation results, which are unknown before simulations. The flow chart to determine the number of simulation runs is shown in Figure 3. A number of simulation runs is needed to be executed first and then the required number of runs can be calculated according to the mean and standard deviation of a performance measure of these runs:

$$N = (t_{\alpha/2} \cdot \frac{\delta}{\mu \cdot \varepsilon})^2 \qquad (2)$$

where μ and d are the mean and standard deviation of the performance measure based on the already conducted simulation runs; e is the allowable error specified as a fraction of the mean μ; $t_{a/2}$ is the critical value of the t-distribution at the confidence interval of 1-a.

All performance measures of interest need to be involved in this calculation and the highest value is the required number of runs. If the current number of runs is already larger than this value, the simulation of this scenario is ended. Otherwise, one additional run is performed and then the required number of runs needs to be recalculated.

At the beginning of each calibration step, we determined the required number of simulation runs for this calibration step. We only considered a system level measure, i.e. Total Vehicle Traveled (VHT), in calculating the required number of runs. A 90% confidence interval and a 5% allowable error were used in the calculation. The simulation run that results in the median VHT was selected as the representative traffic condition for calibration.

3.3 Calibration of Driving Behavior Models

The driving behavior models include car-following (or acceleration) and lane-changing models, which govern vehicular traffic movement and need to be calibrated for the specific region. Global parameters of these models are calibrated within the sub-network level using either disaggregated data or aggregated data.

The driving behavior models of PARAMICS have been extensively studied [4, 5, 6]. Lee et al. conducted a calibration study based on a sub-network of this study network, which shows calibrated values of the two major parameters of driving behavior models, i.e. the mean target headway and driver reaction time, are 0.625 and 0.415 respectively [5]. These two values may be changed in the parameter fine-tuning step in order to match the observed congestion patterns.

3.4 Calibration of Route Choice Model

The calibration of the route choice behavior model must be conducted on a network-wide level. The route choice behavior model can be calibrated using either aggregated data or individual data obtained from driver surveys.

Due to the existence of freeways and parallel streets in the study network, the routing algorithm adopted in the PARAMICS simulation was important. We calibrated the network using the provided stochastic route choice model (called stochastic assignment) provided by PARAMICS. Stochastic assignment in PARAMICS assumes that different drivers perceive different costs from a decision node to the destination. The perceived cost is calculated based on the given perturbation factor with a random number assigned to the DVU, and the shortest perceived route is chosen at the decision node.

There were two parameters for the route choice model, perturbation and familiarity. Since we had no data to calibrate them, the perturbation factor was assumed as 5% for all drivers based on the assumption that most drivers in the morning peak were familiar drivers who have a good knowledge of the road network and traffic condition. In addition, the "familiarity" attribute affects the route choice behaviors in PARAMICS. Since we calibrated the network using the demands of the morning peak when most travelers were commuters, we assumed that 95% of drivers were familiar drivers, who could choose their route from among both arterials and secondary streets.

3.5 OD Estimation

This step is OD estimation and/or model adjustment. This step involves several sub-steps if applicable.

3.5.1 Reference OD matrix

A PARAMICS simulation model needs to have an origin and destination (OD) demand pattern as a starting point of the calibration. A good source of this is from the planning models, such as Transplan and TransCAD based on the social-economic data of the target network. Or, this OD demand pattern can also be obtained from the traditional four-step model calculation using those social-economic data.

We sub-extracted the OD demand matrix from the OCTAM 2000 model. This OD matrix could be used as the reference OD matrix directly because the transportation analysis zones in our established simulation model were obtained from OCTAM.

3.5.2 Modifying and balancing the total OD demand matrix

The reference OD matrix obtained from the planning model, i.e. OCTAM, is not accurate enough for two reasons:

(1) It is for the morning peak hours from 6 to 9. However, the congestion in the study network cannot be totally cleared at 9 o'clock. Consequently, the OD demand matrix needs to be further expanded to 4 hours, i.e. from 6 to 10;

(2) It is not accurate because the data sets of OCTAM model are generally limited to the nearest decennial census year and the sub-extracted OD matrix is based on the four-step model of TRANPLAN.

Since we had 15-minute interval traffic counts at all cordon points of the network, the total traffic attractions and generations of each zone were known. We assumed the same trip distribution as that of the reference OD matrix was applied to all zones in the adjusted OD matrix. The FURNESS technique was then used for balancing the adjusted OD table [11]. If the total attractions were not equal to the total generations, the total generations were used as the total.

3.5.3 Fine-tuning the total OD matrix

The purpose of this sub-step is to estimate a total OD demand matrix based on the matrix from the last sub-step. This is a static OD estimation problem, which has many solution methods and the least square method is most frequently used [13, 14]. This OD estimation process can be also conducted outside of the microscopic simulation model. There are some software tools, such as TransCAD, QueensOD that can help the estimation of a static OD. However, this may cause some OD estimation errors if different traffic assignment methods are used in the OD estimation process and the microscopic simulation. The microscopic simulation models have started to develop their own OD estimation tool in order to avoid this problem. For example, INTEGRATION provides QueensOD as its OD estimation tool and PARAMICS provides an OD estimator tool in its latest software package.

Fine-tuning method

In the OD estimation process, all model parameters and route choice behaviors need to be fixed first since this process is based on the traffic assignment matrix that is affected by any change in simulation input or parameters.

The estimation of the total OD matrix is an iterative process to match simulation results with the aggregated traffic volume observations at some specific measurement locations. We evenly loaded the adjusted OD matrix for the whole simulation period (subject to a flat demand "profile"). Based on the simulation results, we compared the observed and simulated total traffic counts at selected measurement locations. In this study network, there were 52 selected measurement locations, including 13 mainline loop stations, 29 on-ramp loop stations, and 10 arterial links. The measure of the overall quality of the OD estimation was the GEH statistic:

$$GEH = \sqrt{\frac{(VOL_{obs}(n) - VOL_{sim}(n))^2}{(VOL_{obs}(n) + VOL_{sim}(n))/2}} \quad (3)$$

Based on a simulation run and its resulting GEH values at measurement locations, if the GEH values for more than 85% of the measurement locations were less than 5, the adjusted OD was acceptable. If the above criteria were not satisfied, both the total OD matrix and the route choice needed to be modified and an iterated process was required:

(1) Modification of route choices
We find, under the stochastic assignment in PARAMICS, travel delays caused by intersection signals and freeway ramp control are not considered. In order to have reasonable route choices (which should be based on survey data), additional costs (such as decreasing speed limit value of the link, increasing link cost factors, and adding tolls to the link) were added to on-ramp links to reflect on-ramp control and arterial links to reflect signal control.

(2) Elements of the total OD matrix
Most efforts on fine-tuning the total OD matrix were focused on the adjustment of the values of elements of the total OD matrix. This adjustment was performed according to the assumption of the proportional assignment [15], which assumed that the link volumes are proportional to the OD flows.

Result

Multiple simulation runs for each parameter combination were required. After multiple iterations, the calibration criteria were satisfied and an acceptable total OD matrix was obtained. Table 1 shows the calibration results at this step (on the right side). It shows that, except for a single on-ramp location and one arterial link location, all other measurement locations have a GEH value lower than 5, which satisfies the calibration acceptance criteria of this step.

3.5.4 Reconstruction of time-dependent OD demands

In order to obtain a more accurate simulation model, the dynamic (or time-dependent) OD estimation is required. Theoretically, it is a dynamic OD demand estimation problem. So far, there is not an effective method that can solve this problem [16, 17]. Practically, the FREQ model was used for the rough estimation of time-dependent OD of a freeway network for micro-simulation [7]. But for a corridor network, no good method exists. Though some existing OD estimation tools, i.e. QueenOD and Estimator of PARAMICS, have a certain potential to handle the dynamic OD estimation, their capabilities are not recognized.

We estimated the time-dependent OD based on the total OD demand matrix, estimated in the previous sub-step. The proposed dynamic OD estimation process could be regarded as a process that assign the total OD to a series of consecutive time slices. Our method tries to simplify the complex time-dependent OD estimation problem through reconstructing the dynamic OD demands based on a set of demand profiles. PARAMICS has an enhanced feature of demand loading, i.e. the ability to specify different demand profiles for each OD pair. Through the use of "matrix" and "profile" files, a profile can be specified for a specific OD pair.

Initial assumption of demand profiles

Since the 15-minute interval traffic counts at all cordon points of the network were known, the profile of vehicle generation from any origin zone and that of vehicle attraction to any destination zones were thus known. We further assume a number of initial demand profiles for all OD pairs based on the following criteria:

(1) The demand profile from an arterial origin zone to any arterial destination zone has the same profile, which is the same as the vehicle generation profile from this origin zone;
(2) The profile from a freeway origin zone to an arterial destination zone can be estimated based on the 15-minute loop data at a corresponding off-ramp location.
(3) The profile from an arterial origin zone to a freeway destination zone can be estimated based on the 15-minute loop data at a corresponding on-ramp location.
(4) The demand profiles from a freeway origin zone to a freeway destination zone can be estimated based on the traffic count profile at corresponding loop stations placed on freeway mainline.

Parameter fine-tuning method

This step had two calibration objective functions. The first one was an easy one, which was to minimize the deviation between the observed and corresponding simulated traffic counts at selected measurement locations for the peak hour of the simulation period:

$$\min \sum_{n=0}^{N} (VOL_{obs}(n, peak\_T) - VOL_{sim}(n, peak\_T))^2 \qquad (4)$$

where N is the total number of measurement locations; $VOL_{obs}(i, peak\_T)$ and $VOL_{sim}(i, peak\_T)$ are total observed and simulated traffic counts for the peak hour at measurement location i, respectively. The selected measurement points were the same as those in last step. The peak hour was defined as from 7 to 8 AM. The same criteria as that of Section 3.4.3 was applied here. If the GEH values for more than 85% of the measurement locations were less than 5, we thought the objective function shown in Equation 3 was reached.

The second objective function was to minimize the deviation between the observed and corresponding simulated traffic counts at selected measurement locations at five-minute interval. It could be formulate as:

$$\min \sum_{t=1}^{T} \sum_{n=1}^{N} (VOL_{obs}(n,t) - VOL_{sim}(n,t))^2 \qquad (5)$$

where N and T were the number of measurement locations and time periods, respectively; $VOL_{obs}(n, t)$ and $VOL_{sim}(n, t)$ were observed and simulated traffic counts of time period t at measurement location i, respectively. The length of each period was 5 minutes in this study.

This step of calibration was an iterative process. We mainly modified the demand profiles from a freeway origin zone to a freeway destination zone, from a freeway origin zone to an arterial destination zone, and from an arterial origin zone to a freeway destination zone in order to match the traffic counts at selected measurement locations. The trial-and-error method was used for the modification of demand profiles. The profiles from the freeway origin zones to the freeway destination zones are major things to be adjusted.

Result

The OD estimation process is related to the other calibration process. Without the calibration of other components of the PARAMICS simulation model, the dynamic OD demands are almost impossible to be obtained because the traffic during peak hours involves the capacity of the network, which is what the calibration needs to find out. As a result, the traffic count calibration here was an initial match of volume data; volume calibration was further conducted at the next step.

Multiple simulation runs for each parameter combination were required. After multiple iterations, the calibration criteria were satisfied. The calibration results of this step were shown in Table 1 (on the left side), which shows the comparison of traffic counts of peak hour at those selected measurement locations. It shows that for 87.5% of all measurement locations, their GEH values are lower than 5, which satisfies the calibration acceptance criteria of this step.

3.6 Model Fine-tuning

The last step of calibration is to use aggregated traffic data for fine-tuning the established simulation model in order to reflect network-level congestion effects. The driving behavior models need to be further validated locally (intersection-by-intersection or junction-by-junction) and adjusted to reflect the local characteristics. The local characteristics can be basically examined through the comparison of volume-occupancy curves drawn based on aggregated point detector data from both simulation and the real world.

Some previous calibration efforts actually started from this point [2, 8]. This is the reason that we think that the current studies represent only an incomplete process of model calibration and validation process. Under the following situations, there is no problem to start calibrating a network from this step:

(1) The network has been coded and roughly calibrated.
(2) The driving behavior models have been calibrated and validated based on previous studies on the same network.
(3) There is no data that can support the calibration of route choice model, or one of the route choice models in the microscopic simulator can be accepted.
(4) The OD demand matrices have been given.

3.6.1 Objective functions

This step of calibration is performed as a two-objective optimization process:

$$\min \quad \sum_{t=1}^{T}\sum_{n=1}^{N}(VOL_{obs}(n,t) - VOL_{sim}(n,t))^2 \tag{6}$$

$$\min \quad \sum_{t=1}^{T}\sum_{n=1}^{N}(TT_{obs}(n,t) - TT_{sim}(n,t))^2 \tag{7}$$

The objective functions are to minimize the deviation between the observed and the corresponding simulated 5-min volume and point-to-point travel time measurements. They can be called volume match and travel time match. In our study, the point-to-point travel time match was performed only for the northbound and southbound freeway I-405 between the interchanges at Irvine Center Drive and Culver Drive due to the lack of data for other trips.

3.6.2 Fine-tuning method and results

The following parameters were fine-tuned using the trial-and-error method in order to re-construct traffic variations and match the congestion pattern of the study network.

(1) Link specific parameters, including the signposting setting or the target headway of those links at critical bottleneck locations where a very minor change in capacity can have a major effect on congestion.
(2) Global parameters for the car-following and lane-changing models, i.e., the mean target headway and driver reaction time. They are two key user-specified parameters in the car-following and lane-changing models that can drastically influence overall driver behaviors of the simulation.
(3) Demand profiles from freeway origin zones to freeway destination zones may need to be further modified in order to adapt traffic congestion along freeways.

Multiple simulation runs for each parameter combination were required and the simulated data of the median simulation run were always used for the comparison with the observed data. Because of the high traffic demands during the peak hour, and recurrent congestion along the northbound I-405, some network coding problems showed up and were corrected. Because of the congestion and queuing phenomena on freeways, especially the northbound I-405, extra efforts were taken to modify demand profiles from the freeway origin zones to the freeway destination zones.

The final calibrated mean target headway and driver reaction time were 0.78 and 0.66, respectively. Figure 4 shows the calibrated demand profiles for several major OD pairs.

4. MODEL VALIDATION RESULTS AND DISCUSSIONS

4.1 Methodology

Model validation is typically an iterative process linked to each model calibration. The model validation is generally conducted with a different data set of larger area within the modeling network in order to check if the calibrated model parameters are suitable. Model validation is regarded as a final stage to investigate if each component adequately reproduces observed travel characteristics and the overall performance of the model is reasonable.

Here we only presented the validation of the overall performance of the calibrated simulation model. The traffic volume at several major measurement locations and the point-to-point travel time data need to be evaluated. The measure of goodness of fit we used for evaluating the calibrated simulation model was the Mean Abstract Percentage Error (MAPE), which can be calculated by:

$$MAPE = \frac{1}{T}\sum_{t=1}^{T}((M_{obs}(t) - M_{sim}(t)) / M_{obs}(t)) \tag{8}$$

4.2 Validation results

Based on the method described in Section 2.1, we used two performance measures, i.e. VHT and the northbound point-to-point travel time from Irvine Center Dr to Culver Dr. for determining the required number of simulation runs. 95% confidence interval and 5% allowable error were used in the calculation. We found that 31 runs could achieve statistically meaningful performance measures.

We compared the simulation results with the loop data and the floating car data of Oct. 17, 2001. Figure 5 shows the comparison of observed and simulated 5-minute traffic counts at eight major freeway measurement locations. The MAPE error of traffic counts at these measurement locations range from 5.8% to 8.7%. The travel time calibration results are shown in Table 2. Figure 6 and 7 show the comparison of observed and simulated point-to-point travel time for the northbound and the southbound I-405, which have the MAPE errors of 8.5% and 3.1%, respectively.

In summary, simulated traffic counts and point-to-point travel time data correspond well to the observed measurements. The calibrated simulation model accurately captures the congestion patterns of the target network shown on Oct. 17, 2001.

4.3 Discussion

A major concern in model calibration/validation is error inherent in the collection of input data. In spite of the methodology we took to calibrate the simulation model, some of the calibration errors might have been derived from problems in observed data, such as data discrepancy, poor quality, or data missing. Problems with input data or validation data can lead to erroneous corrections to models that will damage model performance, credibility and results.

The calibration of microscopic simulation models depends on the quality of the observed data. One important reason for the calibration error is that the data, especially the arterial data, we used for calibration were not in good quality. That is why most measurement points with GEH values larger than 5 were arterial measurement points as shown in Table 1. We already mentioned that they were not collected at the same day because of the short resources. The assumption that the traffic patterns under all data collection days were the same seemed to underestimate the variation of the traffic patterns. Based on our analysis on the arterial data, we did find some potential inconsistencies among those arterial data.

For the freeway data, they were collected by loop detectors, which can provide a typical 98% accuracy for a well maintained detector. Although the loop detectors in the study network are well maintained by Caltrans, the loop detector errors should not be ignored. We found the quality of loop data on I-405 was good, but that of I-5 and SR-133 was not. The MAPEs of up to 9% in validation results were partially accrued by the quality of the data. As for the travel time, we used probe vehicle data with about 15-20 minute intervals. This frequency of probe vehicles could not provide a good variation of the travel time data during the study period.

The calibration of microscopic simulation models also depends on the quantity of the observed data. The observed data need to cover every part of the network. However, due to unavailability of data, we did not have observed data at several off-ramp and mainline loop detectors on freeways I-5 and SR-133. As a result, some parts of the network were still un-calibrated, which might be a source of the calibration errors.

In summary, the completeness and quality of the observed data are especially important for the calibration of a simulation model. It is also important to recognize that uncertainty is inevitable in microscopic simulation model calibration and validation due to variability of traffic condition as well as the quality of data.

5. CONLUCUDING REMARKS

This paper proposed a calibration procedure for the PARAMICS microscopic simulation model. While previous studies focused mostly on driving behavior model calibration to study a section of freeway, this study provides a general scheme of model calibration and validation for network-level simulation, responding to the extended use of microscopic simulation models. Such extension requires more systematic approach in model calibration since various model components are included in the process. The proposed procedure is demonstrated via a case network that involves multiple steps, and the calibrated model showed reasonable performance in replicating the observed flow condition. Although our procedure was based on PARAMICS, the proposed calibration procedure (as shown in Figure 2) can be potentially applied to other microscopic simulation packages as well.

In this paper, various components of models were addressed in the model calibration process; however, we used the default route choice model in PARAMICS because of the interaction between the route choice model and OD estimation problem. In the network level model calibration/validation process, the inter-relationship between route choice and OD estimation make the problem complicated unless one of them is externally determined. This will be one of topics to be further studied in the micro-simulation calibration/validation process. A future task is to develop an automated and systematic tool for microscopic simulation model calibration/validation by incorporating optimization-based model calibration methods within the proposed multiple stage approach.

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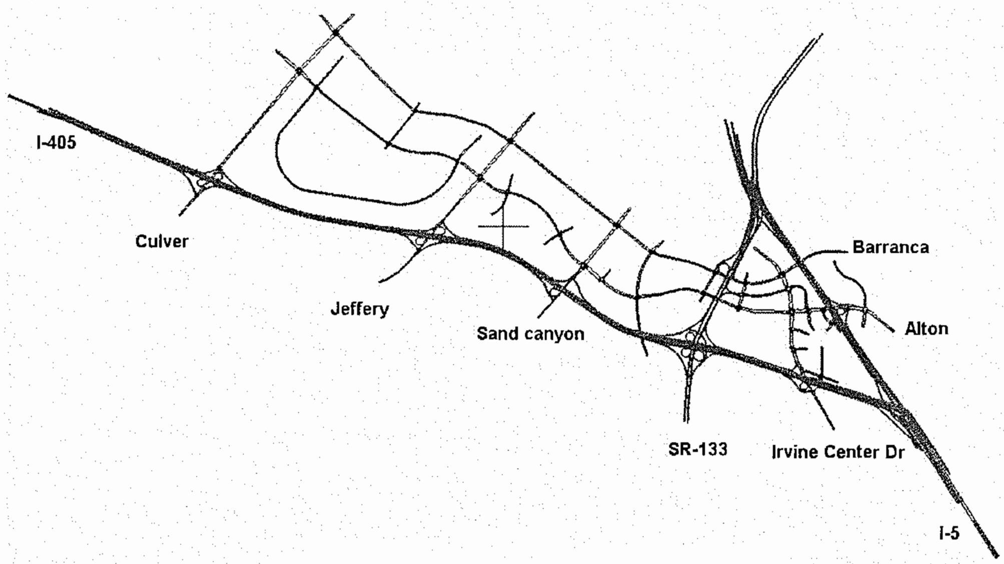

Figure 1 Overview of the study network

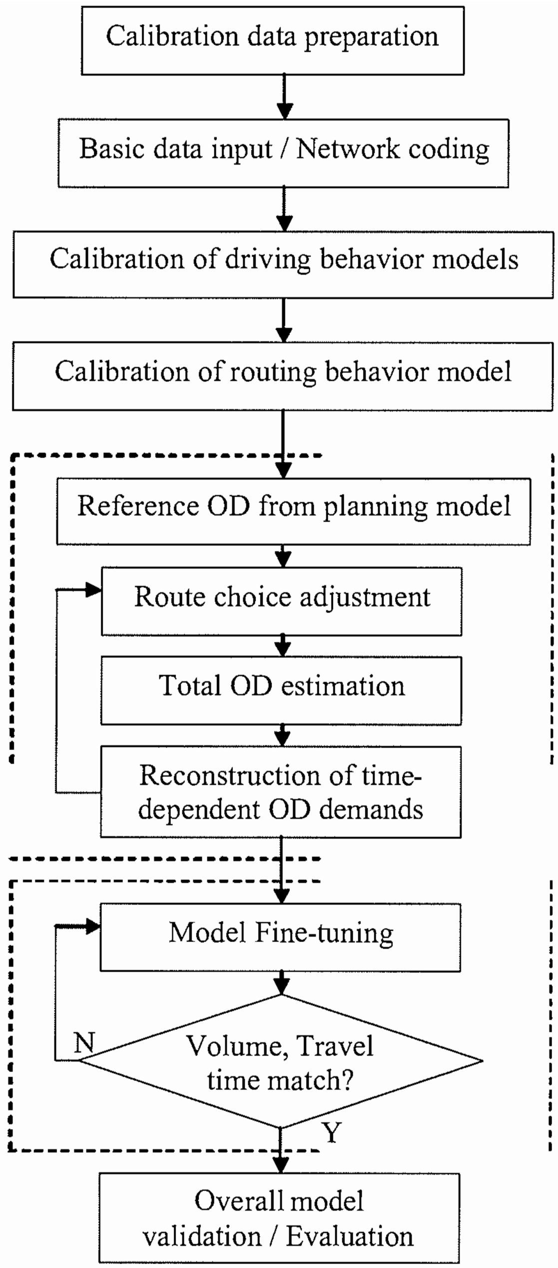

Figure 2 Flow chart of calibration procedure

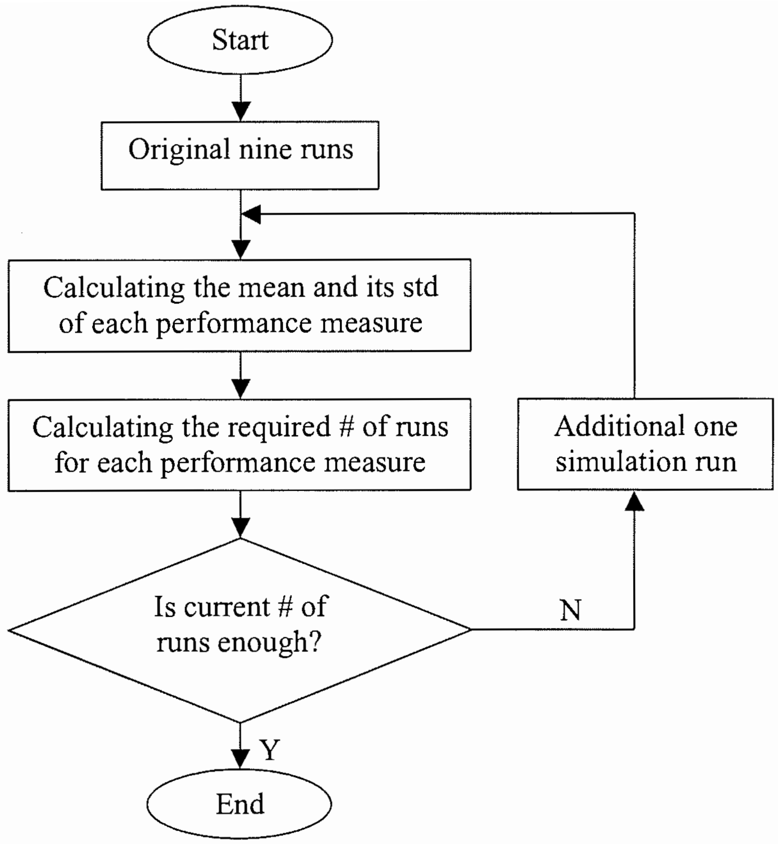

Figure 3 Flow chart of the determination of number of simulation runs

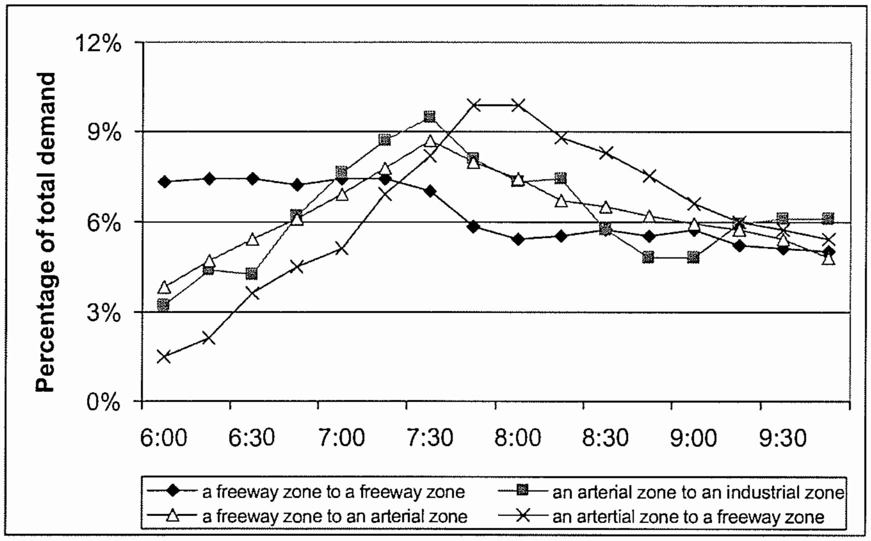

Figure 4 Demand profiles for major OD pairs

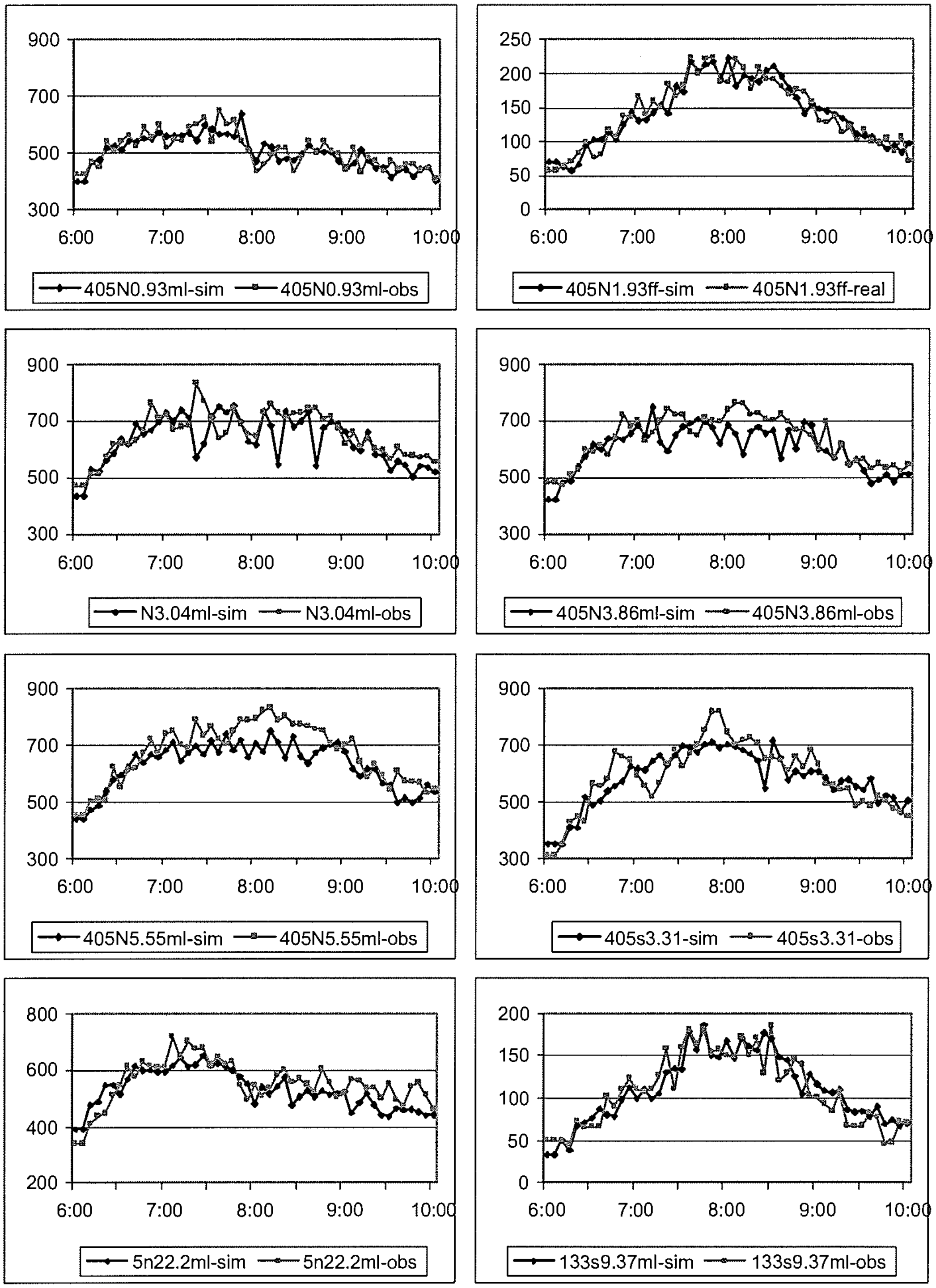

Figure 5 Traffic counts calibration (5-minute volume) at major freeway measurement locations

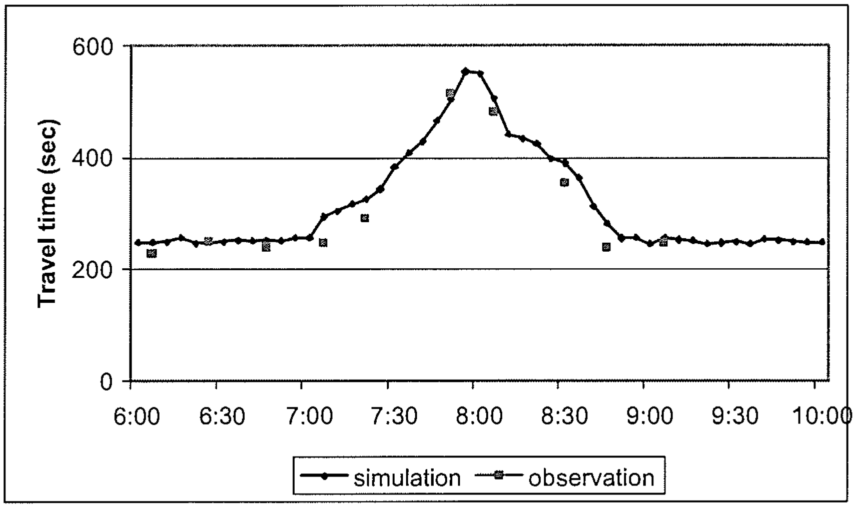

Figure 6 Observed and simulated travel time of northbound I-405

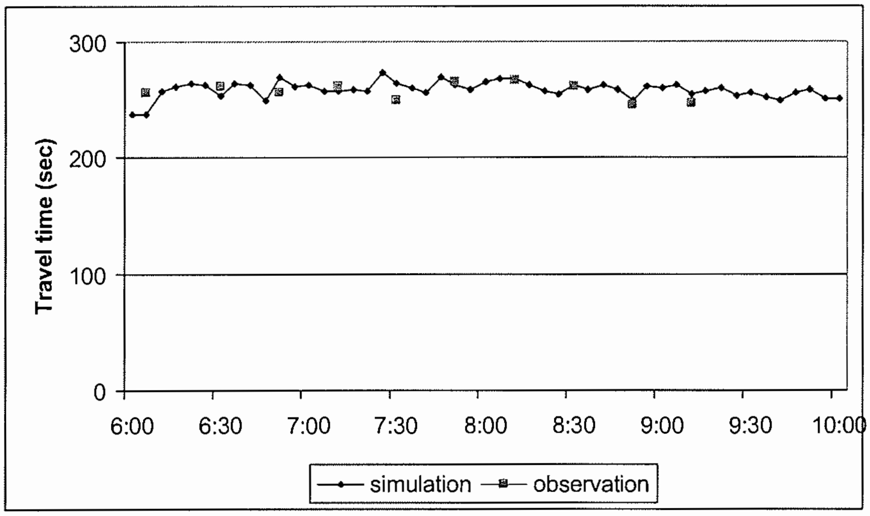

Figure 7 Observed and simulated travel time of southbound I-405

Table 1 Traffic counts calibration results of the total AM peak period and the peak hour

	Peak Hour (7-8 AM)			AM Peak Period (6-10 AM)		
Mainline Detectors	**Observed**	**Simulated**	**GEH**	**Observed**	**Simulated**	**GEH**
405n0.93ml	6803	6808	0.06	24505	24428	0.49
405n3.31ml	9127	9006	1.27	33274	32646	3.46
495n3.86ml	8322	8248	0.81	30589	29890	4.02
405n5.74ml	9545	9377	1.73	34277	33475	4.36
405s6.21ml	7960	8135	1.95	28255	27904	2.09
405s3.31ml	8098	8010	0.98	28501	27795	4.21
405s0.77ml	5583	5514	0.93	20057	19638	2.97
5n22.2ml	7533	7686	1.75	26830	26614	1.32
5s22.14ml	6499	6974	5.79	24464	24025	2.82
133n9.37ml	510	471	1.76	1496	1498	0.05
133n10.05ml	804	817	0.46	2534	2607	1.44
133s10.05ml	2752	2674	1.50	8557	8557	0.00
133s9.37ml	1760	1652	2.61	5233	5429	2.68
Ramp Detectors						
405n0.93fr	160	162	0.16	546	564	0.76
405n0.93orb	512	507	0.22	1815	1760	1.30
405n1.11orb	110	149	3.43	447	445	0.09
405n1.73ff	56	54	0.27	213	197	1.12
405n1.93ff	2227	2166	1.30	6887	6987	1.20
405n2.99fr	165	196	2.31	726	705	0.79
405n2.99orb	436	442	0.29	1418	1358	1.61
405n3.86fr	709	731	0.82	2737	2704	0.63
405n3.86orb	307	320	0.73	931	963	1.04
405n4.03orb	816	809	0.25	2889	2686	3.84
405n5.55fr	460	426	1.62	1626	1659	0.81
405n5.55orb	682	670	0.46	2161	2134	0.58
405n5.74orb	1026	1075	1.51	3567	3576	0.15
405s5.69fr	853	959	3.52	3182	3139	0.76
405s5.69orb	316	276	2.32	983	921	2.01
405s5.5orb	241	281	2.48	940	914	0.85
405s4.03fr	409	392	0.85	1602	1554	1.21
405s4.03orb	183	212	2.06	647	664	0.66
405s3.84orb	624	567	2.34	2112	1904	4.64
405s2.88fr	864	817	1.62	2937	2743	3.64
405s2.88orb	152	159	0.56	468	505	1.68
405s1.58ff	592	573	0.79	1881	1953	1.64
405s1.57ff	70	117	4.86	315	319	0.22
405s0.96fr	1546	1496	1.28	4906	4907	0.01
405s0.96orb	20	33	2.53	58	123	6.83
405s0.77orb	9	11	0.63	43	43	0.00
5n22.1fr	742	802	2.16	2443	2600	3.13
5n22.1orb	84	94	1.06	289	339	2.82
5n22.2orb	199	232	2.25	752	735	0.62
Arterial Detectors						
Jeffery 405-Alton	2119	1963	3.45	6563	6317	3.07
	882	1057	5.62	3520	3505	0.25
Alton E of Jeffery	758	604	5.90	1987	2038	1.14
	439	446	0.33	1470	1386	2.22
Alton E of Sand	624	443	7.84	1675	1480	4.91
	729	777	1.75	2443	2469	0.52
Alton E of Laguna	804	619	6.94	2102	2382	5.91
	491	606	4.91	1714	1921	4.86
Barranca SR133-ICD	428	420	0.39	1287	1240	1.32
	959	962	0.10	3235	3161	1.31

Table 2 Travel time calibrations

Travel time							
Mainline Trip Analysis	**Start time**	**Arrival Time**	**Observed**	**Start time**	**Arrival time**	**simulated**	**% diff**
Southbound I405 from Culver to ICD	6:00:22	6:04:38	256	6:00:00	6:15:00	264.5	7.0%
	6:25:14	6:29:36	262	6:25:00	6:30:00	257.8	3.3%
	6:47:01	6:51:17	256	6:45:00	6:50:00	255.7	5.4%
	7:06:34	7:10:56	262	7:05:00	7:10:00	259.6	1.7%
	7:24:45	7:28:54	249	7:25:00	7:30:00	263.1	5.9%
	7:46:23	7:50:48	265	7:45:00	7:50:00	278.9	1.1%
	8:05:14	8:09:41	267	8:05:00	8:10:00	326.8	0.3%
	8:24:23	8:28:44	261	8:25:00	8:30:00	262.6	0.6%
	8:43:42	8:47:47	245	8:45:00	8:50:00	259.5	2.1%
	9:04:27	9:08:34	247	9:05:00	9:10:00	246.4	3.2%
MAPE							3.1%
Northbound I405 from ICD to Culver	6:00:58	6:04:45	227	6:00:00	6:05:00	247.7	9.1%
	6:19:32	6:23:40	248	6:20:00	6:25:00	248.3	0.1%
	6:40:51	6:44:50	239	6:40:00	6:45:00	252.2	5.5%
	7:00:58	7:05:05	247	7:00:00	7:05:00	294.2	19.1%
	7:23:06	7:27:57	291	7:25:00	7:30:00	325.1	11.7%
	7:40:53	7:49:29	514	7:45:00	7:50:00	504.4	1.9%
	7:57:57	8:05:58	481	8:00:00	8:05:00	505.1	5.0%
	8:22:06	8:27:59	353	8:25:00	8:30:00	390.4	10.6%
	8:40:27	8:44:25	238	8:40:00	8:45:00	281.6	18.3%
	8:59:57	9:04:03	246	9:00:00	9:05:00	256.0	4.1%
MAPE							8.5%