

Word count: 5032+10\*250=7,532 words equivalent

## **A Streamlined Network Calibration Procedure for California SR41 Corridor Traffic Simulation Study**

**Henry X. Liu<sup>1\*</sup>**  
**Liang Ding<sup>1</sup>**  
**Jeff X. Ban<sup>2</sup>**  
**Anthony Chen<sup>3</sup>**  
**Piya Chootinan<sup>3</sup>**

<sup>1</sup>Department of Civil Engineering  
University of Minnesota-Twin Cities  
500 Pillsbury Drive S.E.  
Minneapolis, MN 55455  
Phone: 612-625-6347, Fax: 612-626-7750  
Email: [henryliu@umn.edu](mailto:henryliu@umn.edu)

**\* Corresponding Author**

<sup>2</sup>California Center for Innovative Transportation (CCIT)  
University of California - Berkeley  
2105 Bancroft Way  
Berkeley, CA 94720-3830

<sup>3</sup>Department of Civil and Environmental Engineering  
Utah State University  
Logan, UT 84322-4110

**Paper #06-3050**

Reviewed by  
TRB Committee AHB25 –Traffic Signal Systems Committee

Submitted to 85<sup>th</sup> Transportation Research Board Annual Meeting

November, 2005

## **ABSTRACT**

This paper presents the calibration procedure and results for a large scale corridor management simulation study on State Route SR41 in Fresno, California. The corridor management aims to incorporate detailed multi-modal performance measurement and operational analysis into the traditional corridor planning efforts. Micro-simulation software Paramics is used to evaluate and test different traffic management strategies for an integrated multi-modal traffic system. Alternative modes of transportation could be microscopically simulated to assess and maximize operational characteristics. A complete streamlined and practical calibration procedure is described in the paper, including methods for data collection and analysis, capacity calibration, origin-destination demand estimation and calibration, and calibration and validation. Calibration results are also shown by the proposed calibration procedure.

## **1. INTRODUCTION**

Micro-simulation becomes more and more popular and effective in solving transportation problems. It provides visualization of traffic flow on the transportation system given current and proposed conditions. In this study, Paramics (PARAllel MICROscopic Simulation) is used as our evaluation tool. The corridor management aims to incorporate detailed multi-modal performance measurement and operational analysis into the traditional corridor planning efforts. In this procedure, micro simulation can offer appropriate reactions to traffic over an integrated multi-modal system. In addition, alternative modes of transportation could be micro-simulated to assess and maximize operational characteristics. For any micro-simulation study, the calibration procedure is always a very crucial step. In particular for large scale networks, the calibration is normally difficult and time-consuming.

The calibration for a simulation study ultimately requires comparing simulated data with field-observed traffic data. Because field observations vary from day to day due to the stochastic nature of traffic, the calibration objective is to re-construct the typical real world traffic variation in the Paramics simulation. The calibration efforts are focused on the use of aggregated data to calibrate the most critical parameters in Paramics, including OD matrix adjustment, route choice parameters, the mean target headway and driver reaction time, and signposting settings of important freeway links in Paramics (4, 9).

The traditional process of simulation model calibration heavily relies on the engineering judgment, i.e., to adjust the model parameters (usually demands and network) until reasonable (quantitatively and qualitatively) matches between field data and simulated model results are reached (6,7,8,9). Without a clearly defined streamline procedure, these adjustments can be very time consuming and tedious. Especially for large scale networks, because the number of parameter is large, the trial-and-error method sometimes cannot get the reasonable result. Another deficiency for this method is, because mainly relying on the human knowledge, for the large scale network with many traffic analysis zones (TAZs), the demands matrix is difficult to adjust manually. The widely used way to handle this is to use the planning model and then apply some limited human adjustments.

Some researchers therefore focus on systematic approaches by formulating the steps of the calibration as an optimization problem. Then the calibration procedure becomes determining a combination of parameter values. By using certain approaches such as gradient and genetic algorithms, the combination of parameters with the best performance is found (3,10,14). This optimization method has the potential to achieve the global solution of the calibration problem. However most of them can only handle a limited global parameters in driving behavior and route choices. For large scale networks, OD demands can not be well represented in the procedure. Further, this method is not easily understood and conducted by practitioners.

In this paper, we present a streamlined and practical calibration procedure for large scale corridor network simulation study, namely the California SR41 corridor network simulation study. The procedure includes methods for data collection and analysis, capacity calibration, OD matrix estimation including both hourly and dynamic demands, and calibration and validation. New approaches for demand pattern matrix updating and dynamic OD generation are proposed along with the calibration procedure. Calibration results show that such a procedure can provide reasonably accurate matches with the field data.

The paper is organized as follows. Section 2 introduces the background information for the SR41 corridor network simulation study and outlines the overall calibration procedure. In Section 3, data collection and analysis methods for the simulation study are provided and the procedure for capacity calibration is discussed in Section 4. Section 5 presents in detail the methods for OD estimation and calibration, including the pattern matrix updating, hourly OD estimation in Paramics Estimator, and dynamic OD matrix generation. The final tuning of the calibration is given in Section 6. Finally, the calibration and validation results are shown in Section 7, followed by conclusions and future research directions in Section 8.

## **2. PROJECT DESCRIPTION AND CALIBRATION PROCEDURE**

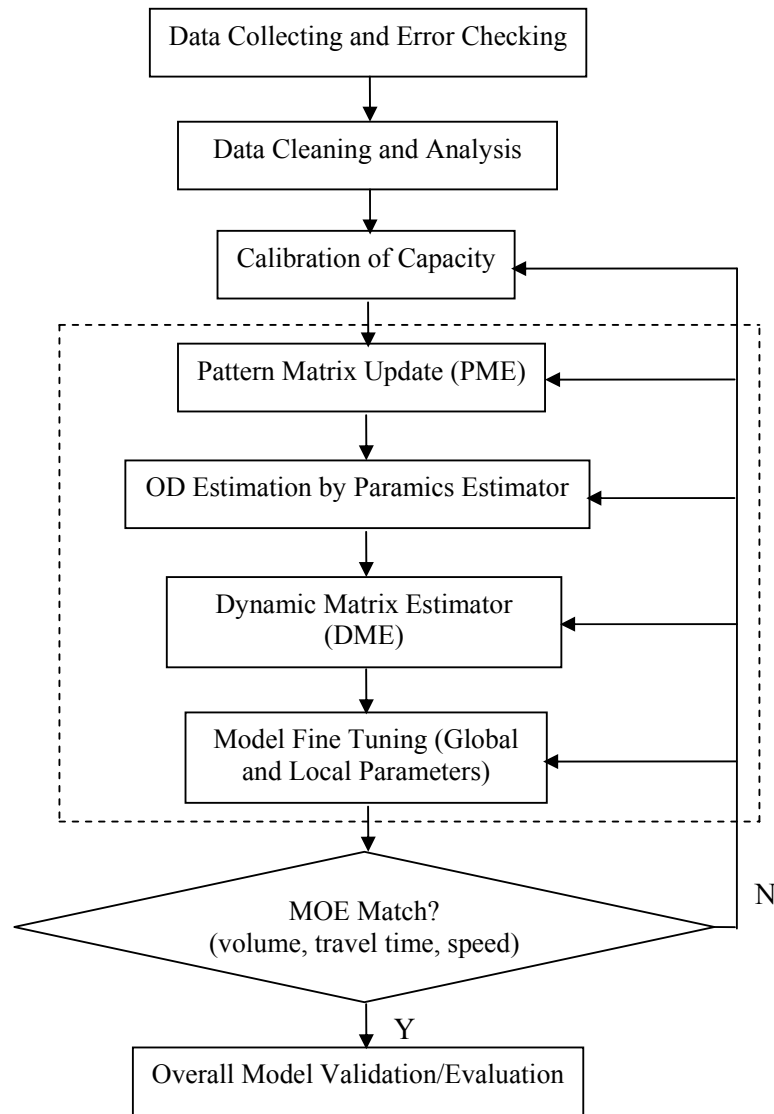
### **2.1 Project Description**

The SR41 corridor network is located in the City of Fresno, California, as shown in FIGURE 1. The network is about 16 miles long in North-South and 4 miles wide in East-West. It contains one major freeway (SR41) and two parallel streets with other adjacent surface streets. There are totally 176 TAZs and 89 signalized intersections, and 15 ramp metering controllers. The freeway SR41 has different congested patterns in AM and PM peak hours. For AM peak hours (6-9AM), the congestion happens in the southbound and for PM peak hours (4-7 PM), the congestion happens in the northbound. In this paper, Paramics is used as the tool for simulation study and PM calibration will be conducted as an example of the streamline procedure.



**FIGURE 1 Layout of the Study Network**

Comparing and analyzing the traditional calibration methods, a clearly defined streamline calibration procedure will be described in the paper. It follows the traditional step-by-step calibration framework which can be easily understood and used by traffic engineers. In particular, we put extensive effort on the OD demand estimation and calibration and develop some new methods for this purpose. The calibration procedure can be depicted in the flow chart shown in FIGURE 2.



**FIGURE 2 Flow Chart for the Calibration Procedure**

The following sections will further detail the calibration steps in Figure 2.

### **3. DATA COLLECTION and ANALYSIS**

#### **3.1 Data Collection**

A reliable and complete dataset is crucial for the simulation calibration study. The dataset should cover not only the demand data, but also the actual traffic performance data (volume, travel time, speed, and etc.). It is only when a reasonable set of traffic data is available that a model can be calibrated and validated against real-life traffic conditions. Previously collected SR41 data has a number of limitations and are outdated that cannot reflect current traffic conditions. Additional new dataset

reflecting the most recent traffic conditions on the SR41 peak hours are therefore collected as listed below.

*(1) Freeway loop detectors count data*

Freeway traffic volume data, including mainline, on ramp and freeway interchange data, were collected by the loop detectors from real count locations. Data for five consecutive days were collected from Tuesday to Friday (November 16 – 18, 2004) to present the typical traffic conditions. The collecting interval is five minutes. Since the congestion in this study happens mainly in the freeway system, the freeway volume data is the most important one to match in the calibration.

*(2) Arterials traffic data*

There are historical arterials count data for most of the signalized intersections in the area in previous years. But most of them are outdated and were only collected by hours. So they cannot fit the calibration requirement. New count data collection was conducted from Tuesday to Thursday (November 16 – 17, 2004) which can reflect the typical week day traffic pattern. Totally 18 counting locations were selected and all of which are at the major intersections of the study area and cover most of the in/out traffic of the corridor.

*(3) Travel time data*

Vehicles with GPS device (floating car) were sent out to traverse the study roads (SR41 freeway, and two parallel arterials). Every second the vehicle location was recorded. At the end of the trip, all records were output to a text file and processed. The travel time and speed data between sections were generated. With multiple days and multiple vehicle running, the final travel time data can be used in calibration.

*(4) Reference OD demand*

By using the sub-area analysis method on the county travel demand model in TP+ (17), the study area planning demand OD matrix can be retrieved. These planning demand matrix were mapped into Paramics network by a zonal system matching.

### 3.2 Data Analysis

Data come from different sources have different accuracies and confidential levels. Some of the data, especially the traffic count data, may have discrepancies with each other since they were collected during multiple days. Some of the discrepancies are very high and these data will affect the OD estimation adversely. They need to be further massaged. Basically, lower weight data will be adjusted according to the higher weight data, i.e. new collected data, freeway mainline data will have higher weight than the historical data and arterials data.

On the basis of the multiple runs of floating cars in multiple days, a speed contour map can be created to present the speed change both spatially and temporarily. Figure 3 depict the speed contour map for PM peak hours of the freeway mainline for NB and SB, respectively. In the figures, each cell of the time-space diagram represents

the average speed over multiple runs for a specific mainline freeway subsection. Thus speeds in the figure are shown over time (row summary) and over space (column summary). Three levels of speed are represented by different colors of shading: below 49 mph, between 50 and 59 mph, and over 60 mph. The resulting speed contour map provides an effective tool to visualize the level of performance of the freeway, to identify the location of the bottlenecks, and the extent of congestion conditions.

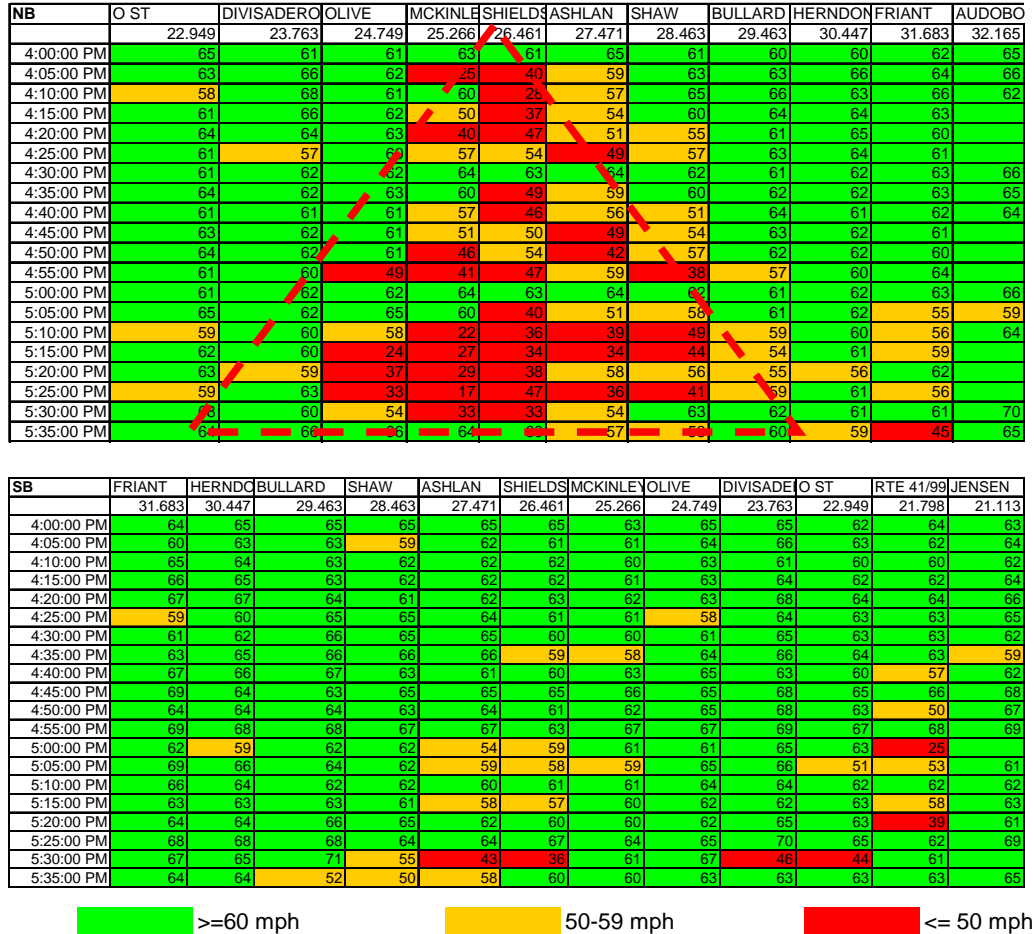


FIGURE 3 Speed Contour Map for PM Peak of Freeway

We can see from the figure that PM congestion mainly appears on NB of the freeway from 4:00 PM to 5:30 PM. The most congested areas are the Mckinley Ave., Shields Ave., and Friant Ave. However, for SB, there is almost no congestion in the period.

### 3.3 Network Coding Error Checking

The network geometry and signal timing were coded in Paramics and need to be checked to ensure they reflect the actual field conditions. The network geometry is a major factor affecting the vehicles behavior. If the geometry was not coded correctly, some revisions need to be conducted, including curb positions, stop line positions and angles, link and intersection description (link gradients, link headway factor, link end speeds, intersection visibility, etc.), barred turns, closures and restrictions, lane usage and behavior of traffic, signposting, and the next lane function.

Signal timing and ramp metering are also crucial parts in network coding. Because in this project, the Paramics plug-ins for signal and ramp controls will be applied, the detectors locations and names also need to be checked. The other items should be checked, including cycle length, phase green time, movement priorities, ramp control rate, etc. (4,9,11).

## **4. CAPACITY CALIBRATION**

### 4.1 Global Parameters

Capacity calibration is to find a set of (global) model parameters that enable the model to produce as close as possible results to match field measurements of traffic capacities. The choice of locations for field measurements of capacity depends upon existing traffic conditions within the study area. For non-signalized facilities (freeways, rural highways, and rural roads), the analyst should identify locations where queues persist for at least 15 minutes and measure the flow rate at the point where the queue discharges. This observed flow rate is measured only while an upstream queue is present. It is summed across all lanes and converted to an equivalent hourly flow rate. This is the field measured capacity of the facility at this point. In Paramics, on the other hand, several parameters affected capacity should be tested in order to match with the field observed data. These parameters are listed as follows.

#### *(1) Time Steps per seconds*

The simulation time step determines when calculations are carried out during every second of simulation. The default time step is 2 which means that calculation are done every 0.5 seconds of simulation.

#### *(2) Speed Memory*

Speed memory in Paramics simulation determines the number of time steps for which a vehicle remembers its speed. In conjunction with the time step change, speed memory can also be changed (e.g. from 3 to 8 time steps) to calibrate the capacity. Changing the size of the speed memory allows the modeling of the same reaction time with smaller time steps.

#### *(3) Headway and reaction time*

Three basic models are implemented within Paramics to control the movement of individual vehicles in the network: the vehicle following, gap acceptance and lane changing models. These models are strongly influenced by two key user specified parameters: the mean target headway and the mean reaction time. The overall behavior of the model can be changed considerably by increasing or decreasing the mean headway and the mean reaction time.

### 4.2 Method for Capacity Calibration

The capacity calibration can be formulated as an optimization problem. The goal is to minimize the Mean Square Error (MSE) between the model estimates of maximum

achievable flow rates and the field measurements of capacity. The MSE is the sum of the squared errors averaged in multiple locations over several model run repetitions (5). Each set of repetitions has a single set of model parameter values ( $p$ ) with different random number seeds for each repetition within the set.

The optimization model can be formulated as follows:

$$\min_p MSE = \frac{1}{N} \sum_N \sum_L (S_{nlp} - O_l)^2 \quad (1)$$

subject to:  $p \in [p_{\min}, p_{\max}]$ , for all user adjustable model parameters and  $p_{\min}, p_{\max}$  denote the lower bound and upper bound of the parameters respectively.

$MSE$  = mean squared error of capacity for parameter combination  $p$

$S_{nlp}$  = in the  $n$ th run, the simulation count for location  $l$ , with  $p$ th parameters combination

$O_l$  = the observed capacity flow at location  $l$

$N$  = the number of simulation runs with each parameters combination

To solve model 1, a number of parameters combinations are tested in Paramics, the optimal values for parameters, which generate the least MSE, can be obtained. The search range of headway is 0.6-1.0 seconds; range of reaction time is 0.6-1.0 seconds; time step range is 2-8/second; speed memory range is 5-8. The final optimal value for the parameter is, 0.75, 0.7, 5, and 8, respectively. The searching ranges come from experience from other studies and projects.

## 5. OD ESTIMATION

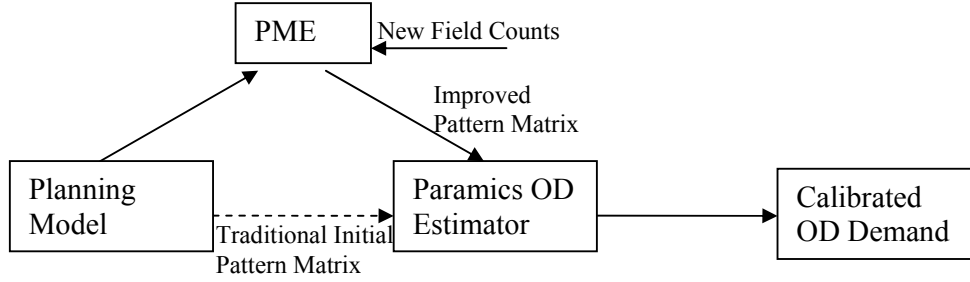
Origin-Destination (OD) demand data is a vital component to the microscopic traffic simulation. To obtain a reliable OD demand, data from multiple sources need to be synthesized. Generally, one can start with an initial OD matrix from the transportation planning models. However, such models are developed for long-term planning purposes, and its demand data may not reflect the pattern of up-to-date traffic. Therefore substantial amount of work will be needed for fine-tuning the demand data to match the field measurements from the traffic network if direct use of demand data from planning models is applied in micro-simulation studies.

Integrated with the core PARAMICS suite, PARAMICS Estimator is an OD matrix estimation tool developed by Quadstone, aiming to help the OD estimation process. Estimator provides an open/visual framework which places engineers, including their skills and knowledge, at the heart of the system (16). It can partially solve the difficulty in OD estimation while considering the interactions between OD demand and other parameters such as those for behaviors and route choices.

### 5.1 Paramics Pattern Matrix Estimator

In order for Estimator to generate reasonable results, however, it needs an initial OD demand pattern matrix as the input. In current state-of-the-practice, the demand data from planning models are usually used for this purpose. As aforementioned,

nevertheless, since the planning models can not reflect the up-to-date traffic pattern, the demand pattern matrix from them may be obsolete and differ far from the real pattern. On the other hand, for most simulation studies, data collection will be performed in the model calibration process. These data may include link counts for road segments and turning volumes for intersections. In this project, we develop a Paramics Pattern Matrix Estimator (PME) together with a user-friendly Graphical User Interface (GUI) to better estimate the initial demand pattern matrix for Estimator. PME utilizes newly collected link counts and turning volume data and the historical demand matrix from planning models, and the results from PME can be either directly used in the simulation studies, or used as the input to Estimator to generate more reliable OD estimations. The role of PME in the entire OD estimation procedure is depicted in Figure 4.



**FIGURE 4 The OD Estimation Procedure**

The relationship between O-D matrix and link flows can be expressed through an assignment mapping, i.e., link use proportion ( $\mathbf{A}$ ). Basically, it represents the proportion of trips from a particular O-D pair on a specific link and is critical to the estimation problem. The representative methods for deriving O-D matrix from traffic counts includes the entropy maximization method (13), maximum likelihood method (12), and the generalized least square (GLS) method (1,2).

In this study, the constrained generalized least square (CGLS) method proposed by Bell (1) was applied to calibrate the O-D matrix used in PARAMICS Estimator. In fact, the proposed procedure is similar to a bi-level programming approach proposed by Yang *et al* (15). Basically, the O-D matrix is adjusted according to CGLS objective, and the link use proportion ( $\mathbf{A}$ ) is updated by the mean of traffic simulation. This procedure will be iterated until the goal of calibration is met (e.g., a distance measure is less than a certain threshold). In addition to traffic counts, the prior O-D matrix can be used to assist the calibration.

The Generalized Least Square (GLS) approach utilizes the information from different data sources of which accuracies are always different. The equivalent optimization of problem has the following form.

$$\text{Minimize: } f(\mathbf{q}) = \omega_1 \cdot (\mathbf{q} - \bar{\mathbf{q}})^T \cdot \mathbf{U}^{-1} \cdot (\mathbf{q} - \bar{\mathbf{q}}) + \omega_2 \cdot (\bar{\mathbf{v}} - \mathbf{A}\mathbf{q})^T \cdot \mathbf{W}^{-1} \cdot (\bar{\mathbf{v}} - \mathbf{A}\mathbf{q}), \quad (2)$$

Subject to:  $\mathbf{q} \geq 0$

The inputs to this formulation are a vector of prior O-D demand ( $\bar{\mathbf{q}}$ ), a vector of traffic counts ( $\bar{\mathbf{v}}$ ), variance-covariance matrices for the prior O-D demand and traffic counts ( $\mathbf{U}$  and  $\mathbf{W}$  respectively), and link use proportion ( $\mathbf{A}$ ).  $\omega_1$  and  $\omega_2$  are the preferences (weights) given to different data sources (the prior O-D matrix and traffic counts). Under the assumption that the non-negativity constraints in equation (2) are inactive, the optimal solution to the problem can be explicitly expressed as:

$$\mathbf{q} = (\mathbf{U}^{-1} + \mathbf{A}^T \mathbf{W}^{-1} \mathbf{A})^{-1} \cdot (\mathbf{U}^{-1} \bar{\mathbf{q}} + \mathbf{A}^T \mathbf{W}^{-1} \bar{\mathbf{v}}) \quad (3)$$

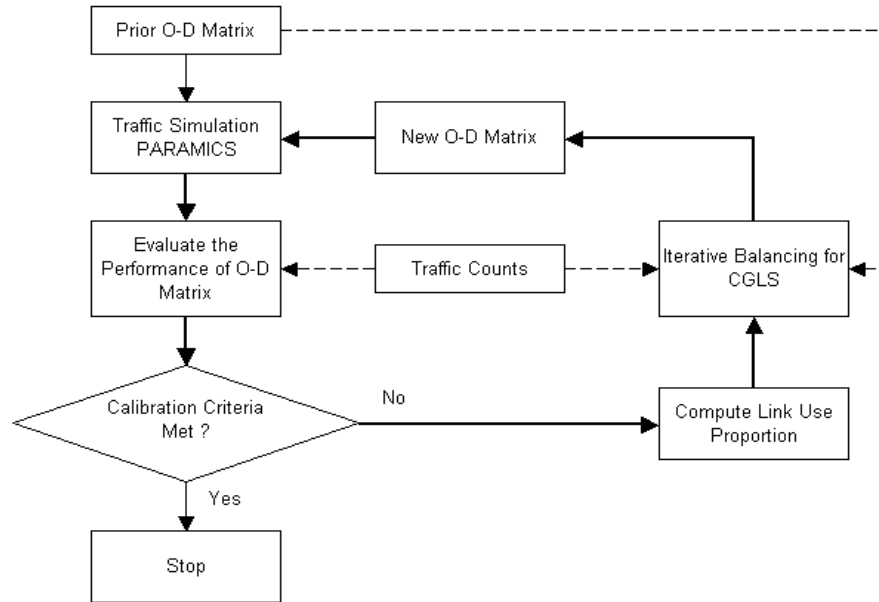
This expression is very useful in practice. When all information is available, the optimal (adjusted) O-D matrix can be determined using only matrix inversion and multiplication. Unfortunately, due to the assumption made above, we cannot prevent the adjusted O-D matrix from being negative. This assumption is more likely to be violated when a relatively high weight is given to one of data sources, either the prior O-D matrix or traffic counts. Bell (1) relaxed this assumption and proposed an iterative balancing procedure to adjust the optimal solution obtained by equation 3.

Another issue worthy to consider is the prior information about trip production and trip attraction at any TAZ. Because of the physical constraint, a traffic generator or TAZ can release only a certain number of vehicles during a certain time period. If the estimated demand exceeds this level, there exists unreleased vehicles, which contribute nothing to the simulation results. In this study, only the constraint related to trip production (Equation 4) is incorporated to the CGLS formulation.

$$\mathbf{Bq} \leq \mathbf{C}, \quad (4)$$

where  $\mathbf{B}$  is the matrix representing the relationship between O-D pair and the origin (which O-D pair belongs to which origin), and  $\mathbf{C}$  is the vector of capacities of TAZs.

As mentioned earlier, the method applied here has a similar structure to the bi-level programming approach proposed by Yang *et al* (15). The adjustment process iterates between CGLS problem and traffic simulation. Firstly, the prior O-D matrix is assigned onto the network in the simulation model. After that the link use proportion is determined from the simulation results and fed back to the CGLS to determine the new O-D matrix. This process is repeated until the calibration criteria. This adjustment procedure is summarized in Figure 5.



**FIGURE 5 Procedure for Pattern Matrix Update**

## 5.2 Hourly OD Estimation Using Paramics Estimator

After updating the pattern matrix, it can be input into Paramics Estimator for hourly OD estimation. Paramics estimator is an OD matrix estimation package specifically designed to operate at the microscopic level and integrate seamlessly with the core Paramics tools. Compared with the traditional “black box” OD estimation tools, Estimator is a visually interactive tool for OD adjustment. It combines the automatic and manual adjustments, and human intelligence can also be easily imported in the package.

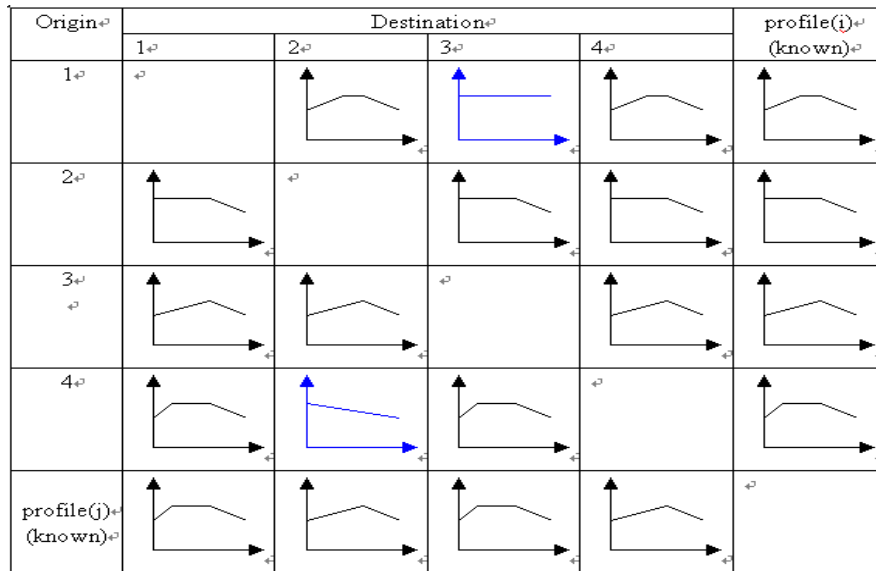
## 5.3 Dynamic Matrix Estimation

Paramics Estimator can only provide hourly OD demand matrix. However, for Paramics simulation, dynamic (time-dependent) demand, e.g. in a 15-minute interval, is needed. In the reviewed literatures, no plausible method has been provided for performing dynamic OD estimation based on hourly demand.

Our proposed method estimates the time-dependent OD based on the pattern of trip production and attraction. It simplifies the complex time-dependent OD estimation problem through reconstructing the dynamic OD demands based on a set of demand profiles. Since the 15-minute interval traffic counts at some important cordon points of the network are known, the profile of vehicle generation from origin zones and that of vehicle attraction to destination zones are thus known. We further assume a number of initial demand profiles for all OD pairs based on the trip production and attraction patterns, and then use the Furness algorithm to balance the time-dependent trip table. PARAMICS can specify different demand profiles for each time period through the use of file “demands” and “profile”.

The process can be illustrated in Figure 6, and the procedure for dynamic OD estimation is as following:

1. Prepare the profiles of all zones Attraction and Production; if no profile exists, use uniform distribution.
2. Set each zone's Attraction and Production, and each OD trip (cell) to the first 15-minute demand
3. Using Furness Algorithm to balance the 15- minute demand matrix
4. Conduct the next 15- minutes time period
5. Using the "Profiles" function to code the decomposed OD into network



**FIGURE 6 Dynamic OD Demand Generation**

In which the Furness algorithm can be listed as below.

1. Denote  $A_i$ , the coefficient of each row (production),  $B_j$ , the coefficient of each column (attraction)
2. Set  $B_j=1$ , then for each cell, solve  $A_i$  to satisfy the production constraint
3. With the latest  $A_i$ , solve for  $B_j$  to satisfy the trip attraction constraint
4. Keep repeating the steps above, until the changes are sufficiently small.

## 6. MODEL FINAL TUNING

The last step of calibration is to use aggregated traffic data to fine tune 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 and link-by-link) and adjusted to reflect the local characteristics.

Results from model fine tuning will be feedback to previous stages, and the simulation model will be repetitively modified until the best matching with field data is achieved.

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

(1) Link specific parameters, including the signposting setting, the headway and reaction times of those links at critical bottleneck locations where a very minor change in capacity can have a major effect on congestion. These parameters can be modified with the need of increasing/ decreasing congestion level.

(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 may need to be further modified in order to adapt traffic congestion along freeways. Due to the congestion and queuing phenomena on freeways, especially the northbound SR41, extra efforts are taken to modify demand profiles from the freeway origin zones to the freeway destination zones.

(4) Route choice adjustments. Due to the existence of freeways and its parallel streets in the studied network, the routing algorithm adopted in the simulation calibration process is important. As observed on site, there is little diversion traffic in the current real world situation. The three assignment algorithms provided by Paramics, namely the all-or-nothing (AON) assignment, dynamic feedback assignment and stochastic assignment are tested in the calibration process. Finally, we adopt the dynamic feedback assignment plus stochastic in our simulation study. Feedback assignment requires the following parameters to be set properly.

- Vehicle familiarity

Dynamic feedback assignment diverts vehicles when congestion happens. However those diversions are only applied on the drivers who are familiar with the network. In other words, if no driver is familiar with the network, no diversion will be made.

- Cost coefficient

In Paramics simulation, the link travel cost is defined as a combination of travel time, distance, and road price (or toll). Three coefficients can thus be defined. User can decide which factor should be given high weight when calculate the cost. Given distance 1 weight and others 0, the assignment will collapse to AON.

- Feedback interval, smooth and decay factor

The feedback function effectively allows the user to adjust vehicles routing where multiple routes are available. By changing the feedback interval, smooth and decay factor, user can emulate the driver decision process when congestion builds up. The factors effect when and how the routes diversion will happen.

## 7. CALIBRATION RESULTS ANALYSIS AND VALIDATION

### 7.1 Validation methodology

The calibrated parameters presented in the previous section were applied to the refined SR41 network. Output statistics gathered by the model were checked for validity, in a qualitative and quantitative way. The simulation runs for the base conditions were first studied at the macroscopic network-wide level: overall simulation statistics were computed, and the relationships between speeds, flows and densities were analyzed.

Further analysis consisted in comparing the model outputs to real-life traffic performance, specifically measured speed and flow data. The same comparisons were performed for the three days of analysis.

The objective of model calibration is to get the best match possible between model performance estimates and field measurements of performance. However, there is a limit to the amount of time and effort anyone can put into eliminating error in the model. There comes a point of diminishing returns where large investments in effort yield small improvements in accuracy. The analyst needs to know when to stop. In the study, the calibration criteria are specified in the California Guidelines for Applying Microscopic Traffic Simulation Software (5).

The GEH statistics is the calibration criteria and can be computed as follows:

$$GEH = \sqrt{\frac{(V - C)^2}{(V + C)/2}}$$

V = model estimated directional hourly volume at a location.

C = directional hourly count at a location.

Generally, a GEH value of less than 5 for more than 85% of the locations is considered acceptable for the calibration.

## 5.2 Validation of PME

To test the PME effectiveness, we conduct four different scenarios: original OD matrix from planning model, optimized OD matrix by Paramic Estimator, OD matrix from PME, and OD matrix from PME and further updated by Paramic Estimator, all of the scenarios don't have any manual adjustment. They were put into Paramics Modeller, the measurement are shown in Figure 7. The scenario combined PME and Paramics Estimator has the highest performance, for both the average GEH and the probability which GEH less than 5, they performed the best among all scenarios.

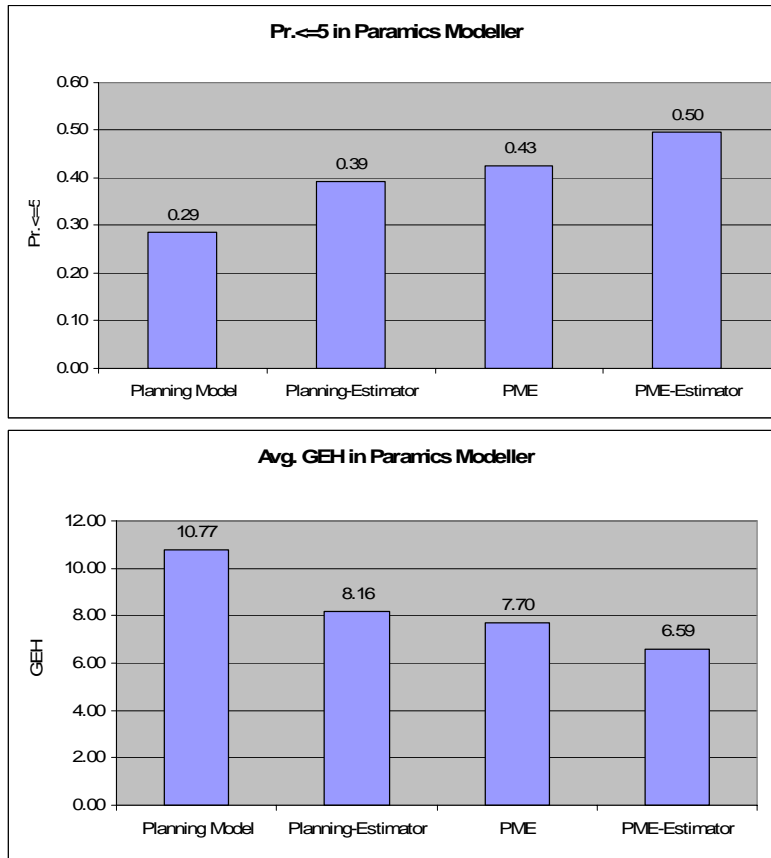


Figure 7 Performance comparison for Planning model, Paramics Estimator, PME

## 5.2 Validation of volume

We compared the simulation volume results with the collected field data. Totally 20 major freeway locations and 36 major arterials locations are compared. To test the dynamic matrix estimation efficiency and the network robust, data are collected from 3 hours consecutive simulation, in 15 minutes time intervals.

From Figure 8, we can conclude that simulated traffic counts correspond well to the observed measurement.

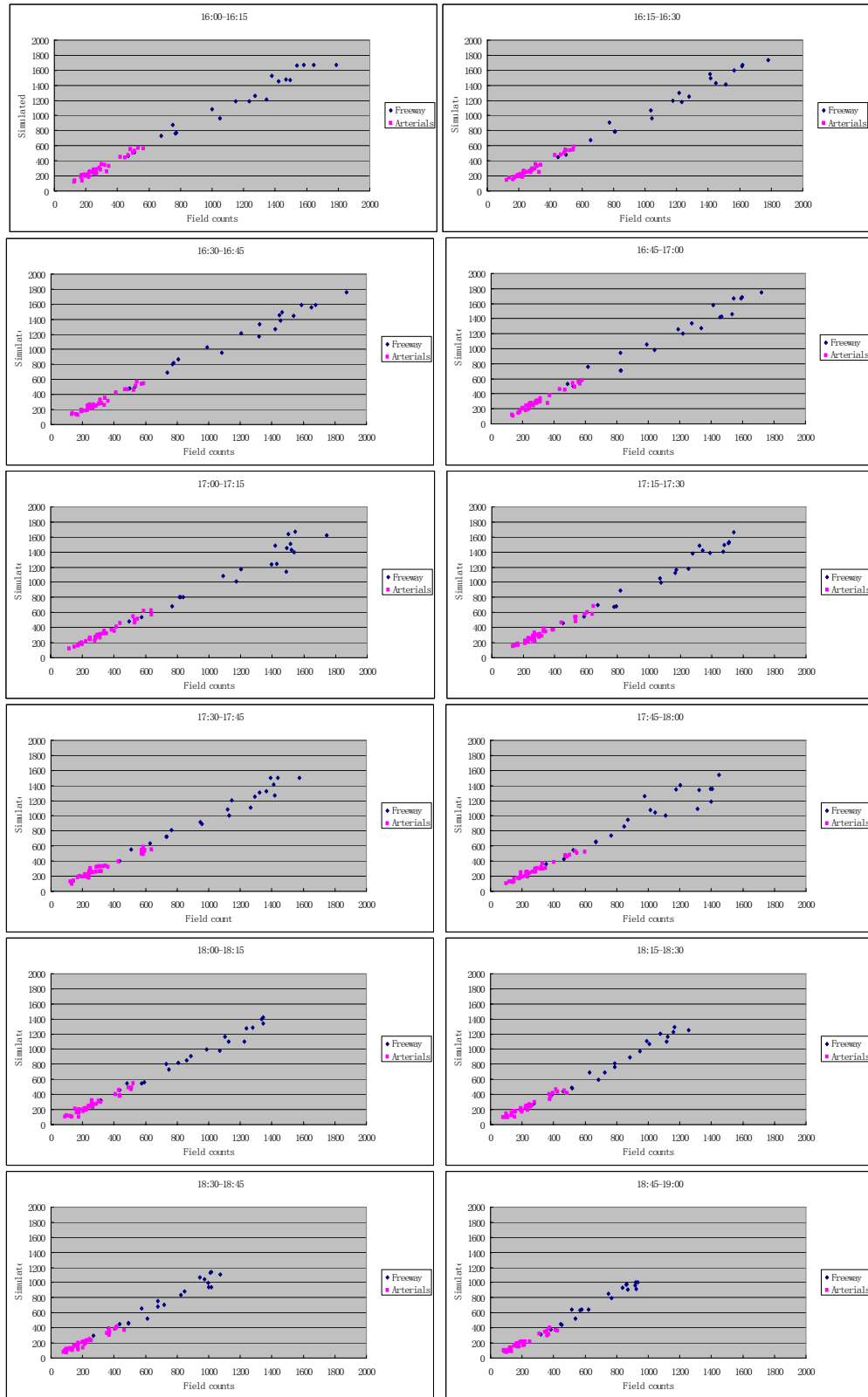


Figure 8 Traffic volume calibrations (15 minutes) at major measurement locations

### 5.3 Validation of travel time

The freeway travel time calibration results are shown in Table 1. From the results we can see that for all of the time periods travel times have small difference with observed data (less than 15 %). For the travel time changing trends, the simulated results also are very similar to the observed data. Note that the observed travel time drops quicker than simulation does. This is because comparing to real world, micro simulation relieve congestion much slower, once congestions build up.

Table 1 Freeway mainline travel validation

	Periods	Avg.Tachrun (sec)	Avg.Simulated (sec)	Diff. (sec)	% diff.
Northbound	16:00-16:15	559	538	-21	-3.7
	16:15-16:30	553	510	-43	-7.7
SR41 from	16:30-16:45	549	483	-66	-12.0
	16:45-17:00	562	528	-34	-6.0
O street to	17:00-17:15	609	553	-56	-9.2
	17:15-17:30	723	680	43	-6.0
Friant Ave.	17:30-17:45	574	636	62	10.8
	17:45-18:00	N/A	571	N/A	N/A
	18:00-18:15	N/A	462	N/A	N/A
	18:15-18:30	N/A	457	N/A	N/A
	18:30-18:45	N/A	452	N/A	N/A
	18:45-19:00	N/A	455	N/A	N/A
Southbound	16:00-16:15	503	452	-51	-10.1
	16:15-16:30	499	475	-24	-4.8
SR41 from	16:30-16:45	504	461	-43	-8.5
	16:45-17:00	492	543	51	10.3
Friant Ave.	17:00-17:15	515	506	-9	-1.7
	17:15-17:30	529	471	-58	-10.9
To O street	17:30-17:45	564	495	-69	-12.2
	17:45-18:00	N/A	451	N/A	N/A
	18:00-18:15	N/A	458	N/A	N/A
	18:15-18:30	N/A	455	N/A	N/A
	18:30-18:45	N/A	450	N/A	N/A
	18:45-19:00	N/A	434	N/A	N/A

### 5.4 Validation of speed contour map

Speed contour map from simulation is shown in Figure 9. Compared to the real world speed contour map from Figure 3, we can see that they have similar pattern: congestion happened at the same locations on almost the same time.

NB	O ST	DIVISADE	OLIVE	MCKINLEY	SHIELDS	ASHLAN	SHAW	BULLARD	HERNDON	FRIANT
16:00	66.78314	64.48697	57.28026	51.31713	67.43327	64.91564	67.39054	65.30153	59.41277	
16:05	71.9884	67.11719	54.71194	48.85124	59.31175	42.70973	70.38919	68.89531	62.03029	
16:10	69.25281	62.78851	54.13703	44.63664	66.60417	53.16873	58.91444	66.85691	66.03756	
16:15	71.9884	65.59018	58.54592	50.8256	65.91652	63.45883	60.75024	65.30153	51.18137	
16:20	72.60435	67.32374	61.41506	58.16308	67.07903	63.86011	62.33567	53.84221	51.09376	
16:25	72.799	67.60522	60.41481	59.47485	70.2695	67.75267	68.89669	66.91917	49.57204	
16:30	72.50741	65.16494	54.55102	60.3995	69.4775	67.86976	70.22473	69.76486	56.15636	
16:35	71.70326	66.32715	54.02665	60.45824	67.19248	65.99434	66.89061	65.40853	58.65007	
16:40	70.45674	66.48129	56.78918	56.47216	68.33548	67.14774	67.37796	64.63196	64.32969	
16:45	71.42037	64.65513	52.11393	56.166	68.06229	64.30156	67.85968	59.73218	66.24274	
16:50	71.79806	66.1855	57.90617	51.1302	69.70778	66.30382	64.59065	63.65858	44.33016	
16:55	71.27041	63.74637	57.47551	52.28526	68.71636	67.12223	67.36537	41.88006	35.79873	
17:00	71.30784	65.41712	56.44354	62.33782	66.34463	66.14253	61.98216	61.42743	34.57144	
17:05	71.30784	66.13842	58.34334	61.73638	67.95879	64.90372	63.43197	63.26625	42.04871	
17:10	70.25621	65.19922	62.32308	61.45734	68.14012	67.97417	54.72223	69.41442	67.21733	
17:15	71.12107	65.46318	48.31297	49.70505	71.44908	65.39606	59.06882	67.88004	66.66686	
17:20	71.53326	66.43379	51.30663	43.95575	60.08928	41.766	71.18101	70.55951	52.72429	
17:25	69.55437	65.41712	54.3751	46.71655	29.50414	67.9611	65.85251	65.93669	66.31141	
17:30	71.15835	66.05619	56.13604	54.55341	43.91196	64.77289	61.46459	67.99566	64.01697	
17:35	72.68208	66.76774	59.40854	56.87817	68.91504	60.42148	40.11949	68.06006	54.11345	
17:40	73.38926	68.06302	61.61909	61.62271	50.63464	24.87969	70.67885	68.40995	46.38295	
17:45	71.81705	67.54383	60.73133	61.94732	19.79686	23.34802	70.00664	69.6972	69.40547	
17:50	72.41074	67.67904	59.40854	57.29006	43.30562	60.88987	63.98336	65.99725	62.44556	
17:55	72.0457	65.41712	58.9366	59.70334	68.14012	66.36607	67.91079	68.8821	40.38011	

SB	FRIANT	HERNDON	BULLARD	SHAW	ASHLAN	SHIELDS	MCKINLEY	OLIVE	DIVISADE	O ST
16:00	66.29275	64.94657	67.24669	67.16284	66.01528	63.61178	65.98503	65.11122	65.61604	
16:05	66.17435	67.82194	66.74838	56.50054	65.72371	63.57438	61.64617	65.07697	65.98923	
16:10	64.17804	67.542	64.75697	67.26511	63.6391	64.40764	64.00035	64.13219	63.31209	
16:15	67.39813	65.66925	66.88468	63.96577	66.0519	62.23847	62.85331	67.05256	66.35019	
16:20	65.53065	67.32726	67.43548	64.73912	66.83058	63.56503	61.10908	63.60454	65.34291	
16:25	64.67279	67.82194	67.2216	64.12827	68.01421	63.93154	65.03332	65.55987	61.75896	
16:30	66.89115	68.28506	66.08727	46.94618	68.00126	64.76455	63.10464	65.76903	65.85895	
16:35	64.71044	67.02641	65.09626	59.7988	44.91795	64.37888	63.52802	63.80139	65.8427	
16:40	66.23349	68.09133	66.63728	67.52214	64.28053	63.04606	60.46521	65.03135	65.61604	
16:45	68.79552	69.08441	67.67614	68.93132	65.19581	64.42683	56.69971	66.52364	63.28206	
16:50	62.96027	67.51666	63.76	66.25626	62.91045	61.76731	51.7141	64.54494	67.35499	
16:55	67.70602	66.62944	68.24011	65.08488	65.4707	64.73546	49.64011	67.99869	64.44348	
17:00	61.71925	66.69115	67.56193	55.16873	67.50003	64.05464	61.03031	64.5674	67.50834	
17:05	66.75056	63.49186	64.46731	54.68217	67.48727	62.65328	62.21322	66.14418	65.58379	
17:10	67.0829	67.86029	61.02774	28.98711	70.40068	65.12544	57.0241	66.79908	66.48243	
17:15	69.17011	66.50634	67.12142	42.75476	59.44451	63.97883	61.12881	67.60227	68.33814	
17:20	69.48358	68.05271	66.23305	65.8366	65.31504	64.09262	58.21612	66.5475	65.04033	
17:25	67.26557	68.75455	66.47745	65.48284	67.10685	62.8171	56.63189	66.90748	66.69844	
17:30	68.85945	69.65922	66.95926	62.76165	65.2673	61.78496	57.82505	66.42837	65.5033	
17:35	66.07601	69.97062	67.14644	65.14486	68.31344	63.22118	55.53579	65.94435	66.51557	
17:40	67.3063	66.38371	66.62496	34.69915	69.49653	65.16469	65.10039	68.80565	68.25076	
17:45	66.23349	67.542	64.40968	40.3023	65.76002	61.90879	60.91252	66.88336	64.74053	
17:50	67.16397	67.35245	66.66194	67.20116	65.72371	46.3934	40.40474	68.16107	66.46587	
17:55	71.23125	67.44077	66.72366	68.98514	64.97046	60.44631	46.62162	67.12534	66.20205	

Figure 9 Speed contour map of simulation model

## 8. CONCLUSIONS

This paper proposed a general micro simulation calibration procedure for large scale corridor network simulation studies, including data collection and analysis, capacity calibration, OD estimation, final tuning, and calibration validation. A streamline framework of the calibration was presented and reasonably accurate calibration results were achieved. The proposed procedure follows the traditional step-by-step calibration framework and thus can be easily understood and used by traffic engineers.

Based on the calibrated SR41 corridor network, short term traffic operational improvements and long term capital investments will be evaluated. The results of the

study can provide a template for Caltrans to conduct similar planning and operational studies in the future.

## REFERENCES

1. Bell, M.G.H. 1991. The estimation of origin-destination matrices by constrained generalized least squares. *Transportation Research B*, 25, pp13-22.
2. Cascetta, E. 1984. Estimation of origin-destination matrices from traffic counts and survey data: A generalized least squares estimator. *Transportation Research, B*, 18, pp289-299.
3. Cheu, R.L., Jin, X., Ng, K.C., Ng, Y.L., Srinivasan, D. 1998. Calibration of FRESIM for Singapore expressway using Genetic Algorithm. *Journal of Transportation Engineering*, Vol.124, No.6, pp526-535.
4. Chu, L., Liu, H., Oh, J.S., Recker, W. 2004. A Calibration Procedure for Microscopic Traffic Simulation. 84th TRB Annual Meeting CD-ROM.
5. Dowling, R., Holland, J., Huang, A. 2002. California Department of Transportation Guidelines for Applying Traffic Microsimulation Model Software. Dowling Associate INC.
6. Gardes, Y., May, A. D. Dahlgren, J., Skarbardonis, A. 2002. Bay Area Simulation and Ramp Metering Study. California PATH Research Report, UCB-ITS-PRR-2002-6.
7. Gardes, Y., Kim, A., May, A. D. 2003. Bay Area Simulation and Ramp Metering Study-Year 2 Report. California PATH Research Report, UCB-ITS-PRR-2003-9.
8. Gardes, Y., Tang, E., Ma, J., May, A.D. 2003. Advanced Simulation Tool for Freeway Corridor Management. Californian PATH paper, UCB-ITS-PWP-2003-15.
9. Gomes, G., May, A.D., Horowitz, R. 2004. Calibration of VISSIM for a Congested Freeway. California PATH Research Report, UCB-ITS-PRR-2004-4.
10. Lee, D-H, Yang, X., Chandrasekar, P. 2001. Parameter calibration for PARAMICS using Genetic Algorithm. 80<sup>th</sup> TRB Annual Meeting CD-ROM.
11. Liu, H., Chu, L., Recker, W. 2001. Paramics API Development Document for Actuated Signal, Signal Coordination and Ramp Control. California PATH research paper, UCB-ITS-PWP-2001-11.
12. Spiess, H. 1987. A maximum likelihood model for estimating origin-destination matrices. *Transportation Research B*, 21, pp395-412.
13. Van Zuylen, H.J. and Willumsen, L.G. 1980. The most likely trip estimated from traffic counts. *Transportation Research B*, 14, pp281-293.
14. Xu, G., Lam, W.H.K., Chan, K.S. 2004. Integrated Approach for Trip Matrix Updating and Network Calibration. *Journal of Transportation Engineering*, March/April, pp231-244.
15. Yang, H., Iida, Y., and Sasaki, T. 1992. Estimation of origin-destination matrices from traffic counts on congested networks. *Transportation Research B*, 26, pp 417-434.
16. Quadstone Limited. 2004. Quadstone Paramics V5.0 Manual.
17. The Urban Analysis Group. 1998. Get started with TP+-A guide introduction to the TP+.