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Authors

Zhang, Michael
Ma, Jingtao
Dong, Hu

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CALIFORNIA PATH PROGRAM
INSTITUTE OF TRANSPORTATION STUDIES
UNIVERSITY OF CALIFORNIA, BERKELEY

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Simulation Final Report Part II: Calibration
Framework and Calibration of Local/Global Driving
Behavior and Departure/Route Choice Model
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Michael Zhang, Jingtao Ma, Hu Dong
University of California, Davis

**California PATH Research Report
UCB-ITS-PRR-2008-7**

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The contents of this report reflect the views of the authors who are responsible for the facts and the accuracy of the data presented herein. The contents do not necessarily reflect the official views or policies of the State of California. This report does not constitute a standard, specification, or regulation.

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**DEVELOPING CALIBRATION TOOLS FOR
MICROSCOPIC TRAFFIC SIMULATION**

FINAL REPORT

**PART II: CALIBRATION FRAMEWORK, AND CALIBRATION
OF LOCAL/GLOBAL DRIVING BEHAVIOR AND D/R CHOICE
MODEL PARAMETERS**

Michael Zhang, Jingtao Ma, Hu dong
Institute of Transportation Studies
University of California,
Davis, CA 95616

ABSTRACT

The central goal of this research is to develop a systematic framework and the support tools to ease, streamline and speed up the calibration of micro simulation projects. Part II of the final report documents the accomplishments achieved in the first phase of the research project (a review of practice and calibration guidelines is documented in a Part I). These accomplishments include: 1) developed a calibration framework that decouples the calibration process into five components: project scoping and error checking, global parameter calibration, local parameter calibration, departure/route (D-R) choice parameter calibration, and global calibration, 2) developed GA-based calibration tools for local and global parameters, as well as D-R choice parameters, 3) integrated the developed tools into one user-friendly graphical interface, and 4) tested the developed methods and tools on synthetic and real networks. It is shown by working examples that the developed tools can help achieve satisfactory calibration results with much less human intervention as found in the commonly practiced trial-and-error calibration procedure.

Keywords: Traffic Simulation, Route Choice, Model Calibration, Genetic Algorithm.

EXECUTIVE SUMMARY

Calibration refers to the process of adjusting model parameters and certain simulation inputs such that local traffic conditions, as measured by traffic volume, travel speed and/or time, or combinations of them, can be matched closely by simulation outputs. In this research project, we developed a general calibration framework and a series of tools to facilitate the calibration of micro simulations. The framework was proposed to divide the complex calibration process into logical steps, each of which takes care of one subtask to decompose the complex problem into smaller, manageable ones. The major advancements achieved to date include:

Development of a calibration framework. Micro simulation usually involves many parameters that affect simulation results in complex ways. A calibration framework is developed to disentangle the complex interactions among various types of parameters. In this framework, parameters are divided into two distinctive groups: input parameters and model parameters, and calibrated one group at a time. The input parameters include those of geometry, controls, vehicle/driver population, and OD demands, while the model parameters are related to driver behavior and can further be categorized, in a microscopic simulation, as car-following, lane change/gap acceptance, and route choice parameters. It is suggested that the driving behavior parameters that apply to all road sections (called global parameters) be calibrated first, so that the flow capacity at typical road sections can be reproduced. Then driving behavior parameters that affect bottleneck capacities (called local parameters) are calibrated next, so that capacities at bottlenecks can be reproduced. After local parameter calibration, the departure time/route (D-R) choice parameters that affect the distribution of traffic on the network are calibrated to ensure that congestion is occurring at the right places and right times in the network. Finally, OD demands and traffic control parameters are calibrated to make sure the level and locations of congestion are consistent with observations, as measured by traffic volume, and travel times or delays. Since route choice, OD demands and traffic control all affect traffic circulation patterns, the calibration for D-R choice, OD demands, and traffic control parameters may be carried out iteratively to achieve the desired calibration accuracy.

The development of a global parameter calibration tool. We identified four global model parameters in Paramics: Mean Target Headway, Mean Reaction Time, Driver Aggressiveness, and Driver Awareness. These four parameters affect car-following behavior, hence the flow capacities, on all road sections. Two approaches were proposed to calibrate these four parameters, both employ the Genetic Algorithm (GA). The FP (flow profile) approach minimizes the differences between observed and simulated flow on a selected road section, while the FD (fundamental diagram) approach tries to match the observed and simulated capacity and critical density on the selected road section. In order to isolate the effects of these four parameters, road sections that contain no bottleneck features (such as tight curves, steep grades, entry/exit junctions, etc) and are away from bottleneck sections should be selected as calibration sections. The calibration of a SR99 road section yields the following parameter values: Mean Target Headway 0.96 second, Mean Reaction Time, 1.25 second, Driver Aggressiveness 0.23, and Driver Awareness 0.51, quite consistent with the default parameters values in Paramics. A

sensitivity analysis also revealed that the calibration performance is most sensitive to Mean Reaction Time, and the GA-based calibration algorithm found a nearly global optimal parameter set.

The development of a local parameter calibration tool. Local parameters are those driving behavior parameters that further affect road capacity besides global driving behavior parameters. Two types of road sections are selected for local calibration: bottleneck sections on freeways and intersections on arterial roads (the latter will be reported elsewhere). We identified the following local parameters in Paramics that affect bottleneck capacity on a freeway section: Link Headway Factor, Link Reaction Factor, Ramp Headway Factor, Minimum Ramp Time, Ramp Awareness Distance, and Signposting. A GA-based optimization algorithm was developed to calibrate these local parameters using the FD approach. Preliminary calibration results for a SR99 section with a freeway interchange showed marked improvement in simulation results after local calibration was performed.

The development of a D-R choice parameter calibration tool. The D-R choices determine the time-dependent assignment matrix that maps the OD demand onto the link and/or path flows. Many factors affect D-R choices, but we identified demand profile, drivers' perturbation and familiarity factors as the major ones to be calibrated. A GA-based calibration algorithm for D-R choice parameters was developed and tested, with good initial results. It should be noted, however, the GA-based algorithm consumes considerable computational time when applied to networks of realistic size, because it requires many simulation runs and each simulation run may take a couple of minutes to complete for medium to large size networks. Techniques to improve the computational efficiency of the calibration algorithm were explored with limited success. Alternative optimization techniques will be investigated in the next stage to speed up the calibration process.

The development of diagnostic tools. A set of diagnostic tools to check coding errors and flows on selected paths were also developed. These tools, together with the calibration algorithms for global, local and D-R choice parameters, were integrated into the Paramics software through user-friendly graphical user interfaces.

The developed calibration tools can improve calibration accuracy and considerably reduce the amount of time spent on calibration, hence shorten the developmental cycle of transportation projects that use micro simulation such as Paramics in their planning, design or evaluation.

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CHAPTER 1 INTRODUCTION

1.1 Background

The California Department of Transportation has recently embarked on an ambitious state-wide program to support the use of microscopic traffic simulation models. A recent survey shows that in California alone there are some 80 on-going or recently completed projects (mostly sponsored by Caltrans) use traffic simulation to study a wide range of problems, including interchange analysis, corridor traffic management, reconstruction planning, air quality analysis and growth impact assessment (May, 2002). Among these eighty projects, more than 60% use high fidelity traffic simulation models such as **Paramics**. While high fidelity traffic simulation models provide traffic engineers and transportation planners a powerful tool to design and evaluate transportation planning and operation alternatives, they also present significant challenges, and a major one is model calibration, a process of adjusting model parameters to suit local conditions.

When using traffic simulations in transportation applications, model calibration is of obvious importance, for a poorly calibrated model can produce unreliable results and lead to misinformed decisions with serious consequences. Calibration is a challenging task because a micro simulation model could easily have more than a hundred parameters, each of which impacts simulation results in a manner that is often highly correlated with that of the others. At present calibration of micro traffic simulation models is quite *ad hoc*, often depends on a user's experience and trial-and-error. The model user is often trapped in a never-ending process of fixing one problem only to find that a new one appears somewhere else. Consequently, calibration is easily the most time-consuming task of a project. A streamlined calibration process therefore would greatly benefit the users of micro simulation—it would considerably shorten the calibration phase, allowing them to spend more of their productive time solving the transportation problem at hand.

1.2 Project Scope and Objectives

A model must be validated before it can be applied. Without a valid model, calibration is a futile exercise. In the context of microscopic simulation, a validation would check if the car-following, lane-changing and route choice logic is a good representation of real traffic behavior. Since the focus of this project is model calibration, not validation, we assume that the model we calibrate is already validated.

Calibration refers to the process of adjusting model parameters and certain simulation inputs (such as signal control plans and Origin-Destination [O-D] demand tables) such that local traffic conditions, as measured by traffic flow, travel speed and/or time, or combinations of them, can be matched closely by simulation outputs. In this research, we develop a general calibration framework and a series of tools to facilitate the calibration of micro simulations. The framework is proposed to divide the complex calibration process into logical steps, each of which takes care of one subtask to decompose the

complex problem into smaller, manageable ones.

This project starts with an extensive literature review and summary on the application of microscopic traffic simulation models. The summary is listed as a separate report that also includes a series of microsimulation development guidelines:

- ✧ Determining the spatial and temporal scope of a microscopic simulation;
- ✧ Collecting and assembling necessary input data;
- ✧ Checking the network coding errors.

In this report, we describe our calibration framework and a series of support tools for calibrating different categories of model parameters. Although the methods developed here apply to micro simulation in general, the specific calibration tools were designed for Paramics in particular, because of its wide usage in California.

1.3 A Systematic Calibration Framework

In our calibration framework, parameters that affect simulation outcomes are divided into two distinctive groups: input parameters and model parameters. The input parameters¹ include those of geometry, controls, vehicle/driver population, and O-D demands. These are often obtained from various sources with differing degrees of accuracy. The model parameters are related to driver behavior and can further be categorized, in a microscopic simulation, as car-following, lane change, gap acceptance, and route choice parameters. Each simulation package has its own default values for the model parameters, which are supposedly representative of “population” averages of some sort and should be calibrated against local conditions.

The majority of input parameters, such as those related to geometry (e.g., number of lanes, lane width, curvature, grade, etc), are usually not subject to calibration. Rather their accuracy is checked before calibration is initiated, although some researchers consider this as part of the calibration process. This error-checking process must be done before the calibration of other parameters is carried out. Although this process may be time consuming, it is nevertheless straightforward.

Some other input parameters, such as O-D demands (a critical input that has major impact on the resulting flow pattern), are subject to calibration because they are often known with uncertainty. These input parameters will be calibrated together with the model parameters that control the behavior of the driver population. Since we want to adjust as few parameters as possible while achieving the desired calibration accuracy, we would like to know which parameters are more critical to influence model outputs. This is

¹ In this research, the term “parameter” is defined more broadly than its usual definition. In our definition, any element whose value can be adjusted in the calibration process is a parameter. In this sense, O-D demands as well as signal timing, inputs to the model, are all parameters (dubbed input parameters).

obviously related to the types of traffic quantities that the parameters are calibrated against. These quantities, at a minimum, should include various flow capacities and counts, and travel times on major routes. If possible, delays and queues at bottleneck locations should also be included.

When the parameter set has a high dimension, a brute-force, one-sweep-fixes-all strategy is doomed to failure. To disentangle this complexity, we apply a five-step calibration procedure, shown in Figure 1-1, to carry out the calibration process in a one-at-a-time manner. The logic behind this five-step procedure is that we want to identify the sphere of influence of various parameters, and calibrate each group of parameters with minimal influences from the other groups.

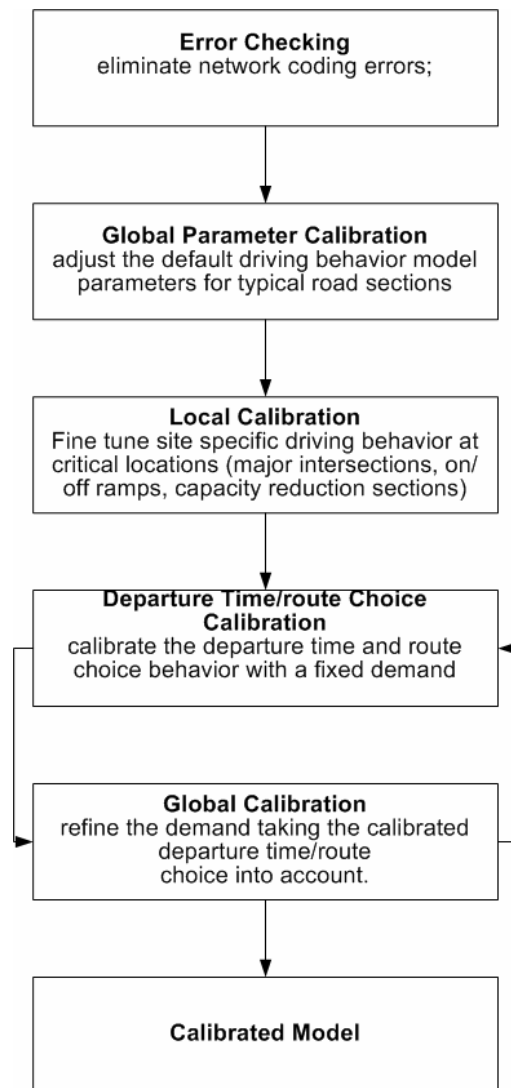


Figure 1-1 Microsimulation Calibration Schema

The above calibration procedure starts after the initial network coding has been finished and the network is screened to eliminate coding errors. For example, one checks if every viable origin-destination pair is connected by at least one path and if unusual ‘hot spots’

(congested area) are observed under low traffic load. We refer to Zhang, Ma and Dong (2006) for a more detailed description of how to check coding errors in a micro simulation.

The remaining four steps deal with the calibration of four different groups of parameters: 1) global parameters that affect driving behavior throughout the network, 2) local parameters that are peculiar to bottleneck locations, such as lane-drop locations or junctions where several roads meet, 3) departure time and route choice parameters that affect the distribution of traffic in the network, and 4) input parameters such as O-D demand that affect congestion levels throughout the network. We suggest that the first three steps, global parameter calibration, local calibration, and D-R (Departure Time-Route) choice calibration be carried out sequentially, so as to isolate the influences of different groups of parameters as much as possible in the calibration process. On the other hand, the last step, global calibration, can be carried out iteratively with the D-R choice calibration to account for cross influences between travel demand and route choice.

The idea of calibrating first the global model parameters then the local model parameters is akin to highway capacity analysis, where one first identifies a set of ideal conditions and the ideal capacity under such conditions, then adjusts the ideal capacity for non ideal conditions through discount factors to obtain the prevailing capacity. Similarly, we want to identify typical road sections for the calibration of global parameters, and road sections with special features (such as sharp curvatures, lane drops, on-ramps and intersections) for the calibration of local model parameters. Through such calibration, we want to obtain a set of parameters that can reproduce the flow capacities of various types of road sections.

In a network with more than one route connecting certain origin destination zones, D-R choice plays a major role for the baseline simulation to replicate the observed aggregate measures such as link counts, path travel times and so on. Based on a reasonable demand input, D-R choice calibration will come up with the demand releasing pattern of specific origin-destination zones and traveler groups' (vehicle types) routing selection propensities.

Demand refinement, the last step in the calibration process, can be carried out iteratively with D-R choice calibration, for both O-D demand and D-R choice significantly influence the resulting flow pattern on the road network. At this step, demand re-estimation and D-R choice is performed alternatively, each feeding the other as known inputs. The goal is to obtain a stable and calibrated model that can reproduce the baseline traffic conditions observed in a road network.

The most important feature of the proposed calibration procedure is that it categorizes the parameters into relatively distinct groups, namely those related to driving behavior, departure time and route choice (D-R choice) behavior, and O-D demand. In this way one can decouple the calibration process into several sequential steps so as to reduce the dimension of the search space in the parameter set to be optimized.

In the remaining chapters, we will present our calibration methods step by step, with

illustrative examples, starting from the calibration of global driving parameters (Step 2 in Figure 1-1).

CHAPTER 2 GLOBAL PARAMETER CALIBRATION

In this chapter, we present the method and the tools developed to assist calibrating the general driving behavior parameters in microscopic simulation. We shall use Paramics to illustrate this calibration process. It should be noted that before conducting global parameter calibration, all input data required to code the network have been checked against the real world situation. These data include network layout and road geometries, striping and controls, a basic demand structure and traffic composition.

2.1 Methodology of Global and Local Parameter Calibration

In the Paramics micro simulation package, nine parameters were identified as the main parameters that influence car-following, lane-changing and merging behavior. They are: 1) mean target headway; 2) mean reaction time; 3) driver aggressiveness; 4) driver awareness; 5) link headway factor; 6) sign posting; 7) ramp headway factor; 8) minimum ramp time; and 9) ramp awareness distance. An additional important parameter, link reaction factor, was introduced after Paramics V5.0 was released. By their application scope, these ten parameters are then classified into two groups: global parameters and local parameters. Global parameters govern network wide driver behavior – it affects each Driver-Vehicle Unit (DVU) on each road link. In contrast, local parameters, or link specific parameters, only impact DVUs on a particular road link. Table 2-1 presents the two categories of these parameters and their functions in the simulation.

Table 2-1 Global and Local Parameters

Parameter Category	Parameter Name	Unit	Description
Global Parameters	Mean Target Headway	Second	Mean headway between a vehicle and its following vehicle
	Mean Reaction Time	Second	Mean time lag between a change in speed in a leading vehicle and the following vehicle's reaction to this change
	Driver Aggressiveness	N/A	A distribution that determines how long a headway is accepted by a DVU
	Driver Awareness	N/A	A distribution that affects the use of a longer headway when a vehicle approaches a lane drop or a ramp
Local Parameters	Link Headway Factor	N/A	Adjustment factor for the mean headway on a link
	Link Reaction Factor	N/A	Adjustment factor for the mean reaction time on a link
	Ramp Headway Factor	N/A	Adjustment factor for the mean headway on a ramp
	Minimum Ramp Time	Second	Minimum time that a DVU remains on a ramp before considering merging into the freeway

	Ramp Awareness Distance	Foot / meter	A distance at which a freeway DVU is aware of an approaching ramp
	Sign-posting	Foot / meter	A distance from the hazard that the most aware vehicles become aware of the hazard ahead.

Global parameters apply to traffic on all road sections; hence they must also apply to road sections with simple geometries. This allows one to use a sub-network for the calibration of global parameters, such that the influences of other factors be kept at a minimum. Generally speaking, the sub-network consists of a *typical* road section, one straight section with no special features such as

- ✧ On-ramps or off-ramps, without lane addition or lane drop
- ✧ Sharp horizontal curves
- ✧ Significant vertical grade
- ✧ Operational restrictions

In this way, one hopes to obtain a set of global parameters that are representative of the population's driving behavior, and when applied in the simulation, reproduce the capacity of typical road sections. These parameters will not be subject to further adjustment on a road section unless it contains special features such as a sharp turn or a lane drop. In the latter case, local parameters kick in to account for the changes in flow capacity.

On the other hand, local parameter calibration deals with locations with features that further affect flow capacity and other traffic characteristics. Because flow capacities at these locations are usually lower than those at typical road sections, they are often called bottlenecks. Through the calibration of local parameters, one wants to ensure that the capacity of the bottleneck is reproduced by the simulation. To achieve this, one does not need an entire network. Rather, a sub-network with the isolated bottleneck would be extracted and used in the calibration. In our research, three types of bottlenecks are calibrated separately. They are 1) ramp junctions, 2) lane-drop sections, and 3) intersections. Other types of bottlenecks such as sharp turns or long climbs can be calibrated in a similar manner.

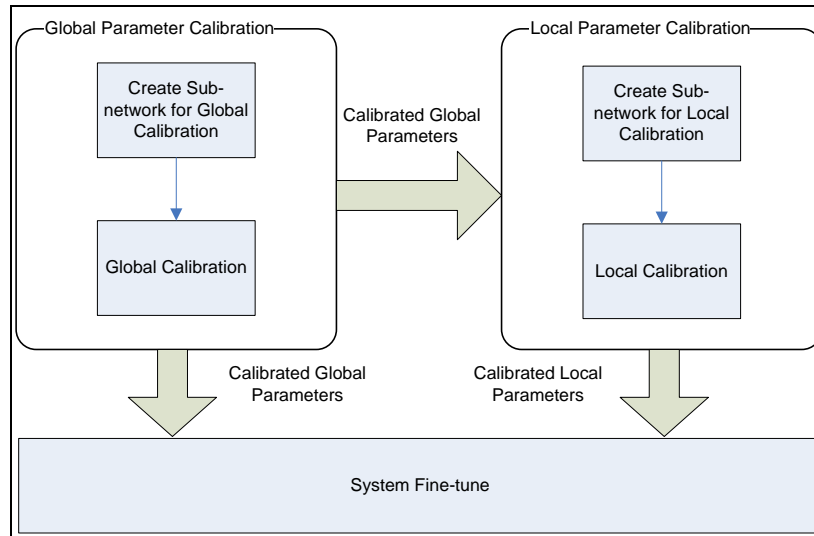


Figure 2-1 Detailed Global/Local Parameter Calibration Process

Figure 2-1 shows global and local parameter calibration in more detail. The process begins with extracting/creating a sub-network from the entire simulation network that has been coded and checked for coding errors. A typical road section is first selected at one location where no capacity affecting road features occur in the vicinity. One then performs calibration to obtain an optimal set of global parameter values. These values will be used as default throughout the network. Then for each bottleneck location, one extracts a sub-network and calibrates its local parameters against the bottleneck capacity and other selected traffic flow characteristics (such as the shape of the flow-density diagram). The process is complete when all bottleneck locations are calibrated. These parameters will not be subject to further calibration when departure time and route choice parameters are calibrated.

2.1.1 Selection of a calibration algorithm

The calibration of a micro simulation model can be formulated as an optimization problem, often a highly complex one (large, highly nonlinear and non-convex). As such, the optimization problem has a huge search space and often no gradient information to aid the search for an optimum. Therefore one often applies ‘soft’ computing techniques such as genetic algorithm (Cheu 1998; Lee 2001; Kim 2004), simulated annealing (Fellendorf 2001), Complex algorithm (Ben-Akiva 2004) and so on. Among all these, genetic algorithm (GA) is the most widely used due to its easy implementation and several other desirable features to be discussed below.

The GA algorithm, as well as other similar heuristic optimization methods, has three features that are attractive to our calibration work: i) it does not require the gradient information of the objective function with respect to decision variables; ii) it performs the optimization from more than one point in the search space, thus reducing the possibility of trapping at a local minimum; and iii) it guarantees convergence with the possibility of finding the (near) global optima (Goldberg 1989). A series of studies using genetic algorithm to calibrate microsimulation models have been documented in the past few

years. Cheu used GA to calibrate FRESIM driving behavior model parameters on a 5.8 kilometer expressway corridor in Singapore (Cheu 1998). Lee *et al* (2001) applies genetic algorithm to optimize the mean target headway and the mean reaction time in Paramics for a freeway section in southern California. This can be seen as a simplified version of the global parameter calibration. Ma (2002) developed a GA-based tool to calibrate both driving behavior and route choice behavior parameters simultaneously and tested it in downtown Toronto, Canada. Kim and Rilett (2004) also applied it to calibrate the driving behavior parameters for both TRANSIMS and CORSIM.

Since GA has been shown to perform satisfactorily in calibrating various parameters in micro simulation models, we also selected it as the main algorithm to obtain optimal parameters in all of our subsequent calibration steps, and developed a general-purpose GA engine to drive this process. Our GA engine allows for real valued gene-coding, user-defined decision variable sets and user-defined calibration resolution, which will be discussed in later sections. It also has a user friendly GUI to facilitate the calibration. In the next few sections, we will focus on the GA- based calibration process, and leave the detailed description of how GA works to Appendix A1.

2.1.2 The GA-based Calibration Process

GA has a number of control parameters that need to be determined before the calibration process starts. These control parameters are listed in Table 2-2. Generally speaking, the larger the population size, the higher probability GA can obtain the global optima. However, each pair of selected chromosomes in a generation triggers multiple simulation runs, which can take minutes to finish even for a small network, a larger population means longer GA processing time. Therefore, one has to strike a balance between accuracy and efficiency when one chooses a population size. Although there are some guidelines for the choice of population size, this process varies from case to case and is subject to experimentation. In the global and local parameter calibration, a few trial runs with different population sizes were conducted and a size of 30 was found to be suitable for both results stability and computation efficiency. Then this population size was chosen for the calibration process.

Table 2-2 GA Control Parameters

GA Control Parameters	Global Calibration	Local Calibration
Population Size	30	30
Maximum generation size	20	60
Crossover rate	1.0	1.0
Mutation rate	0.01	0.01
Stop criteria	Max generation size reached; or Average Fitness value in a generation change rate below 1% during last 20 generation.	

Figure 2-2 shows the GA-based calibration procedure adopted in this project. Each chromosome (representing one set of feasible parameters to be calibrated) in the first generation is generated randomly, based on parameter spaces and reserved length for each parameter. The first chromosome is then decoded and the set of parameter values is plugged into Paramics. Paramics then starts a simulation run, producing a set of simulation data including five-minute volume and five-minute average occupancy. Fitness values can thus be computed based on observed and simulation produced capacities and critical occupancies. Next, the algorithm selects the second chromosome and repeats the above process, until all the chromosomes in the first generation are exhausted. Then it computes the mean fitness value and test if the stopping criteria are met. If the stopping criteria are not satisfied, the above process is applied to a new generation until the stop criteria is met.

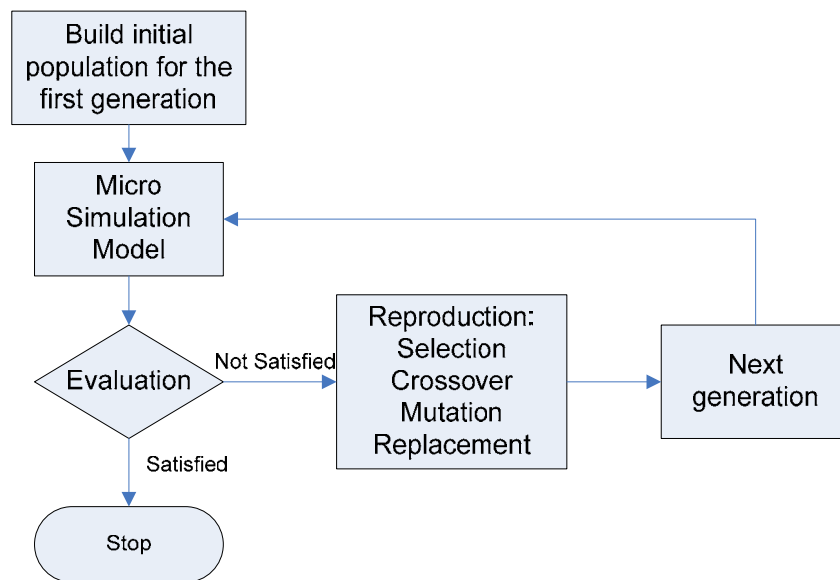


Figure 2-2 Conceptual Procedure of GA based Calibration

2.1.3 The Global Parameter Calibration Interface

Global parameter calibration is conducted via a user friendly graphic user interface (GUI) developed specifically for Paramics. The operational steps in using this GUI are given as follows.

Step1: Setup data collection point(s)

To obtain the traffic counts and occupancy at a location on the road section to be calibrated, one places one or more loop detectors on the section. Once these detectors are placed in Paramics, a Paramics plugin allows one to choose the detectors to be used in the calibration. Figure 2-3 shows the plugin's interface.

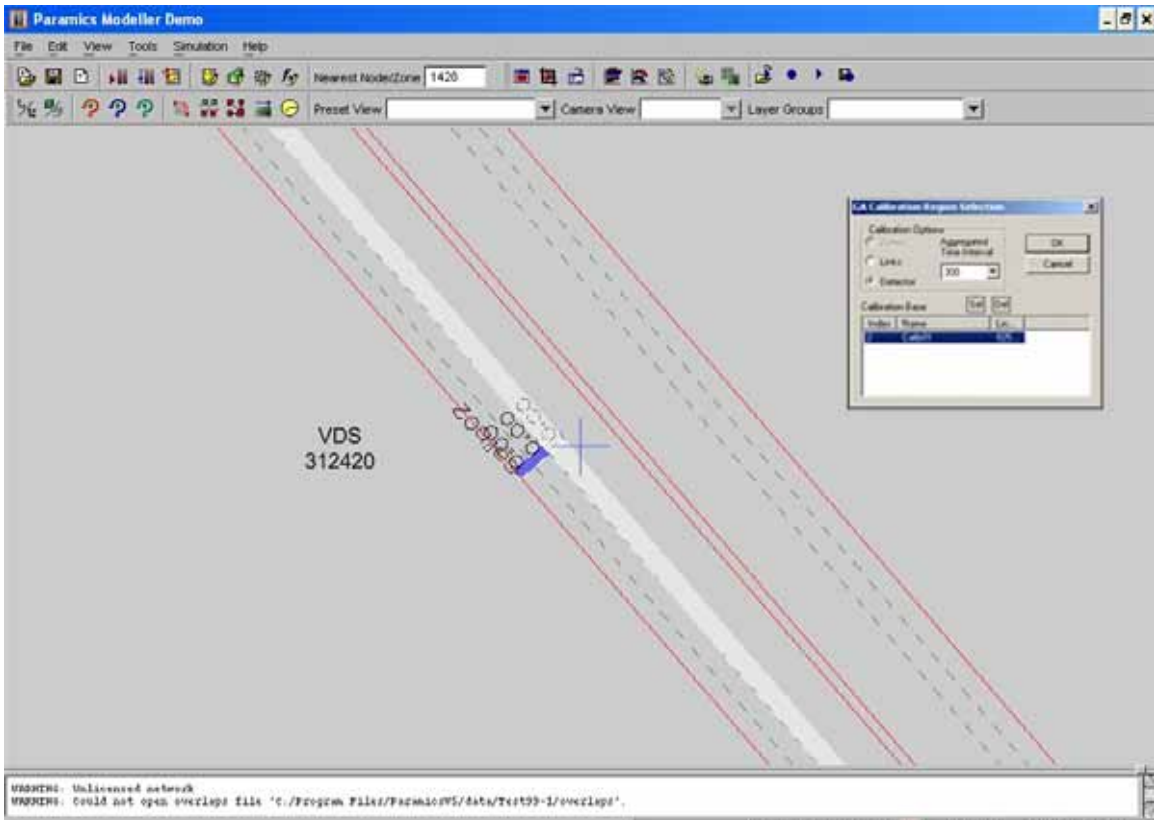


Figure 2-3 Data Collection Station Setup

Step 2: Set up GA Control Parameters

The interface allows users to provide the GA control parameters for different calibration exercises. Figure 2-4 shows this interface with the default values. The GA control parameters for global parameter calibration used in the project are summarized in Table 2-4.

Step 3: Start the GA Calibration Process

To start, click the Run button. A window will pop up as shown in Figure 2-5. This window shows the GA parameters used and how the mean fitness value converges during the calibration process. The convergence curve shown in the figure updates for every generation.

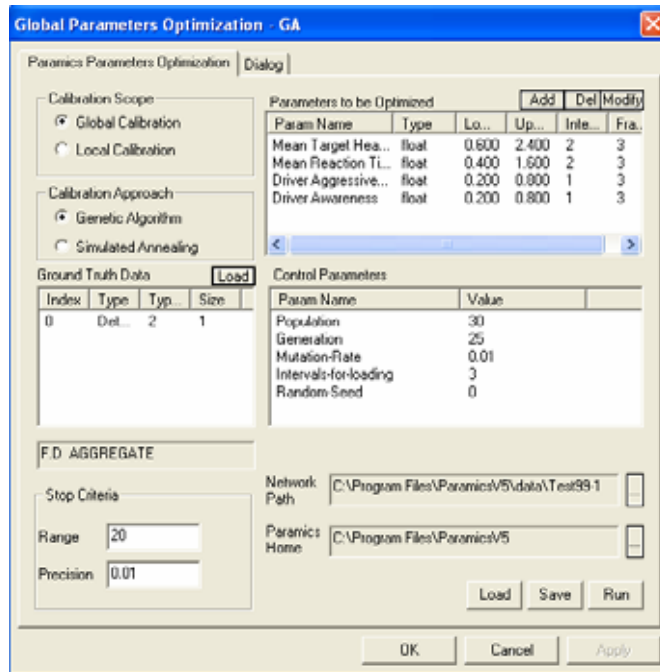


Figure 2-4 Genetic Algorithm Calibration Graphical User Interface (GUI)

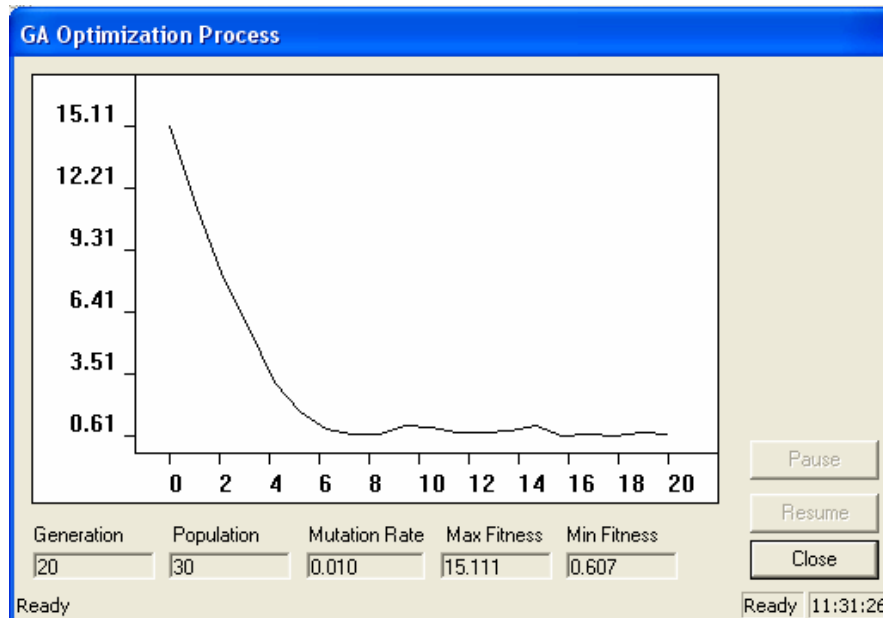


Figure 2-5 GA Convergence Process

2.2 Global Parameter Calibration: a Working Example

2.2.1 The Study Site

The network chosen is a congested corridor in the city of Sacramento, California, as shown in Figure 2-6. It includes a 24-mile section of freeway in southbound SR 99, starting from MP (milepost) 24.35 to the county line. The study period spans one hour of PM peak, from 2:30 to 3:30.

The site for global calibration is selected based on those guidelines discussed above: a straight road section with no drastic changes in geometric features. This section is highlighted in Figure 2-6 (the circled segment).

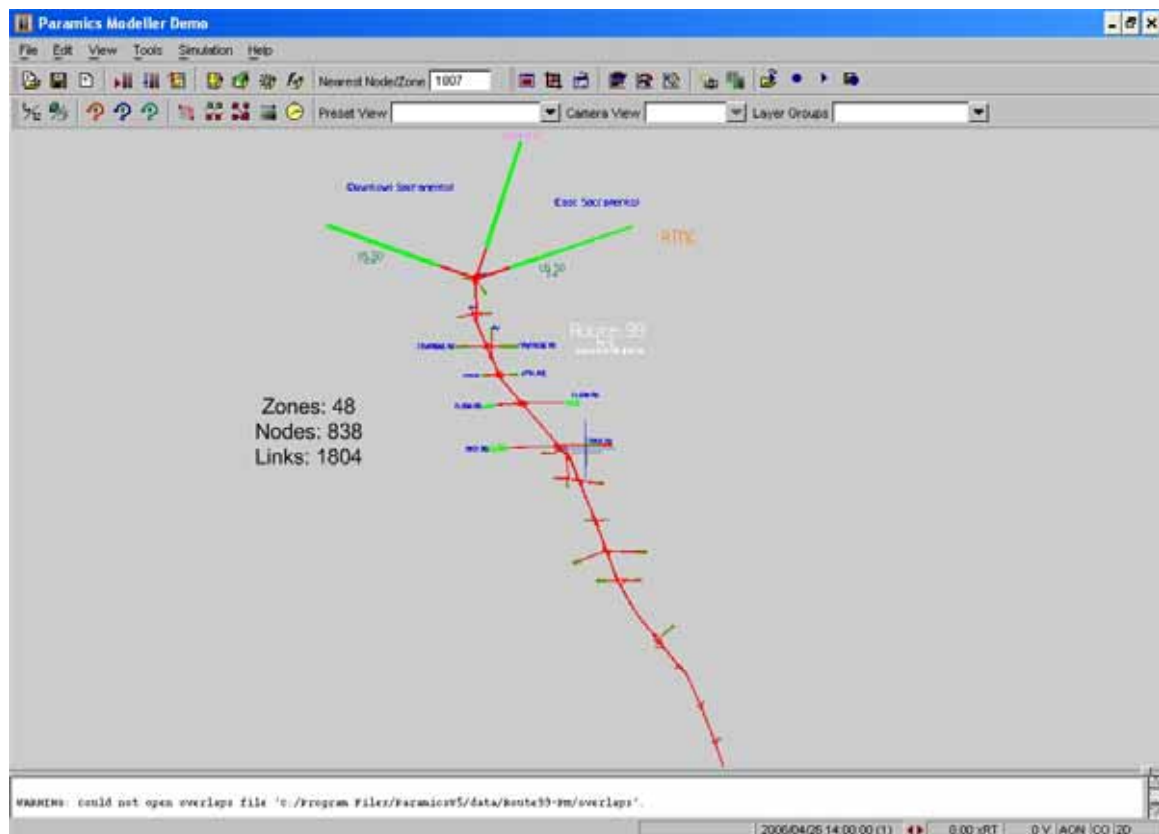


Figure 2-6 Overview of the Study Network in Paramics

2.2.2 The Ranges of Global Parameter Values

Four global parameters have been identified. They are: mean target headway, mean reaction time, driver's aggressiveness, and driver's awareness. The units and descriptions about the parameters were given in Table 2-3.

The default values for the mean target headway and mean reaction time in Paramics are both one second (Quadstone 2003). Previous studies (King 1973; Kunzman 1978) reported that the mean target headway should be 2 seconds for urban traffic control

related applications. Johansson (1971) uses 0.3~2.0 seconds as the range of reaction time in their research. AASHTO Green Book recommends that 2.5 seconds be considered adequate for driver's reaction time. Lee (2001) uses 0.6~2.4 seconds for mean target headway and 0.4~1.6 seconds for mean reaction time. However, these recommended values only indicate a possible range and they will be further investigated.

In Paramics, a driver is assigned a level of aggressiveness and awareness, respectively. They range from 0 through 8, with 8 representing the highest level of aggressiveness and awareness. The driver population is then divided into nine groups, with each group corresponding to a particular level of aggressiveness and awareness. The population in each group, expressed as a fraction of the total, is treated as a global parameter and subject to calibration.

Table 2-3 Global Parameter Search Space

Parameter Name	Unit	Min Value	Max Value
Mean Target Headway	Second	0.6	2.4
Mean Reaction Time	Second	0.4	1.6
Mean Driver Aggressiveness	N/A	0.2	0.8
Mean Driver Awareness	N/A	0.2	0.8

2.2.3 Construction of the Sub-network

A section between Florin Road and Mack Road is selected as the sub-network for global parameter calibration, as circled in Figure 2-7. This segment is 2-mile long with two general purpose (GP) lanes and one HOV lane. It is a very simple freeway section with no lane-drop, no obvious horizontal curve, or close by on/off ramps, therefore effects of such features on traffic flow and its capacity are negligible at this location.

In order to generate sufficient demand to produce a whole range of traffic conditions on the selected freeway section, two auxiliary zones are added to the sub network. One is an origin zone and the other is a destination zone. A loop detector is also added to the sub-network. The loop detector corresponds to VDS 312420 in the PeMS database. Figure 2-7 depicts the sub-network.

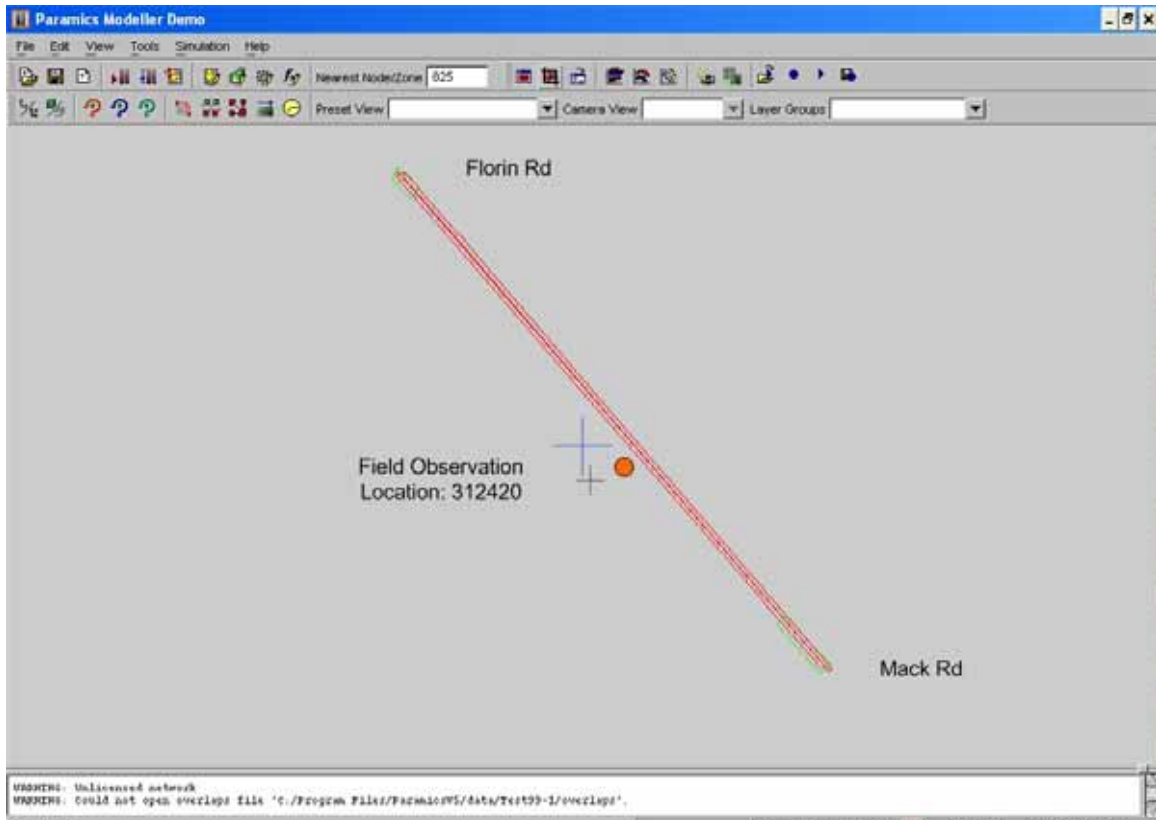


Figure 2-7 Sub-network for Global Parameter Calibration

2.2.4 Traffic Data

Two sets of datasets are used in the calibration of the global parameters. Both of the datasets are collected from the Freeway Performance Measurement System (PeMS) database. The first set (dataset one) is collected on VDS 312420, which is highlighted in Figure 2-7. This dataset includes aggregate five-minute volume and occupancy data between 2:00 PM and 3:30 PM on seven weekdays in March 2005. Figure 2-8 shows peaking on VDS 312420 during the period (2:00PM - 3:30PM). The second dataset (dataset two) is collected on VDS 312564, which is north of VDS 312420 between 12th Ave and the SR50/SR51 junction. Similarly, this dataset also includes aggregate five-minute volume and occupancy data between 2:00 PM and 3:30 PM on eight weekdays in 2005. Dataset one is used for calibration and dataset two is used for verification.

**2005 Southbound SR-99 24-Hour Flow Profile
(VDS 312420 7-Weekday Average)**

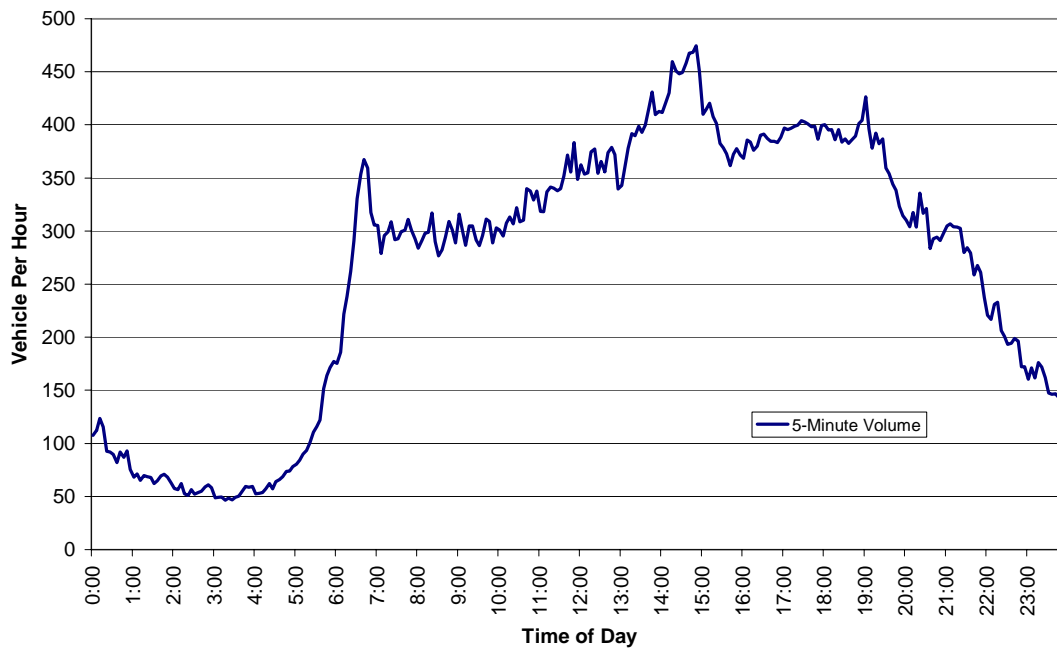


Figure 2-8 SR-99 Southbound Five-minute Volume Profile

2.2.5 The Approaches of Global Parameter Calibration

Two different calibration approaches are adopted in the global parameter calibration process. The first one is called the “Fundamental Diagram” approach (or FD). The second one is called the “Flow Profile” approach (FP), which is used more commonly in traffic simulation practices.

2.2.5.1 The Fundamental Diagram (FD) Approach

The FD approach is based on capacity and the shape of the flow-occupancy diagram (fundamental diagram). If the car-following model is able to reflect reality, field observed capacities of those sections as well as critical occupancies when the capacities occur should be closely replicated. As capacity and critical occupancy are not influenced by traffic volumes, an accurate O-D demand matrix is not necessary. Therefore, it is possible to use an artificial demand matrix in this approach.

In order to identify capacity and critical occupancy, one needs to increase traffic volume gradually so that a peak is clearly created. The goal is to obtain the top portion of the fundamental diagram for capacity and critical occupancy calculation. Paramics provides a demand factor, which globally adjusts volume between each O-D pair by a certain percentage ranging from 0% to 200%. If the O-D matrix is designed so that the volume on the data collection point is close to the capacity, it is not necessary to set demand factor below 80% or over 120%. A demand factor of too low or too high is not necessary

because it will lead to either free flow or jammed condition and neither is useful in identifying capacity and critical density.

In this research, five different demand factors are used to adjust traffic demand. They range from 80% through 120% with a 10 percent incremental increase. Each demand factor will drive one simulation run. All the other Paramics parameters are kept unchanged in the five runs. A simulation run simulates 90 minutes of traffic movement: the first 30 minutes are used for warm-up. Since simulation data are aggregated every 5 minutes, each run will produce 12 data points. Thus totally 60 data points are obtained to calculate capacity and critical occupancy for each global parameter dataset.

The fitness function in the FD approach is given as follows.

$$F = \sum_i^M [GEH(Cap_i) + A \times GEH(Occ_i)]$$

Where:

M : number of data collection locations

Cap_i : capacity of all general purpose lanes in one direction on which the data collection location i is located;

Occ_i : critical occupancy of a link on which the data collection location i is located.

A : a weighting factor. $A=10$ in this report.

2.2.5.2 The Flow Profile (FP) Approach

The FP approach is widely adopted in existing calibration studies. The essential idea is to compare simulation results against field observations for every predefined interval. The fitness function is a combination of GEH statistics of five-minute volume (summed cross all general purpose (GP) lanes) and five-minute occupancy (averaged across all GP lanes). The function takes the form as follows.

$$F = \sum_t^T \sum_i^M [GEH(Vol_i^t) + A \times GEH(Occ_i^t)]$$

Where:

T : number of five-minute intervals in an effective simulation run (warm-up time excluded);

M : number of data collection locations

Vol_i^t : capacity of all general purpose lanes in one direction on which the data collection location i is located;

Occ_i^t : critical occupancy of a link on which the data collection location i is located.

A: a scalar with value $A = 10$.

In setting up the calibration network, the demand profile has to be consistent with field observations from the detectors when FP approach is used. In comparison, the demand can be manipulated using the demand factors (80%-120% in this case) when FD approach is applied.

2.2.6 Results and Verification

2.2.6.1 Global Parameter Calibration Results

The GA calibration process stops either when the maximum number of generations is reached or the average fitness value for several successive (user defined) generations does not change within a tolerance band. The convergence of the fitness value in FD and FP approaches are shown in Figure 2-9 and 2-10, respectively.

The two approaches show similar convergence patterns in the mean fitness value. Fitness values drop down very quickly during the first five generations. The curve becomes flatter and flatter from the sixth generation and fluctuates slightly around a certain value after the ninth generation. The curve of the maximum fitness value in the FP approach changes dramatically even in later generations, showing some kind of instability. But the overall trend that the mean fitness value converges to a certain point is apparent, despite the fluctuations in the maximum fitness value in calibration process.

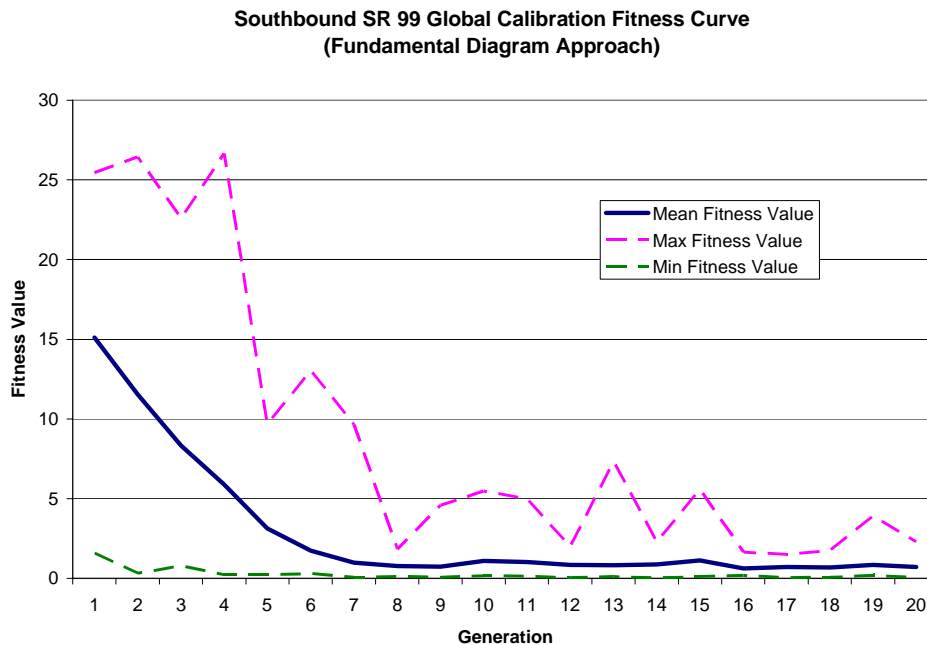


Figure 2-9 Global Parameter Calibration Convergence – The Fundamental Diagram Approach

Location: VDS 312420

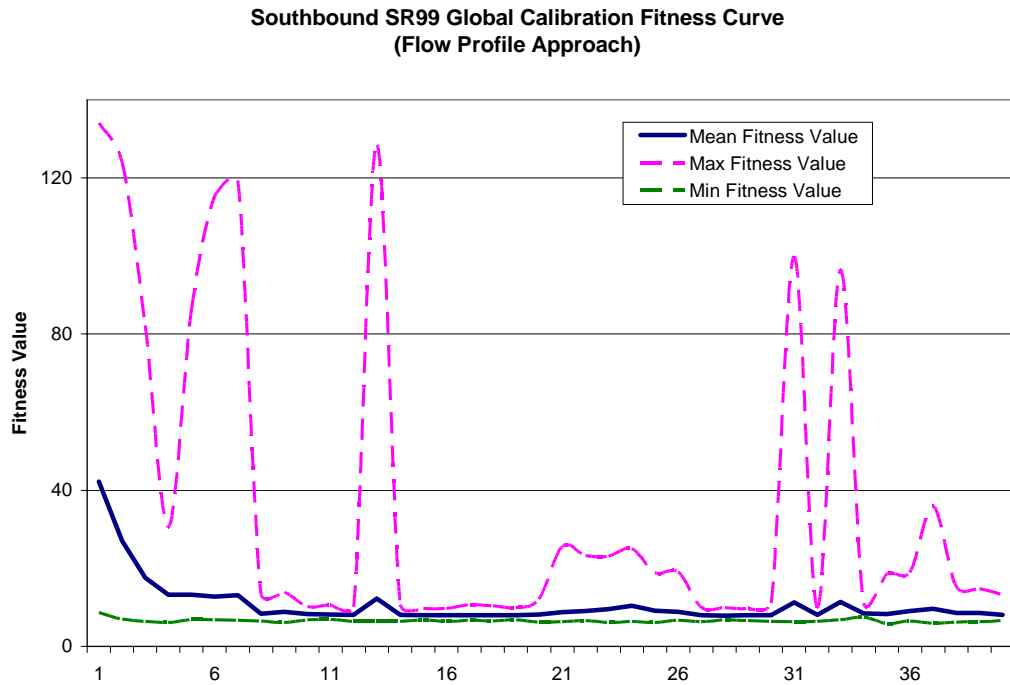


Figure 2-10 Global Parameter Calibration Convergence – The Flow Profile Approach

Location: VDS 312420

The wild fluctuations in the maximum fitness value in each generation were further investigated. Figure 2-11 shows the fitness value distribution in the 13th generation, which represents a high peak in Figure 2-11. The vast majority of fitness values in the 13th generation are below 9. The only outlier, indexed by 17th with a value of 128.449, explains why the maximum fitness value has huge variations as shown in Figure 2-11.

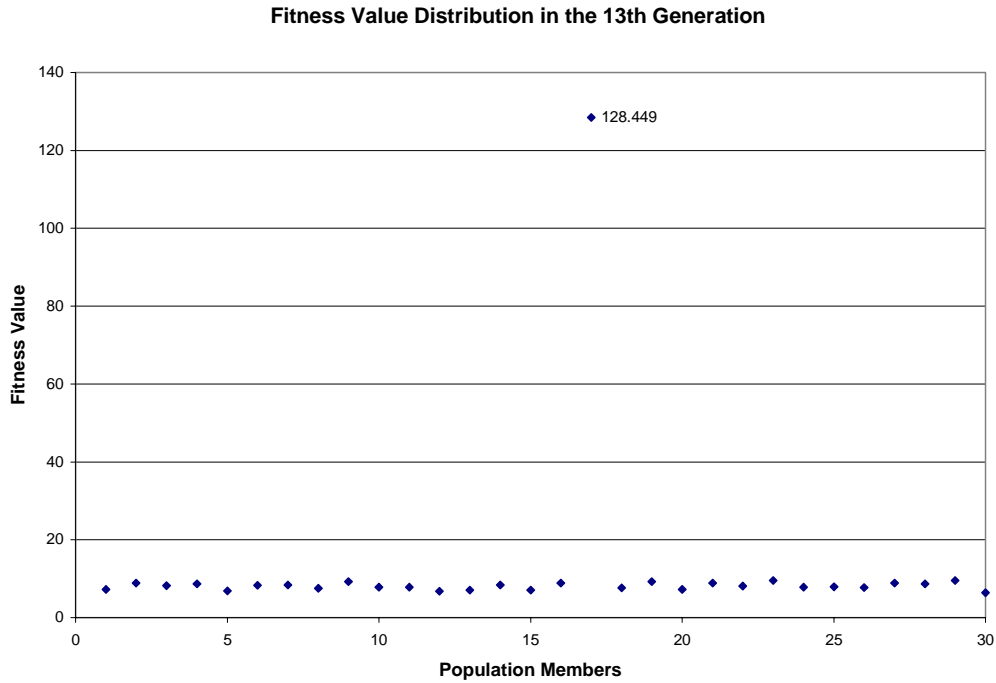


Figure 2-11 Fitness Value of Individuals in the 13th Generation

Table 2-4 presents a comparison between three different chromosomes. The first one is the outlier shown in Figure 2-11. The second one is one generation earlier than the outlier and third one is one generation later than the outlier. The three chromosomes reside in the same location in a generation. The outlier shares the same values on Mean Target Headway, Mean Aggressiveness and Mean Awareness with the third one. The only difference between them is their Mean Reaction Time values. The outlier has a value of 0.45 while others have a value of 1.29. Apparently, this is what caused the large discrepancy in their fitness values. As mentioned earlier, each chromosome contains a set of feasible solutions that are generated in some random fashion, one cannot completely rule out outlier solutions (i.e., solutions that produce poor fitness values). As long as the number of such outliers is few and far between, however, the GA algorithm would still converge in their presence, as our numerical examples illustrate.

Table 2-4 Analysis of Chromosome Fitness Value Outliers

Chromosome (Pop Index, Gen Index)	Fit. Val.	Mean Target Headway	Mean Reaction Time	Mean Aggressiveness	Mean Awareness
17 th , 13 th	128.499	1.06	0.45	0.76	0.46
17 th , 12 th	9.065	1.06	1.29	0.70	0.46
17 th , 14 th	8.515	1.06	1.29	0.76	0.46

Tables 2-5 and 2-6 present the top five sets of optimized global parameters by both the FD and FP approaches, respectively. The solutions are ranked by their fitness values in ascending order. A smaller fitness value means the simulation results are closer to the field observations. The parameter set in the top of each approach is chosen as the optimized global parameter set in our verification studies. One should be aware that the fitness values in the two tables are not comparable because they are calculated by different fitness value functions. Nevertheless, we note that both approaches produced rather close values for the Mean Target Headway and Mean Reaction Time, but quite different values for the other two global parameters.

Table 2-5 Top Five Optimized Global Parameters Using the FD Approach

Rank	Fit. Val.	Mean Target Headway	Mean Reaction Time	Mean Aggressiveness	Mean Awareness
1	0.02	0.96	1.25	0.23	0.51
2	0.04	0.96	1.25	0.27	0.51
3	0.06	0.96	1.24	0.24	0.51
4	0.07	0.96	1.26	0.27	0.51
5	0.08	0.97	1.24	0.23	0.55

Table 2-6 Top Five Optimized Global Parameters Using FP Approach

Rank	Fit. Val.	Mean Target Headway	Mean Reaction Time	Mean Aggressiveness	Mean Awareness
1	5.84	1.04	1.29	0.76	0.39
2	5.91	0.99	1.29	0.76	0.39
3	6.11	1.06	1.29	0.79	0.46
4	6.14	1.06	1.29	0.76	0.46
5	6.15	1.06	1.29	0.76	0.39

2.2.6.2 Global Parameter Verification

In order to evaluate the calibration results, verification is conducted on another sub-network of SR 99. The verification sub-network is located in the north of Fruitridge Road,

a few miles north of the calibration site. The detector VDS 312564 in PeMS provides field observations (dataset two), which is used for the verification exercise.

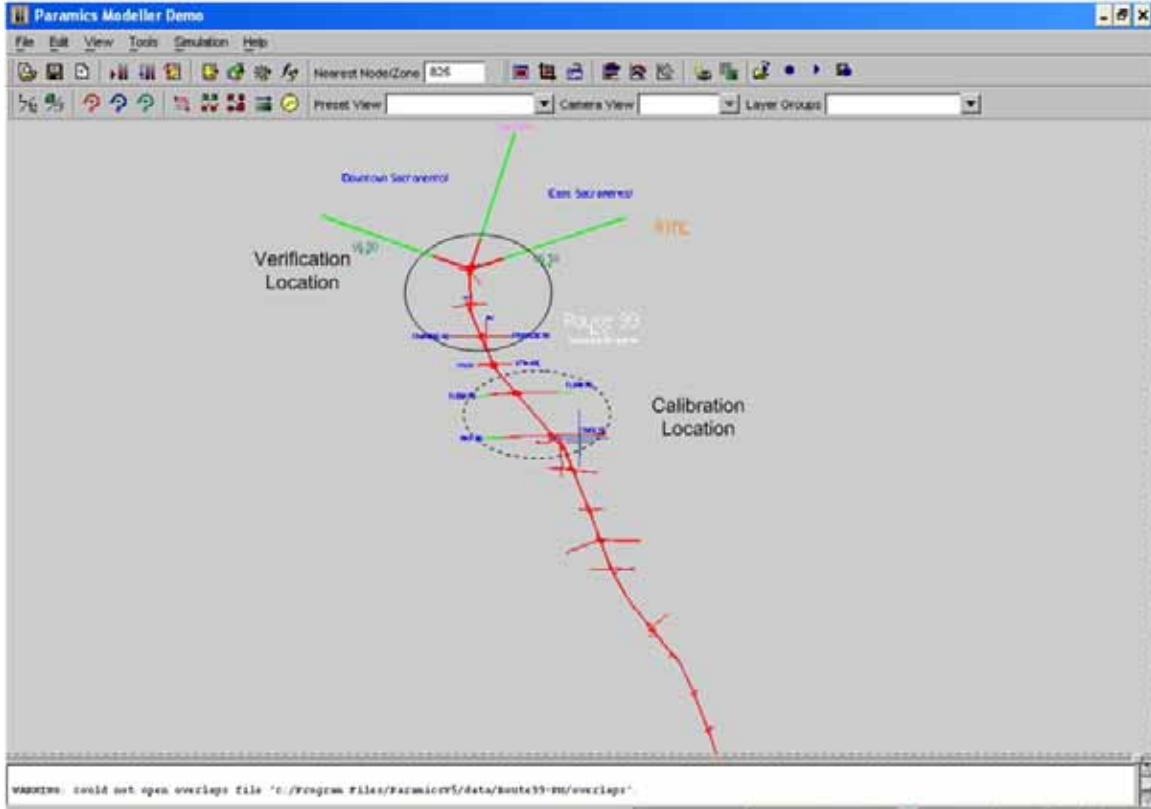


Figure 2-12(a) Global Parameter Verification, Sub-network Overview

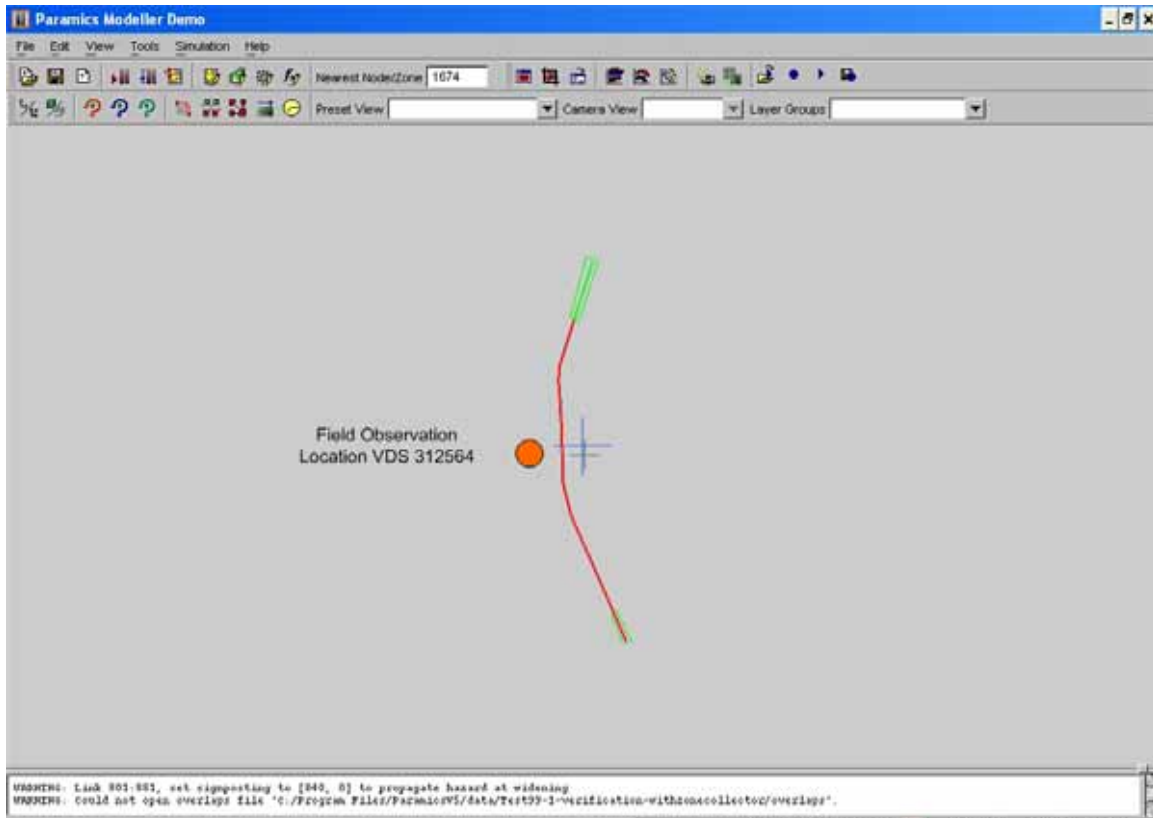


Figure 2-12(b) Global Parameter Verification, Sub-network

The verification procedure is quite simple:

- ✧ Plugin the optimized global parameter values into the sub-network;
- ✧ All other parameters are set to default values;
- ✧ Run multiple simulation runs. Average five-minute volume and occupancy. Compare the averaged simulation results against the field observation data.

Since Paramics is a stochastic model, multiple simulation runs with different random seeds are required to mitigate the random errors which otherwise may distort the simulation results.

To determine the number of simulation runs, the following equation is used.

$$N = \left(\frac{t_{\alpha/2, N-1} \times S}{\bar{X} - \mu_0} \right)^2$$

where:

S : standard deviation of the performance measurement variable based on the already conducted simulation runs;

\bar{X} : average of the performance measurement variable

μ_0 : mean of the performance measurement variable X in the field.

As the standard deviation S and performance measurement \bar{X} are unknown before a simulation is run, and they are updated as number of runs increases, the determination of the number of runs is an interactive process. The decision making process is depicted in Figure 2-13. Only the system level measurement, i.e. the total traffic volume, is used to calculate the number of runs. A seven-weekday average of total traffic volume in dataset two is used as μ_0 . Five simulation runs for each calibration approach are performed to evaluate the global calibration.

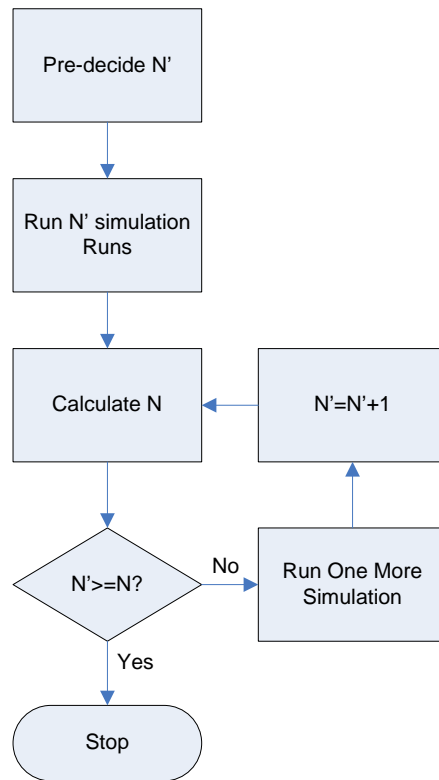


Figure 2-13 The Process that Decides the Number of Simulation Runs

As a comparison, the default values for these global parameters in Paramics are also used. Table 2-7 shows different sets of global parameter values used in the verification process. Table 2-8 shows the verification results in both five-minute intervals and peak-hour. Traffic volume and occupancy obtained using these three different parameter sets are depicted in Figures 2-14 and 2-15, respectively.

One may notice that Figure 2-15 shows large differences between simulated and observed

occupancies in the second half hour. The observed occupancies are significantly higher during the last 30 minutes than those produced by the simulation. The increase in field occupancy was due to the activation of a downstream bottleneck, whose queues grows upstream and caused a traffic slow-down at the observation site. The sub-network, however, did not include this bottleneck hence cannot model its effect on upstream traffic conditions. It should be noted that such interactions will be taken care of when one calibrates the D-R choice parameters and O-D demand, after local and global parameters are calibrated.

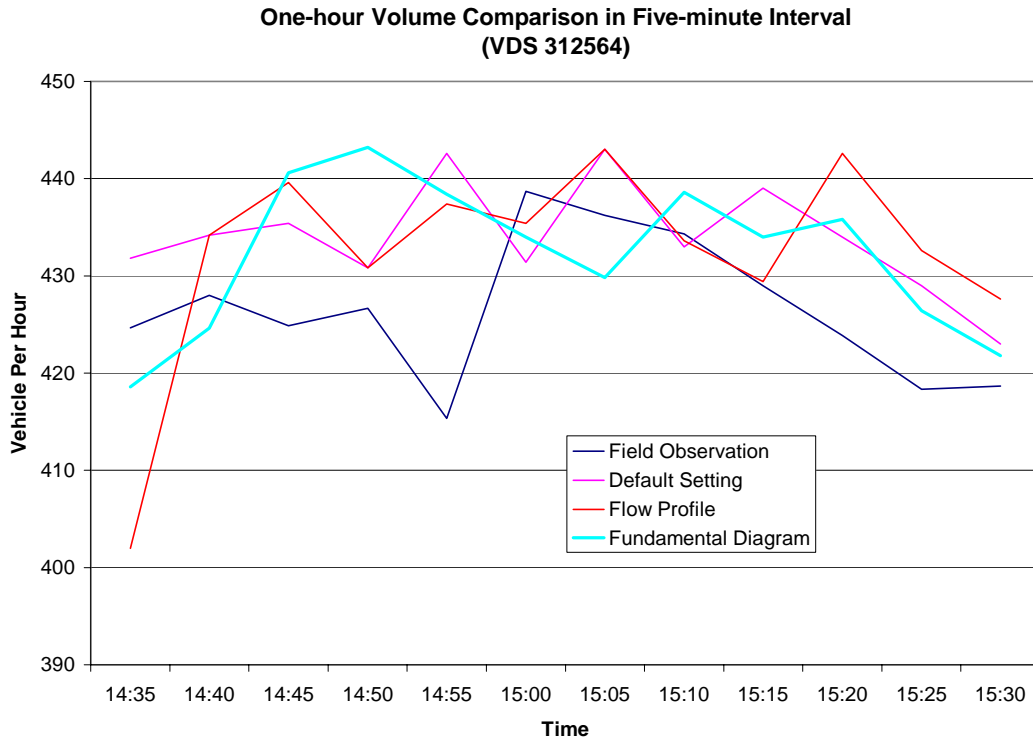


Figure 2-14 Five-minute Traffic Volume Comparison

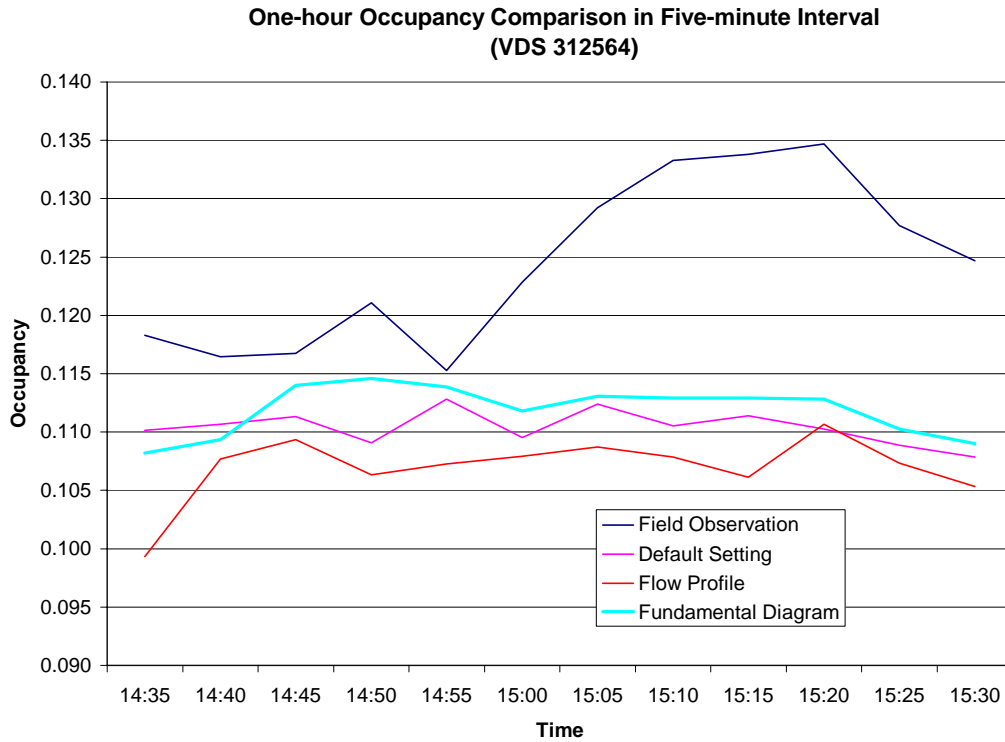


Figure 2-15 Five-Minute Occupancy Comparison

Table 2-7 Global Parameter Sets Used in Verification

	Mean Headway	Target	Mean Time	Reaction	Mean Aggressiveness	Mean Awareness
Default Settings	1.0		1.0		0.26	0.26
FD	0.96		1.25		0.23	0.51
FP	1.04		1.29		0.76	0.40

According to the GEH statistic, the FD approach yields the best results on occupancy, followed by default Paramics parameter values. But the default values produce the best results on traffic volume, followed by the FD approach. However, their GEH values are very close to each other (5.100 vs. 5.221). Measured by the peak-hour, the FD approach

produces the closest match to the field observations. The FP approach produced the worst GEH but its results are still comparable to those obtained from the other two. At least for this stretch of the road, the default Paramics parameter values for the four global parameters are quite reasonable.

Table 2-8 Global Parameter Calibration Verification Results

Time	Field Observation		Default Setting		FP		FD		GEH					
	Vol	Occ	Vol	Occ	Vol	Occ	Vol	Occ	Default Setting		FP		FD	
									Vol	Occ	Vol	Occ	Vol	Occ
14:35	425	0.118	432	0.110	402	0.099	419	0.108	0.345	0.024	1.115	0.058	0.295	0.030
14:40	428	0.116	434	0.111	434	0.108	425	0.109	0.299	0.017	0.299	0.026	0.165	0.021
14:45	425	0.117	435	0.111	440	0.109	441	0.114	0.507	0.016	0.708	0.022	0.755	0.008
14:50	427	0.121	431	0.109	431	0.106	443	0.115	0.200	0.035	0.200	0.044	0.793	0.019
14:55	415	0.115	443	0.113	437	0.107	438	0.114	1.316	0.007	1.069	0.024	1.116	0.004
15:00	439	0.123	431	0.110	435	0.108	434	0.112	0.348	0.039	0.156	0.044	0.223	0.032
15:05	436	0.129	443	0.112	443	0.109	430	0.113	0.323	0.048	0.323	0.059	0.309	0.046
15:10	434	0.133	433	0.111	434	0.108	439	0.113	0.064	0.065	0.035	0.073	0.204	0.058
15:15	429	0.134	439	0.111	429	0.106	434	0.113	0.480	0.064	0.019	0.080	0.241	0.059
15:20	424	0.135	434	0.110	443	0.111	436	0.113	0.488	0.070	0.899	0.069	0.575	0.062
15:25	418	0.128	429	0.109	433	0.107	426	0.110	0.518	0.055	0.692	0.059	0.393	0.050
15:30	419	0.125	423	0.108	428	0.105	422	0.109	0.211	0.049	0.434	0.057	0.153	0.046
Peak hour	5119	0.124	5207	0.110	5188	0.107	5186	0.112	5.100	0.490	5.948	0.615	5.221	0.437

Note:

1. Field observation is seven-weekday five-minute aggregate traffic data average.

2. Default Setting, FP, and FD are all averaged traffic data over five simulation runs

2.3 Benchmarking the Performance of Genetic Algorithm in Obtaining Global Optimal Solutions

In order to find out if the proposed GA algorithms find the global optimal solution or a nearly global optimal solution in the parameter set, an exhaustive search through the feasible solution space was conducted. In Paramics, the search space has four dimensions: namely mean target headway (MTH), mean reaction time (MRT), mean driver aggressiveness and awareness, as shown in Table 2-9. After properly discretizing each dimension, the size of feasible solutions is near five million. In the above calibration process, the genetic algorithm sampled only 600 (population 30 times generation 20) within this pool to converge to a solution. Naturally one would wonder how good this solution is. Also, an exhaustive search through the parameter space can also reveal how sensitive the simulation results are to the parameters and their values.

Table 2-9 Global Parameter Calibration Search Space

Parameter Name	Unit	Min Value	Max Value	Search Step	# of Solutions
Mean Target Headway (MTH)	Second	0.6	2.4	0.02	90
Mean Reaction Time (MRT)	Second	0.4	1.6	0.02	60
Mean Driver Aggressiveness	N/A	0.2	0.8	0.02	30
Mean Driver Awareness	N/A	0.2	0.8	0.02	30
Total Combination	---	---	---	---	4,860,000

Two separate exhaustive searches were carried out on the sub-network and the results are shown in Figure 2-16. The searches are based on the global calibration result which is shown in Table 2-10. The first exhaustive search keeps aggressiveness and awareness unchanged, and enumerates MTH from 0.6 through 1.3 and MRT from 0.6 through 1.8, with the increment of 0.02 for each parameter.

Table 2-10 Global Calibration Result (Fundamental Diagram Approach)

	Mean Target Headway (MTH)	Mean Reaction Time (MRT)	Mean Aggressiveness	Mean Awareness
Fundamental Diagram	0.96	1.25	0.23	0.51

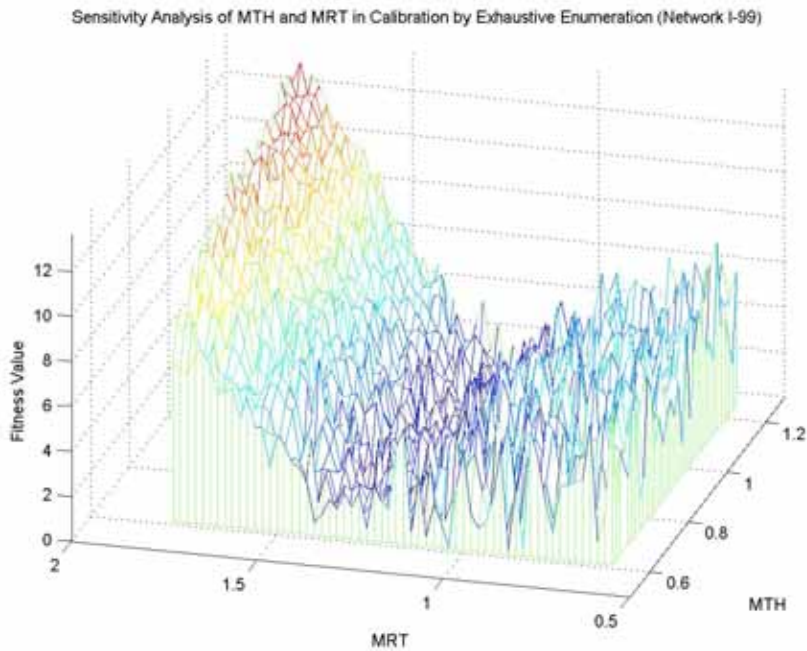


Figure 2-16(a) Mesh Figure of MTH and MRT Sensitivity in Global Parameter Calibration (SR-99) (with Fixed Aggressiveness and Awareness)

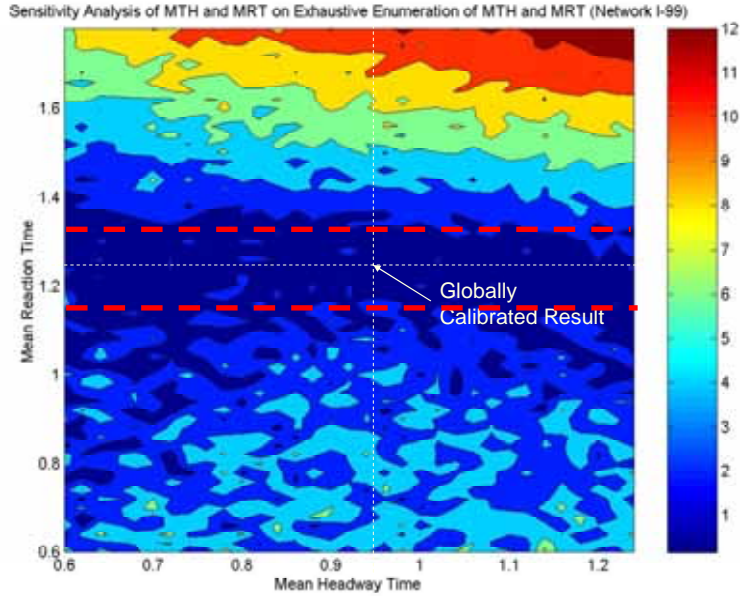


Figure 2-16(b) Contour Map (MTH-MRT) and GA-obtained Solution in Global Parameter Calibration (SR-99) (with Fixed Aggressiveness and Awareness)

Figure 2-16(a) shows how mean reaction time (MRT) and mean target headway (MTH) affects the mean fitness. Figure 2-16(b) shows a 2D contour plot of the mean fitness values. The dark blue band in the 2D plot (enclosed by the thick dash lines) indicates that the fitness values in this band are quite close to zero, which means those solutions are “good” solutions. The solution obtained by the genetic algorithm falls in the middle of this band, implying that it is a nearly optimal solution even if it was not the globally optimal solution. These two figures also reveal that the mean fitness value is more sensitive to changes in MRT than MTH, and within the blue band, a wide range of MTH values can produce similar simulation results.

The second search keeps MRT and MTH constant, and enumerates both aggressiveness and awareness values from 0.2 through 0.8, with the same increment of 0.02 on each parameter. The result is shown in Figure 2-17. The parameter values obtained from the genetic algorithm in the calibration are marked in Figure 2-17(b) with a red arrow. From these figures one cannot tell which parameter, aggressiveness or awareness, is more influential because the fitness value surface has peaks and valleys scattered all over the search space.

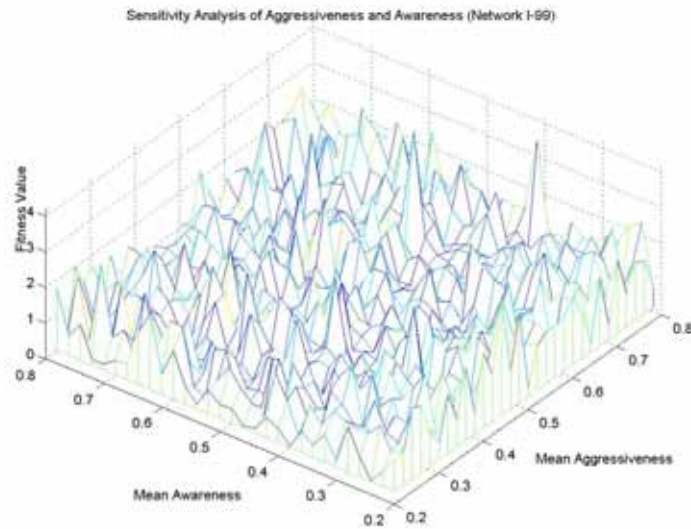


Figure 2-17(a) Z-Mesh Figure of Mean Aggressiveness and Mean Awareness Sensitivity (SR-99) (with Fixed MTH and MRT)

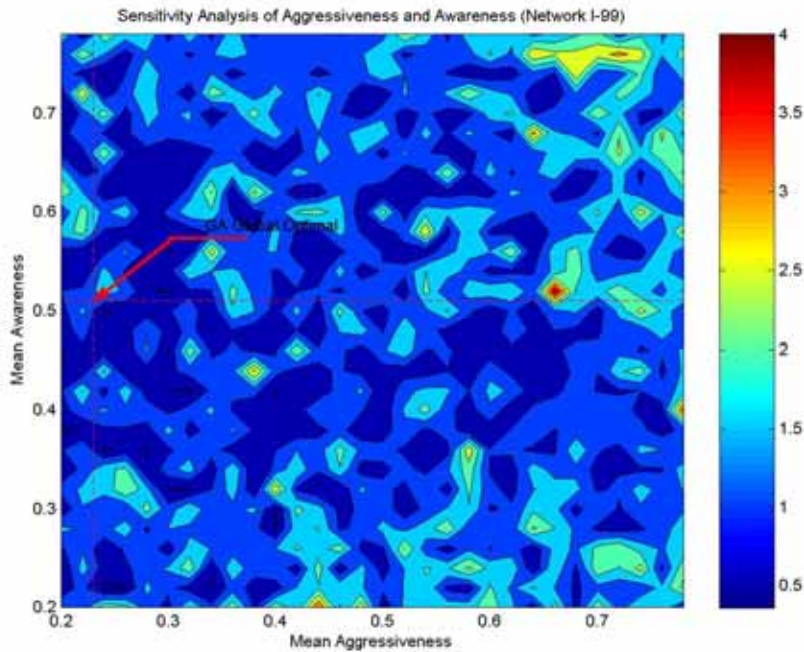


Figure 2-17(b) Contour Map (Aggressiveness-Awareness) and GA-obtained Solution (SR-99) (with Fixed MTH and MRT)

With a working example, we have demonstrated how the developed calibration tool with a friendly GUI can be used to calibrate global parameters, and investigated the quality of the calibration through a comparison of between the GA-optimized solutions and those

from exhaustive searches. These preliminary results show that the proposed calibration procedure and developed methods are quite effective in obtaining nearly optimal solutions of the global parameters.

CHAPTER 3 LOCAL PARAMETER CALIBRATION

After global parameter calibration is completed, the parameters that affect the capacity of a basic road section have been calibrated. However, many road sections have unique site specific features that further influence capacities at these locations. These features can be a lane drop, a sag, or a steep grade, to name a few. In this chapter, we discuss how to calibrate site-specific or local parameters so that the simulation model can reproduce the traffic flow characteristics at such sites.

3.1 The Local Parameter Calibration Procedure

The procedure and method used to calibrate local parameters in Paramics is quite similar to those used in the calibration of global parameters. In fact, the same GUI is used for local calibration as well. The specific steps are as follows:

- ✧ Step 1: identify local calibration targets;
- ✧ Step 2: decide the parameter search space and GA control parameters;
- ✧ Step 3: construct a sub-network for local parameter calibration;
- ✧ Step 4: perform local parameter calibration;
- ✧ Step 5: verification

All the five steps are discussed in detail in the following paragraphs.

Step 1) Identify Local Parameter Calibration Targets

Local parameter calibration tends to be more complicated than global parameter calibration, since the search space is often larger and even more convoluted in the case of local parameters. For example, in addition to global parameters like mean target headway and mean reaction time, each link has both a link headway factor and a link reaction factor, and each ramp has its own ramp reaction time, ramp headway factor, and ramp awareness that all can affect the local capacity.

Ideally these parameters should be calibrated for each link, but this is often impossible due to a lack of field data and the tremendous amount of effort involved. To reduce the amount of calibration effort, we suggest that links are grouped into different categories, with members in each group sharing major local characteristics. For this purpose, we have selected three groups, namely simple bottlenecks, ramps, and intersections. For example, a simple bottleneck can be a continuous section with a lane-drop or sharp turn, but no junctions. Each group has its common parameters that affect the capacity of all members in this group, although their capacities can differ, and so do the values of these parameters. Since we cannot calibrate the “bottleneck” capacity for every site, we will use our engineering judgment to select a few representative sites in each group to perform

local calibration.

Step 2) Decide Local Parameter Search Space and GA Control Parameters

The main local parameters in Paramics have been identified and listed in Table 3-1. Unlike global parameters that apply to all road links, local parameters apply to specific locations, such as an on-ramp or a lane drop. Thus they are site dependent and each local section of interest will have a set of local parameters. Thus the chromosome length in the genetic algorithm varies depending on how many calibration targets are selected for calibration.

Table 3-1 Local Parameter Search Space

Parameter Category	Parameter Name	Unit	Min Value	Max Value
Local Parameters	Link Headway Factor	N/A	0.5	2.0
	Link Reaction Factor	N/A	0.5	2.0
	Ramp Headway Factor	N/A	0.5	2.0
	Minimum Ramp Time	Second	1	3
	Ramp Awareness Distance	Foot / meter	1	---
	Sign-posting	Foot / meter	400	3500

The GA control parameters used in local calibration are the same as global parameter calibration (Table 2-2).

Step 3) Construction of the Sub-network for Local Parameter Calibration

As in the case of global parameter calibration, a sub-network containing the section of interest needs to be first extracted from the overall Paramics network, and auxiliary O-D zones be added to the sub-network to produce a range of demand so that the full spectrum of traffic conditions can be simulated on the section. Typically, at least one such sub-network should be extracted for each type of “bottlenecks”, but usually more would be needed since bottlenecks of the same type can have different capacities and flow-density diagrams as well. Figure 3-1 shows an example of such a sub-network.

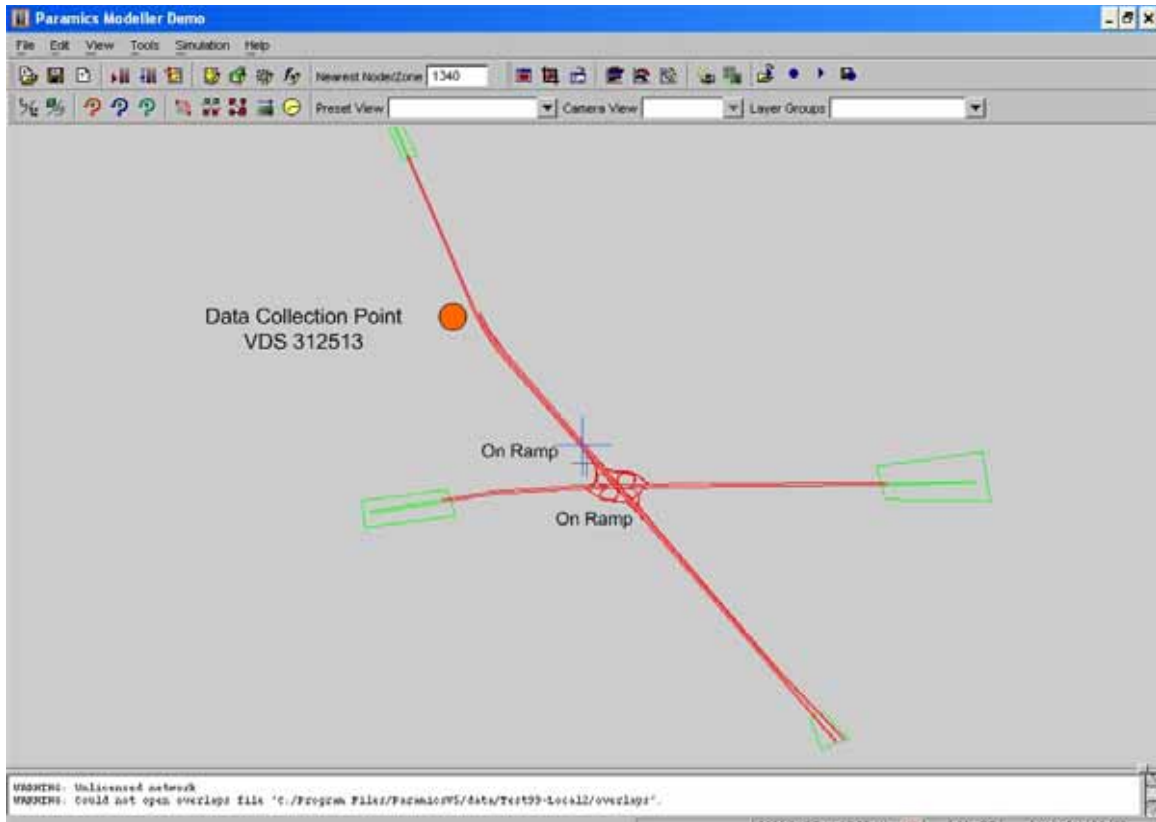


Figure 3-1 Sub-network for Local Parameter Calibration

Step 4) Perform the Local Parameter Calibration

The same graphic user interface (GUI) for global parameter calibration also drives the local calibration process. Figure 3-2 shows the local parameter calibration interface in the GUI, in which one simply selects the local calibration button, then fills in the proper control parameters for the GA algorithm, and hits the run button to start calibrating the local parameters.

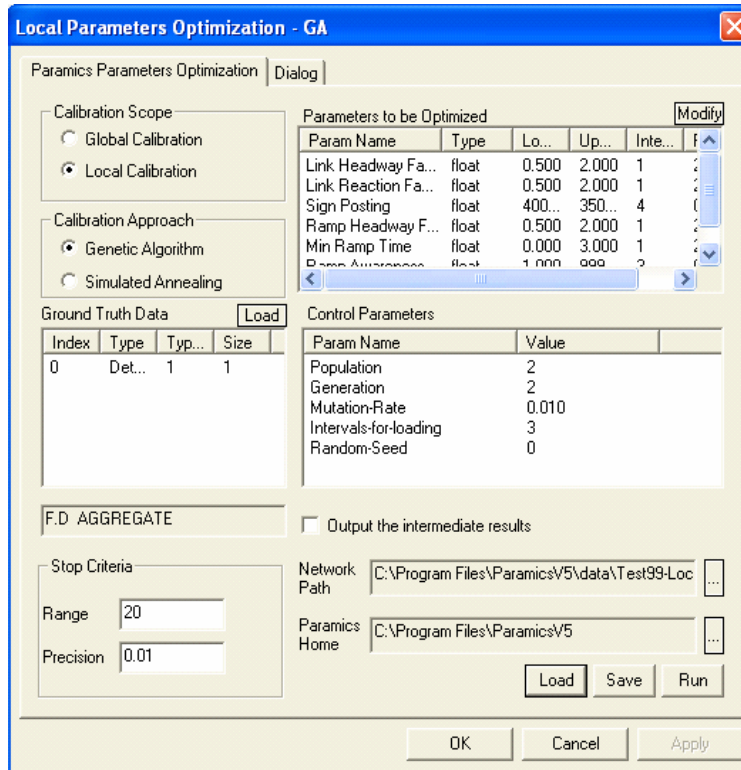


Figure 3-2 Local Parameter Calibration Graphical User Interface (GUI)

3.2 A Working Example

3.2.1 The study site

The sub-network is located between Fruitridge Road and Mack Road, including the Florin Road / SR-99 interchange. The interchange is a full clover leaf shaped with two on-ramps and two off-ramps in the southbound. In the north of the interchange, SR-99 southbound has three general purpose (GP) lanes and one HOV lane. In the south of the interchange, one GP lane ends. So there are only two GP lanes in the south direction after this point.

The link with two GP lanes in the south is the bottleneck. During the peak hour, queue may back up to the upstream so that the mainline north of the lane drop will be affected due to the lane drop. Consequently, the extracted sub-network contains the link north of the bottleneck, the bottleneck link, and the on-ramps from Florin Road (Figure 3-1).

3.2.2 The calibration approach and results

Only the FD approach is used in local parameter calibration. Figure 3-3 depicts the convergence pattern of the local calibration process. The mean fitness value drops significantly to lower than 10 during the first eight generations. It takes another seventeen generations before the value lowers down to around eight. After that it fluctuates around eight during the remaining generations and is considered to have converged.

Southbound SR 99 Local Calibration Fitness Curve

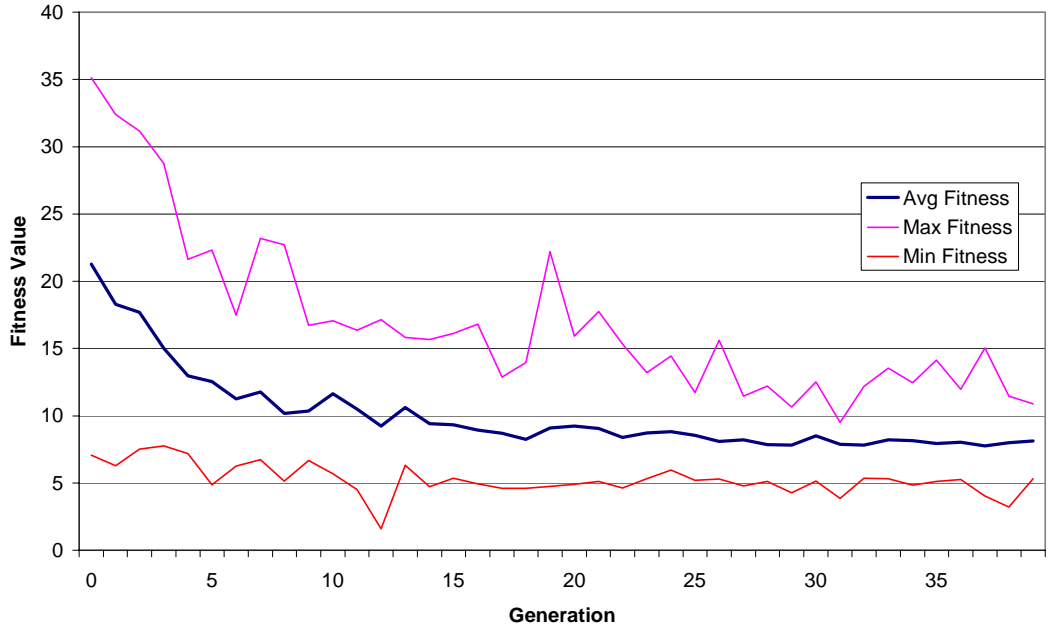


Figure 3-3 Local Parameter Calibration Convergence

Table 3-2 shows the optimized local parameters. The fitness value associated with this set of parameters is 1.59. Note that the EB Fruitridge on ramp has a much lower link headway factor and ramp aware distance than those for the WB Fruitridge on ramp, perhaps due to its relatively short merging length and poor sight visibility for SB traffic on the freeway, respectively.

Table 3-2 Best Optimized Local Parameters

	Bottleneck (mainline north of the interchange)	On-Ramp from Fruitridge Road WB	On-Ramp from Fruitridge Road EB
Link Headway Factor	0.63	1.96	0.53
Link Reaction Factor	1.58	0.93	0.80
Sign-posting	3043	924	759
Ramp Headway Factor	---	1.13	1.08

Minimum Ramp Time	---	2.94	1.28
Ramp Awareness Distance	---	212	8.72

Note: Calibration Location: VDS 312513.

Just as in the FD approach for global parameter calibration, the demand factor in the local calibration is also adjusted from 0.8 to 1.2 incrementally for each demand factor level. Thus 60 data samples are collected during simulation runs with the same local parameter set. The simulation result with the optimal parameter set yields a capacity of 4972 vph, slightly less than the field observed value (5010 vph). Table 3-3 presents the capacity and critical occupancy comparison between field observations and three sets of optimized solutions. Figure 3-4 depicts the fundamental diagrams generated by both field and simulated data (produced with the best local parameter set), showing a good match between the two diagrams.

Table 3-3 Flow Characteristics between Field Observation and Top 3 Optimized Solutions

	Capacity	Critical Occupancy	Fitness Value
Field Observation	5020	0.10	---
Optimized 1	4972	0.13	1.59
Optimized 2	4812	0.11	3.22
Optimized 3	4756	0.10	3.85

Note:

Calibration Location: VDS 312513.

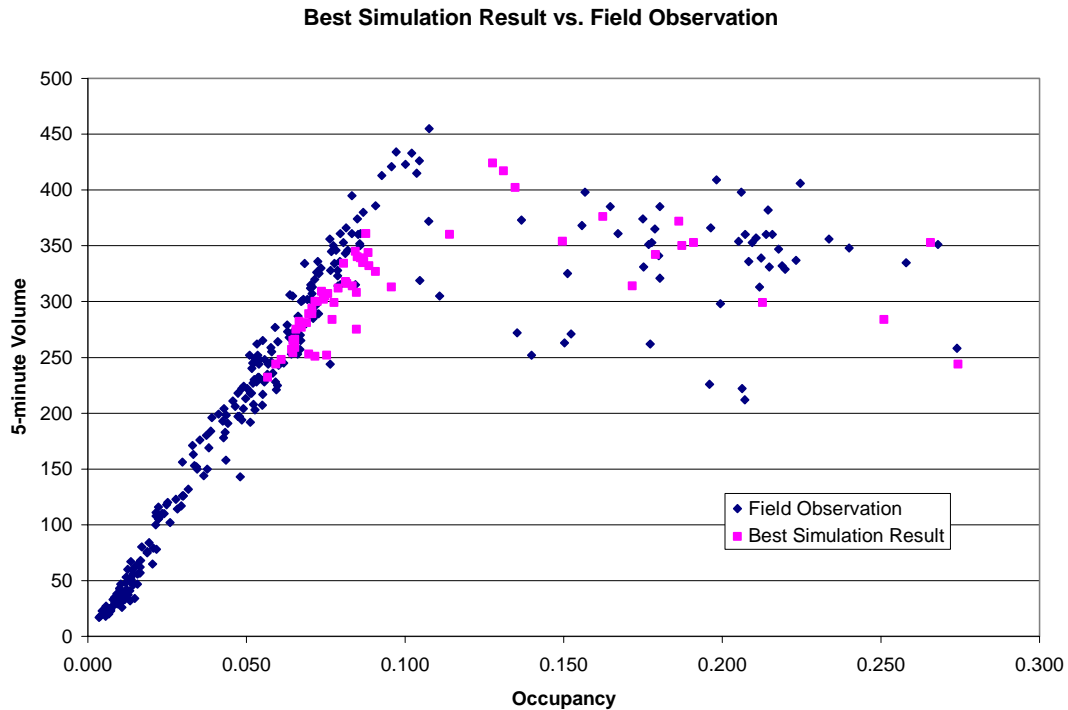


Figure 3-4 Best Simulation Results vs. Field Observation

Note: Calibration Location: VDS 312513

3.2.3 Verification of Local Parameter Calibration Results

The verification of local parameter calibration takes the same steps as in that of the global parameter calibration, with only one difference. The difference is that in local parameter calibration the verification dataset is obtained from the same sub-network and the verification is performed on the same sub-network used for calibration. This is because local parameters are all site specific and it is not appropriate to apply them to a different network other than the one used to obtain them.

Table 3-4 shows local calibration verification results. Figures 3-5 and 3-6 depict 5-minute volume comparison and 5-minute occupancy comparison, respectively. As Figure 3-6 shows, local calibration can dramatically improve model performance as compared with no calibration.

Table 3-4 Local Parameter Calibration Verification Results

Time	Field Observation		After Local Calibration				Before Local Calibration			
	Vol	Occ	Vol	GEH (Vol)	Occ	GEH (Occ)	Vol	GEH (Vol)	Occ	GEH (Occ)
14:35	409	0.090	373	0.931	0.111	0.033	384	0.634	0.099	0.015

14:40	411	0.096	388	0.568	0.115	0.028	398	0.326	0.158	0.087
14:45	437	0.106	383	1.341	0.123	0.026	378	1.471	0.292	0.209
14:50	429	0.112	383	1.142	0.135	0.033	377	1.294	0.350	0.248
14:55	413	0.110	381	0.791	0.130	0.029	369	1.117	0.372	0.267
15:00	373	0.115	366	0.196	0.146	0.042	368	0.142	0.382	0.268
15:05	354	0.148	373	0.508	0.147	0.002	381	0.705	0.369	0.217
15:10	384	0.171	369	0.380	0.139	0.041	350	0.887	0.370	0.191
15:15	373	0.177	370	0.077	0.135	0.053	385	0.302	0.342	0.162
15:20	351	0.196	360	0.233	0.151	0.054	356	0.127	0.402	0.188
15:25	339	0.197	355	0.430	0.176	0.025	351	0.314	0.366	0.159
15:30	342	0.194	361	0.494	0.155	0.046	369	0.722	0.363	0.160
System Level	4615	0.143	4461	7.091	0.138	0.412	4464	8.041	0.322	2.172

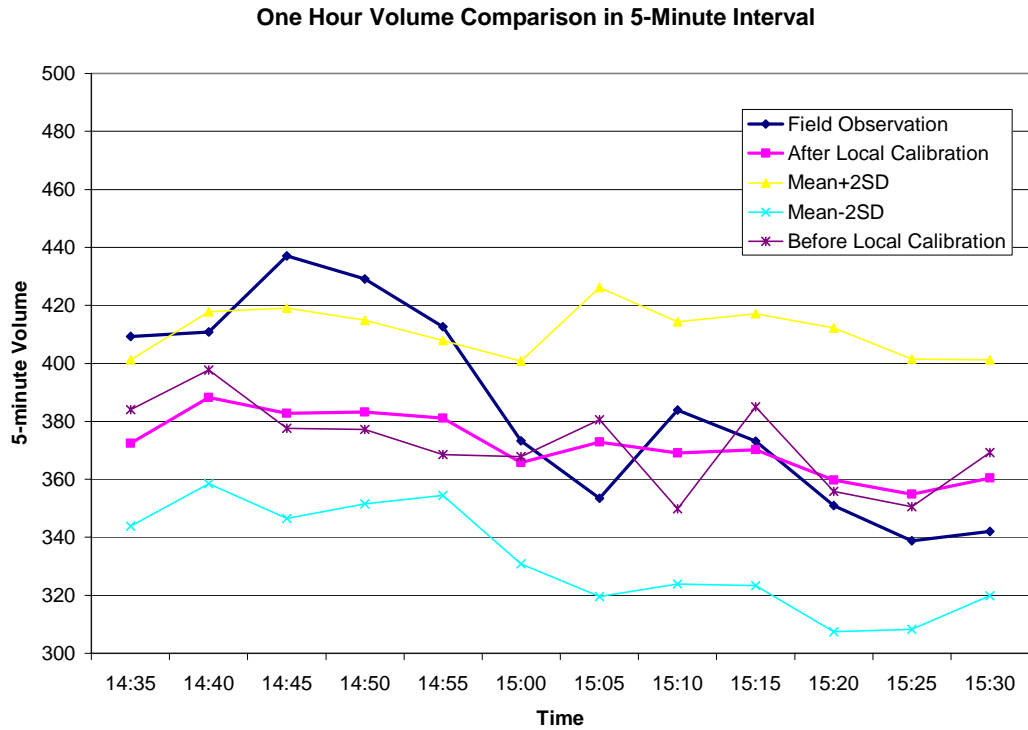


Figure 3-5 Five-minute Volume Comparison for Local Calibration

One Hour Occupancy Comparison in 5-Minute Interval

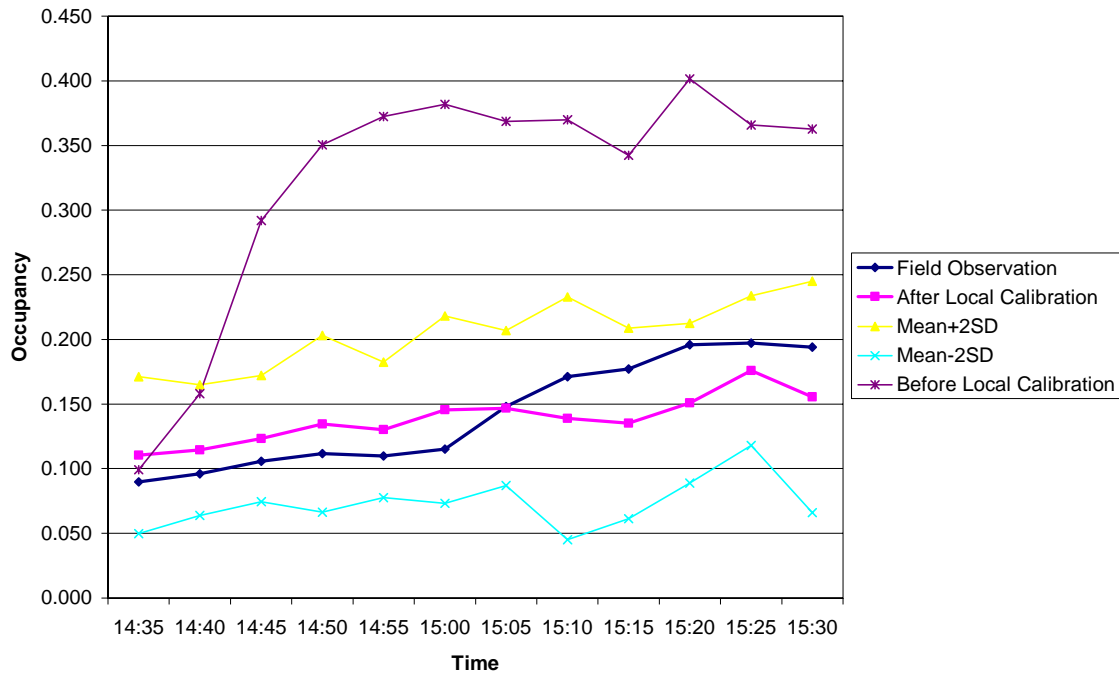


Figure 3-6 Five-minute Occupancy Comparison for Local Calibration

CHAPTER 4 CALIBRATION OF DEPARTURE TIME AND ROUTE (D-R) CHOICE PARAMETERS

4.1 Background of D-R Choice Calibration

The calibration of departure time and route (D-R) choice parameters is the third step in the proposed calibration framework (Figure 1-1). The D-R choices determine the time-dependent assignment matrix that maps the O-D demand onto the link and/or path flows. Provided that reliable parameters are already obtained for driving behavior both at general locations and critical sites, D-R choice parameters, together with O-D demand, are critical to obtain good baseline simulation results. Studies on D-R choice are mostly in the (dynamic) traffic assignment field (e.g., Arnott *et al* 1990, Szeto and Lo 2004), aiming at establishing the dynamic user equilibrium network flow pattern (e.g., Friezs *et al* 1993). A few number of studies discussed the effect of route choice in calibration, using MITSIM (Ben-Akiva *et al* 2004) and Paramics (Ma and (Ma and Abdulhai 2002), but few efforts were made to calibrate the D-R choices simultaneously.

In this chapter, we apply the genetic algorithm (GA) to simultaneously calibrate the joint departure time and route choice parameters. The rest of the chapter is organized as follows. The second section describes the GA-based calibration algorithm and what changes are made to Paramics to implement the D-R choice calibration procedure. In the third section, examples with a small hypothetical network as well as a real network from southern California are presented. The last section summarizes the findings.

4.2 Methodology

The D-R choice calibration applies a procedure slightly different from that of global and local parameters calibration. In the developed D-R choice calibration module, users can define the target vehicle types and origin-destination pairs to be calibrated using their own knowledge about the simulated network (shown in Figure 4-1). This feature of user definable calibration targets will be described in the following sections.

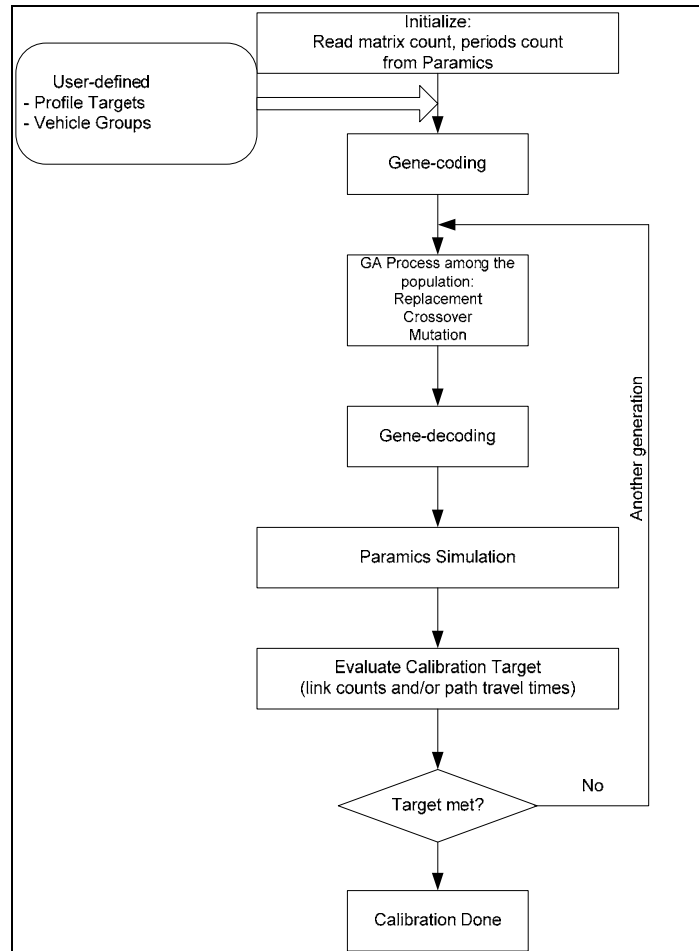


Figure 4-1 Using genetic algorithm to calibrate D-R choices for Paramics networks

4.2.1 Identification of Calibration Parameters

Various microsimulation models have different representations of traffic demand and users' route choice behavior. In Paramics, the following five categories of factors affect D-R choices:

Travel cost function. The travel cost function is a linear combination of travel time, travel distance and monetary toll.

Demand 'profile'. Demand profile divides the simulation horizon into user-definable intervals, and specifies the percentages of demand to be released during each interval. Changing the series of percentages leads to different patterns of departure time. The profile can be OD specific, or for certain origin zones. A detailed description of the demand profile is given in the appendix.

Vehicle type's (user group) perturbation factor. Changing a vehicle type's perturbation factor allows for that group of drivers to perceive travel cost along various routes at different levels so that their choices may differ from each other. The higher the perturbation factor, the higher their route choice variation will be.

Vehicle type's (user group) familiarity factor. Familiar drivers have extra knowledge about the network from their day-to-day driving experiences, and they can take back-road or side street whenever those alternatives offer a better route. Unfamiliar drivers will stick to *major* links in the Paramics context (Quadstone 2003b), observing the fact that unfamiliar drivers generally take preplanned routes and rarely divert unless required to do so. Besides, in dynamic feedback assignment, only familiar drivers will periodically update their route costs.

Assignment methods. Paramics allows for combinations of the following assignment methods: all-or-nothing, stochastic and dynamic assignment (Quadstone 2003b). All three methods are affected by vehicle types' perturbation factor and familiarity factor, e.g., a perturbation factor of zero implies that that vehicle type (user group) will only select the route with the 'least' cost.

Even though all the above parameters can be coded into a chromosome in a genetic algorithm and optimized, past studies (Ma and Abdulhai 2002) suggested optimizing only a sub set of these parameters. Our past experiences with several networks, including Interstate 15 in southern California (Gardes and Bloomberg 2003) and Interstate 580 in the San Francisco Bay area (Gardes *et al* 2003), show that the demand profile, drivers' perturbation and familiarity factors can considerably influence the resulting network flow pattern. In this chapter, therefore, we select these three factors, namely demand profile (departure time), drivers' perturbation and familiarity (route choice) factors, to be calibrated. It should be noted, however, the other two D-R choice parameters can be easily incorporated into the current calibration framework.

4.2.2 Gene-coding of Parameters

Gene-coding is the process that converts a set of parameters to be calibrated into a string of values mimicking a chromosome in biological evolution to perform the genetic operations, i.e., replacement, crossover and mutation. The detailed process is described in Appendix A1.

A vehicle type's perturbation and familiarity factors can apply similar gene-coding methods since they are both single-valued parameters with clearly defined lower and upper limits. However, the gene-coding of the demand profile needs special treatment.

A 'profile' in Paramics defines the vehicle release pattern for the whole simulation duration, spanning all periods (see Table 4-1). Tailored to the needs of genetic algorithm, the profile data structure must be mapped into a corresponding gene sequence in a chromosome.

Table 4-1 Definitions regarding departure time choice models in Paramics

Definition	Description and functionality in Paramics
Period	Optionally, the total simulation duration (horizon) can be divided into periods. Each period occupies one 'demands' file. The data structure of a period has the following components: start time (e.g., start 8:00:00), divisor (divisor 1 or 10, the demands or profile to be divided by this number), interval (interval 5, 10 or 15, in integer times of 5 minutes).
Demands	One 'demands' file defines all the traffic demand to be applied for the network. If only one period is defined, viz., the simulation horizon, only a file named 'demands' is applied. If there are X periods to be applied, there will be X demands file named successively as 'demands.1', 'demands.2', ..., 'demands.X', each one corresponds to one period.
Matrix in demands	If there are mode split and other factors that are defined as various vehicle types, demands can be split into matrices. For example, a certain proportion of drivers in a vehicle type can be categorized as familiar

	drivers, implying they can use dynamic feedback assignment.
Matrix	The file of matrix maps each OD pair to the appropriate profile specified in the profile file. There are exactly as many demand matrices as in demands file. The cross reference of the matrix is organized the same as in OD table, i.e., equal to $(Z * Z)$ where Z is the number of zones in the network.

*The file format of those four types are documented in more detail in PARAMICS-V5 Modeller manual, pp 91.

C++ pseudo code of data structure and an example of profile are shown in the box below. The example tells that profile 2 is defined for the demands starting from origin zone 4 (-1 means the OD pairs of zone 4 to any destination) will fluctuate according to those six values in the first period (5:00pm-6:00pm) and those three values in the second period (6:00pm-6:45pm). When decoding the genes representing profile 2, those nine values will be transformed back into Paramics to perform the simulation.

```

struct PROFILE{
    int ID;
    int origin;
    int destination;
    vector <PERIOD> periods;
}
struct period{
    ID;
    start time;
    subinterval length;
    percentage series;
}

/* Example */
Profile 2 origin 4 destination -1
Period 1 start 17:00:00 duration 60 min interval 10
15 25 20 10 15 15
Period 2 start 18:00:00 duration 45 min interval 15
30 40 30

```

One may notice that the periods in a profile can have different subinterval lengths. This provides the flexibility for users to fine tune network demand in different time periods. For example, if the users know that during the simulation horizon the demand fluctuation is not drastic, she may take a half-hour interval; but if the demand does fluctuate considerably during a simulation period, she may take an interval length as fine as five minutes.

4.2.3 Calibration Targets

The calibration target, or the so-called fitness function in genetic algorithm, characterizes the distance between the simulation results and the aggregate measurements observed from real world traffic. The most commonly used aggregate measurements are link counts from various network locations, and trip travel times or average travel speeds along certain paths. Other studies use various fitness functions, such as mean absolute errors (Ma and Abdulhai 2002), generalized least square (Ben-Akiva *et al* 2004), sum of relative errors (Lee *et al* 2001), etc. Herein a statistic called GEH proposed by British engineers (Highway Agency 1996) is utilized to measure the distance, and the fitness value is calculated as:

$$Fitness = W_C \sum_i GEH^c_i + W_T \sum_j GEH^T_j$$

where W_C and W_T are the weights of link counts and path travel times, and GEH^c_i and GEH^T_j are GEH values for link count location i and path j , respectively.

The GEH is calculated as:

$$GEH = \sqrt{\frac{(V_p - V_m)^2}{(V_p + V_m)/2}}$$

where V_p = value predicted by the model and V_m = value measured in the field. The perfect match will result in a zero *Fitness* value.

Since path travel times capture congestion more accurately than traffic counts (the same traffic count can be obtained from both free-flow and congested traffic conditions), we suggest applying a higher weight to the GEH of path travel times in the fitness function.

4.2.4 Improve Calibration Efficiency and Flexibility through Gene-coding

Genetic algorithm based calibration involves an iterative process that requires numerous simulation runs, while microscopic simulation runs are usually time-consuming and thus take the greatest portion of time in the calibration process. Different from global and local parameter calibration where one can perform the calibration tasks on a sub network, D-R choice calibration has to run the simulation over the entire network for each iteration. Since a single simulation run can take minutes or more, depending on the size of the network and its traffic load, the more simulation runs required by the calibration algorithm, the less efficient the algorithm becomes. We therefore exploited the genetic algorithm and special features of Paramics to increase the efficiency and flexibility of our calibration procedure. The following techniques are applied in the D-R choice calibration.

User defined profile numbers and vehicle types to be calibrated: As described in the previous section, it is not necessary to calibrate the demand profile for each OD pair in fine detail. Rather it is those critical traffic analysis zones (TAZ) or OD pairs affecting the simulation outcome most are subject to calibration. A similar argument applies to the perturbation and familiarity factors of certain vehicle types. For instance, those types that account for a greater proportion in the vehicle composition would be calibrated with finer detail. It is desirable that the calibration tool is flexible enough to make use of users' knowledge of the network when selecting the TAZs or OD pairs for departure time calibration and the vehicle types for perturbation and familiarity factor calibration. Sometime the simulation network consists of only a stretch of freeway where few route alternatives exist, then departure time choice will be the only effectively adjustable factors that can be calibrated to provide a better simulation model in terms of matching aggregate measures.

User defined calibration precision: The parameters in departure time and route choice calibration are all percentages. It is not necessary to specify a percentage of demand with decimal points if the demand for a certain origin zone is only counted in hundreds; therefore, specifying an appropriate precision for the percentage values will reduce the search space vastly.

For example, a precision of 1 percentage points for a single-period demand profile of a 15-minute interval in a one-hour simulation will have a search space of $100^3 = 10^6$ feasible solutions (they must add up to 100, so only three degrees of freedom are left), while a precision of 4 will reduce that space to only $25^3 = 15,625$ feasible solutions, which is much smaller a space, which turns out to adequate in our tested examples.

The user defined calibration variability with adjustable length of chromosomes (select important OD pairs for departure time choice and vehicle type's perturbation and familiarity factors) and adjustable calibration precision can take advantage of the users' knowledge of the network to speed up the computational efficiency, which will be further discussed in the numerical examples.

Real valued coding vs. binary coding: As discussed in Chapter 2, most genetic algorithm based applications apply binary coding method, i.e., the values of genes in the chromosome are coded in a binary string for genetic operations. Also following the same argument in previous chapters, real valued coding is more promising in terms of computational efficiency. In the developed tool, therefore, real valued instead of binary gene-coding is applied.

4.2.5 Algorithm Implementation

The algorithm's work flow is shown in Figure 4-1. First, it requires the input of the users' knowledge about the network, namely selection of target OD pairs for demand profile calibration and vehicle groups for perturbation and familiarity calibration in our D-R choice calibration context. Then the selected parameters are coded into chromosomes ('gene-coding' and 'GA process' in Figure 4-1) through the GA operations, *viz.* replacement, crossover and mutation, to form a pool of feasible solutions, or termed as the population of one generation in genetic algorithm. Each chromosome is then decoded back into the parameter values readable to Paramics and one simulation run will be performed. The simulation outcome is evaluated through the fitness value function to examine if the calibration target is met for this generation, and the process continues until the fitness value satisfies the stopping criteria or the maximum number of iterations is reached.

The genetic algorithm module is implemented as an independent component outside of Paramics, so as to ensure that GA operators are transplantable between global parameter calibration, local calibration and D-R choice calibration. As a matter of fact, the same GA engine has been applied for all three calibration steps: global parameter, local parameter and D-R choice parameter calibration. The application programming interface (API) functions provided by Paramics allows for retrieving the traffic measures and calculating fitness values within the simulation environment. A more detailed technical discussion of how to use both API and Microsoft MFC to build a graphic user interface (GUI) is given in Chapter 5. Another Paramics module, the Processor, allows running the simulation in batch-mode with no need to show the vehicles' physical movements, which saves computational resources. Therefore it is embedded in the D-R choice calibration tool to perform the simulation runs.

4.3 Working Examples

In this section, we present the application of the developed genetic algorithm based D-R choice calibration tool for two networks. The first is a small hypothetical network and the second is a large real network.

4.3.1 Case Study 1: A Small Network

4.3.1.1 Network description

The small network comes with the Paramics software package, titled as 'Estimator Stochastic 2'. The network layout is shown in Figure 4-2.

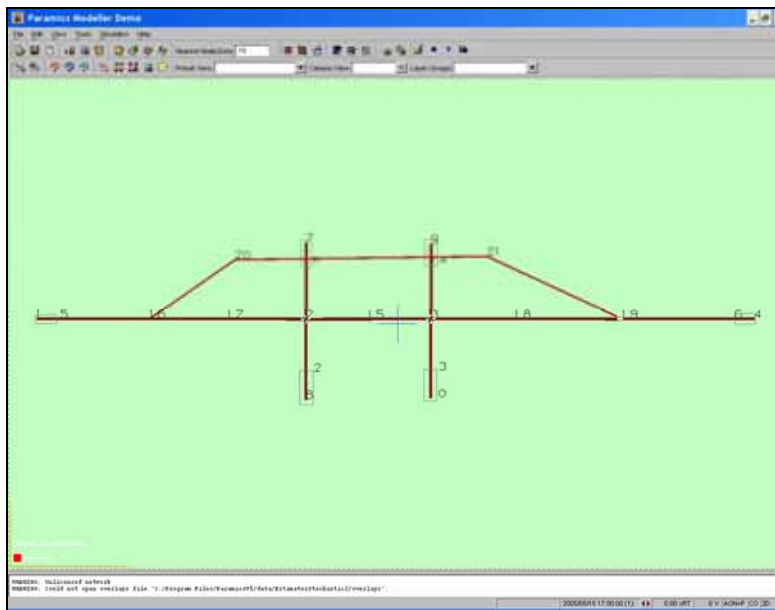


Figure 4-2 Sample network for testing departure time and route choice calibration tools

The network demand structure is clear. One primary OD pair represents the east-west traffic and four other zones generate and receive the side traffic. The major feature is that the bypass provides an alternative route for the arterial street connecting the primary OD pair. The link flow observations are on the bypass link (20, 21) for both directions, with a level of 232 vehicle/hour on link (20, 21) and 266 vehicle/hour on link (21, 20). The fitness value is based only on the simulated link flow on both directions.

Parameters to be calibrated are selected through examining the network layout and vehicle fleet composition. It is obvious that the main OD pair generating the west-east traffic is zone 1 and zone 4; therefore, we select both zones for demand profile calibration. Altogether 15 vehicle types are defined; three types that rank the largest three percentages, namely type 1(car), 3(car) and 12(larger goods vehicles, or LGV), are selected for route choice calibration.

4.3.1.2 Genetic Algorithm Parameters

As suggested in GA literature (Goldberg 1989), the population size is set to be 20, and we set the maximum iterations to be 150. The mutation rate is set to be 0.01, and the precision for both demand profile and perturbation and familiarity factors are set to be 2, implying a search space of $50^4 \times 50^4 \times 50^3 \times 50^3 = 6.25 \times 10^{16}$, while our total simulation runs are 3,000 (population size \times number of generations).

The total 150 generation (3,000 simulation runs) takes about nine hours to finish on a Pentium IV, 3G CPU machine with 1 Gigabyte RAM. Figure 4-3 shows the convergence performance of using the GA-based tool to calibrate the departure time and route choice in the sample network. After 20 generations, the fitness value has dropped to around zero, and becomes stable after about 60 generations or so. The calibrated model provides a flow match of 231 vs. 232 on link (20, 21), and 261 vs. 266 on link (21, 20). As a zero fitness value means a perfect match between observed link counts and simulation results, Figure 4-3 indicates that the tool is able to calibrate the departure time and route choice parameters efficiently, with the users' interactive input. Compared to the long process of trial and error, The D-R choice calibration tool greatly reduces the calibration effort with good results.

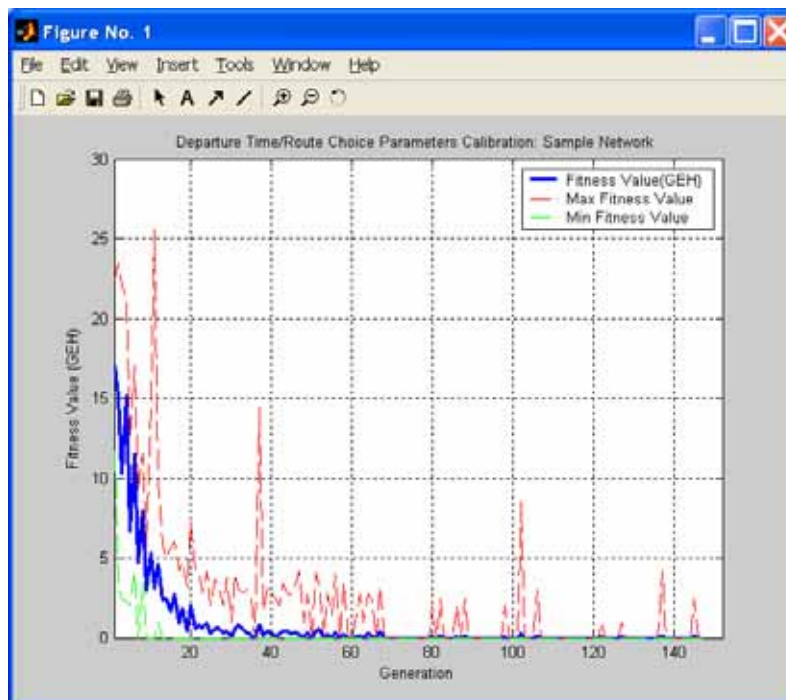


Figure 4-3 GA based D-R choice calibration process for the sample network

4.3.2 Case study 2: The Interstate 15 Network

4.3.2.1 The network and previous calibration efforts

The second network is a real network from southern California. A portion of the Interstate 15 Devore network was built to analyze the traffic operations around a construction work zone (CWZ) located on I-15 between I-10 and I-215 in the San Bernardino County, CA, near the City

of Devore[3]. Because microsimulation has the capability of modeling traffic flow in networks at a fine level of detail, Paramics was used to investigate the impact of the CWZ and the corresponding traffic management plans, such as truck rerouting from the CWZ. The traffic analysis was divided into two phases, level 1 and level 2 traffic modeling. The level 1 network, built to study the work zone traffic impact on the I-15 corridor, modeled a 12-mile stretch of I-15 (from the Kenwood interchange to the Foothill interchange, Figure 4-4) and several parallel arterial streets. It is this network that we shall calibrate using the proposed methodology.

The network consists of 1,600 plus links connecting 32 zones. The study period is a three-hour block. The driving behavior model parameters for the I-15 network have been adjusted based on previous experiences (Gardes and Bloomberg 2003), completing steps 1, 2, and 3 as in Figure 1-1. The Southern California Association of Governments (SCAG) develops and maintains a travel demand model for the entire LA basin (GIS/Trans 1996). The traffic analysis zones used in this study were extracted from the SCAG model. However, the demand estimated from the SCAG planning model is too rough to be used in the Paramics simulation, because the overall difference between the field measurements and the Paramics modeled link counts derived directly from using the SCAG O-D table without further adjustment was as high as 20%, and at some important road sections such as freeway interchanges and major on/off ramps the errors are even higher than 100% percent, which was not acceptable (Gardes and Bloomberg 2003). Therefore, a Paramics module, OD Estimator (Quadstone 2003a), was used to refine the trip table obtained from the SCAG planning model. With the trip table from the SCAG planning model as a seed OD, the estimation process in OD Estimator stabilized at an average GEH of 4.34 (Gardes and Bloomberg 2003), which is considered acceptable for further calibration efforts, according to some microscopic simulation modeling guidelines (Dowling, Holland and Huang 2002).

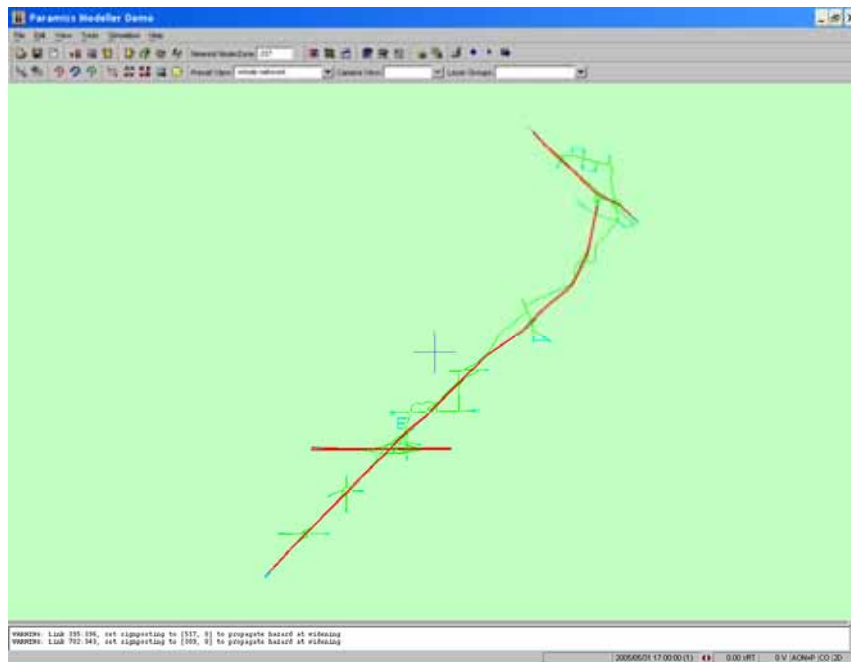


Figure 4-4 Paramics network for Interstate 15 Devore reconstruction project

4.3.2.2 D-R choice calibration parameters and GA parameters

Under the demand obtained from a previous study, calibration is carried out for an hour of the afternoon peak (5pm-6pm). Observing that I-15 and I-215 mainlines are the major demand input sources, their departure time choices are subject to calibration. The traffic in this study has two vehicle types, cars and trucks with 90% and 10%, respectively. The perturbation and familiarity factors for both types of vehicles will be calibrated.

Table 4-2 D-R Choice Calibration Parameters and GA Control Parameters for the I-15 Network

Calibration Parameters		Genetic Algorithm Parameters	
OD pairs for adjustment of departure time choice (demand profile)	OD 7-10 (I-15 southbound) OD 9-6 (I-15 northbound) Zone 15 – All (I-215 to all) Zone 25 – All (I-210WB to all) Zone 29 – All (I-210EB to all)	Population size	30
Profile interval length	10 minutes (6 percentage values for each profile)	Maximum number of generations	80
Drivers' perturbation factor	All vehicles: type 1 (cars) and type 2 (trucks)	Mutation rate	0.01
Drivers' familiarity factor	All vehicles: type 1 (cars) and type 2 (trucks)		
Calibration precision	Demand profile: 2 Drivers' characteristics: 5		

The aggregate measurements available in the network include both link count and trip travel time. Altogether 47 locations of link counts were collected, covering most interchanges, ramps along I-15 and a few arterial street locations, and the trip travel times on I-15 in both directions sampled in 20-minute intervals. All these measurements are taken into account in the fitness function, with the weight on trip travel times as 0.3, and 0.7 on link count, reflecting their relative descriptive power of traffic conditions in the network.

A preliminary calibration run shows that each simulation run takes about four to five minutes, which is the computational bottleneck in the calibration process. Therefore, techniques to increase calibration efficiency, such as picking an acceptable calibration precision, real valued gene-coding and selection of key OD pairs for departure time adjustment, are investigated to increase the efficiency of the algorithm. The GA control parameters and the D-R choice parameters are listed in Table 1.

4.3.2.3 Calibration results

Figure 4-5 shows the convergence pattern of the GA based D-R choice calibration for the I-15 network. It can be seen that after less than five generations, the generation-average fitness value has dropped to below the fitness value when default parameters were used (uniform demand profile, and five percent of perturbation and fifty percent of familiar drivers for both vehicle types). After 30 generations, the average fitness value remains stable and close to the generation wide minimum value.

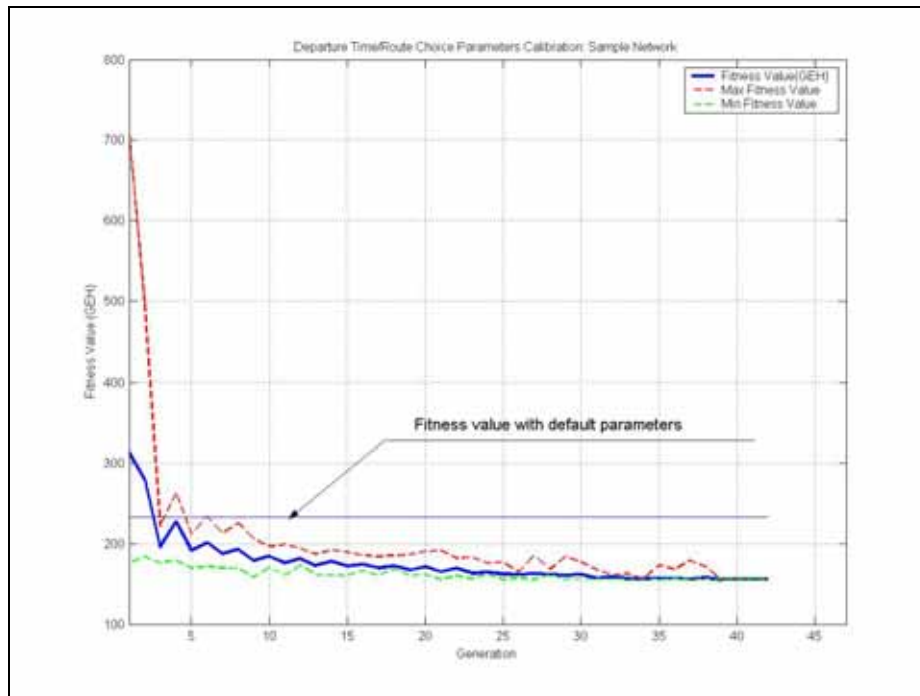


Figure 4-5 GA based D-R choice calibration process for I-15 network

Figures 4-6 and 4-7 show the calibration results in terms of link counts and trip travel times. Figure 4-6 shows that the simulated link counts for three facility types, freeway mainline, on/off ramps and local streets, are generally improved with the calibrated D-R choice parameters. Figure 4-7 shows the observed and simulated link travel times with and without calibration. It is clearly seen that the simulated link travel times after calibration resembles the observed ones much closer than before calibration.

It is noted at some locations the calibration did not help to bring the simulated link counts closer to observed link counts at these locations. Several factors can cause this: 1) OD demand for certain OD pairs may be off, 2) only a part of the OD pairs was selected for D-R choice calibration, and 3) the algorithm stuck at a local minimum. Nevertheless, the calibrated model was able to reproduce the baseline traffic conditions better than without calibration.

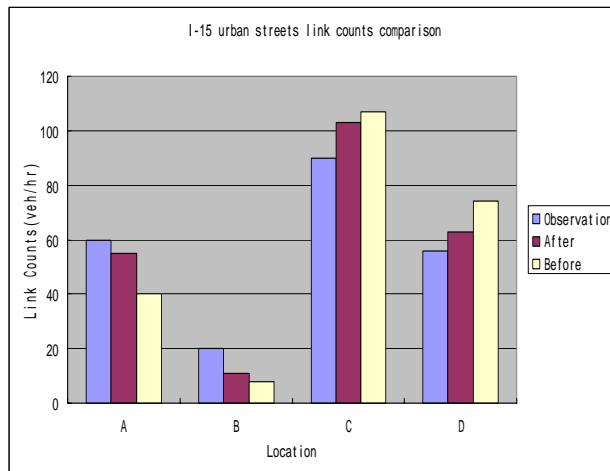
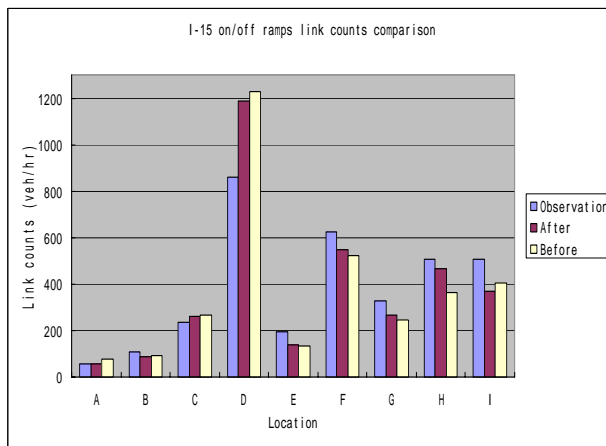
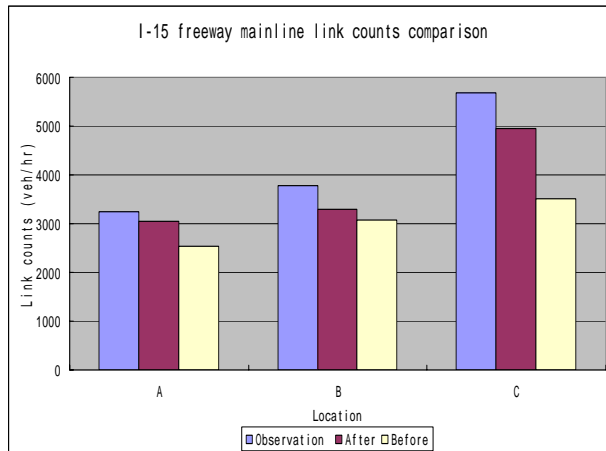


Figure 4-6 Link counts comparison before and after D-R choice calibration: I-15 network

The calibration takes about 60 hours to complete on a Pentium IV 2.2G machine (RAM 1G), which is still quite time consuming. Nevertheless, it is much shorter than the previous trial-and-

error calibration effort on the same work, which took about a month and obtained poorer calibration results. Although further improvements can be made to the D-R choice calibration tool to reduce its running time, our preliminary tests indicate that it is a promising tool for calibrating D-R choice parameters.

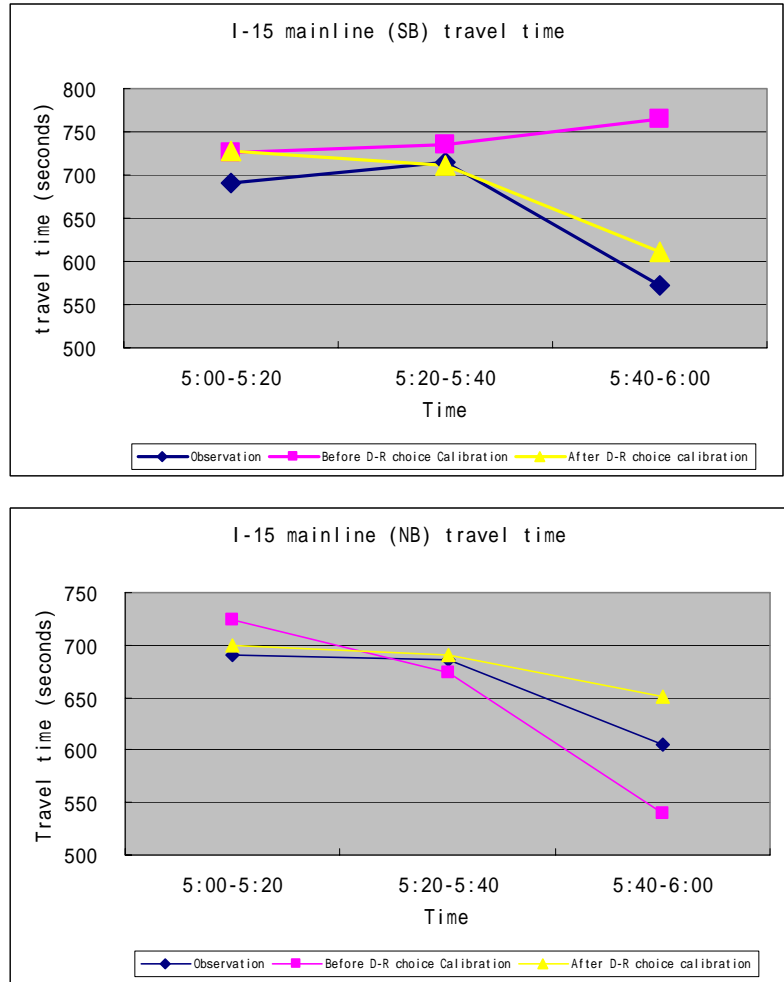


Figure 4-7 Comparison of trip travel time before and after D-R choice calibration: I-15 network

4.4 Summary

This chapter developed a genetic algorithm based calibration module for calibrating the departure time and route choice parameters in Paramics. This module allows users to select, among other things, the scope and precision of calibration, based on their knowledge of the network and its traffic conditions. Further algorithmic techniques were also explored to improve the computational efficiency of the calibration algorithm without sacrificing the accuracy in practical applications. The two case studies show that developed tool can help speed up the calibration process and improve the accuracy of the calibrated parameters.

Since network traffic conditions are also highly related to OD demand, it is anticipated that by performing D-R choice calibration and OD estimation iteratively, the calibration results can be

further improved. The procedure for coupling D-R choice calibration and OD estimation will be discussed in our final project report.

CHAPTER 5 CALIBRATION ASSISTANCE TOOLS

Calibration stage is so important to the reliability of microsimulation results that most users spend at least one third or even more of their time budget for this stage (MnDOT 2003). Besides the major calibration tasks discussed in the previous chapters, any method that reduces the model preparation work is desirable. In this chapter we present two tools in assisting the model preparation and calibration process.

5.1 Background

High fidelity traffic simulation software like Paramics provides a wealth of data, including travel time, delay, route, flow, headway, control, emission, fuel consumption statistics and so forth that cover nearly every aspect of the simulated system. However, the extraction of useful statistics from these data often requires an intimate knowledge of the software that many simulation users may not have the time to acquire. Microsimulation software usually has a data collation module for post processing the data but it does not monitor the status of simulation runs and extract useful run-time statistics.

Some efforts have been devoted to facilitate the data collation in post processing the microsimulation output data. For example, Caltrans released a set of tool, called Paramics Report Analyzer (Smith 2003), to collate the statistics at user-defined link level or path level. The tool can let the analyst define link sets and then extract flow, speed, delay and other information from Paramics Analyzer's output. The statistics are stored and processed in Microsoft EXCEL that eases the presentation and analysis.

However, there are still gaps between the microsimulation software output and analysts' needs. For example, when a network is coded, the user needs to check whether there is error in the code. For example, warning messages should be given when an origin zone and a destinations zone are not connected by even one path. There are few tools available to help users to monitor the status of simulation runs. For example, users are concern whether the demands have been released into the network and whether they have been blocked in the midway instead of arriving at their destination.

In recognition of the above gaps, two diagnostics tools have been developed to help users to check the network connectivity and the status of simulation run. The tools are embedded in Paramics Modeller. The remainder of this chapter will describe their functionalities and the development techniques.

5.2 Calibration/Diagnostics Tool Kit

Two tools, Network Connectivity Check (NCC) tool and Path Flow Diagnostics (PFD) tool, are developed and embedded inside the "calibration/diagnostics tool kit" (displayed in the Paramics Modeller's 'Tool' menu).

The NCC tool is mainly designed to check the coding errors related to the links. This is in addition to the default functions in Paramics in the “View->Link Audit” menu sub-items. The Link /Audit can distinguish links in various colors according to their attributes including major/minor, highway/urban, categories, and etc. However, it cannot examine whether two zones are connected by an available path. The only way to carry out this check is to load some pseudo demand onto the network and watch the Reporter window outputs, which may contain other warning messages at the network coding stage. Therefore, the NCC tool is a useful tool that assist the users to check the network connectivity during the network coding stage, especially when the network size is big and the number of zones is large.

Path Flow Diagnostics (PFD) tool assists the users to analyze how the demand between an origin and a destination is distributed over the network. It helps the users in the calibration of the route choice functions. The usual way of checking the network flow is using “Measurements” to specify the output such as link flows, trips, routes utilization and then use Paramics Analyzer or other tools for post-processing of the output. As expected, the tedious process may not only lower the productivity in a simulation project, but may eventually affect the reliability and accuracy of the results. Therefore, an interactive analysis tool during the simulation runs can provide users with direct information of the demand distribution and simulation status, and help users to decide any corrective action to take. The PFD tool is designed to fulfill the above needs.

The PFD tool collects the information of vehicle paths for the vehicles that have arrived at their destinations. During the simulation run, the information of path flows will be shown in the dialog box. When users select any OD pair of interest, the paths that have been used, the flow and percentage of flow in each path will be summarized and displayed. When any of the paths is selected, the Paramics Modeller will display the path with various colors. By doing this, the users can have a big picture of how the network performance is and how a local congestion affects the path choice of vehicles.

5.3 Tool Functionalities

The calibration/diagnostics tool kit is activated via a menu item “Tool->Error Checking” in the Paramics Modeller. When clicked, the menu item will call a common Windows dialog as shown below which contains all the developed diagnostics tools. The dialog box is always on top of the screen.

5.3.1 Network Connectivity Check Tool

The NCC tool checks the availability of a path connecting any two zones in a Paramics network. The main dialog box, named Error Checking System, is shown in Figure 5-1.

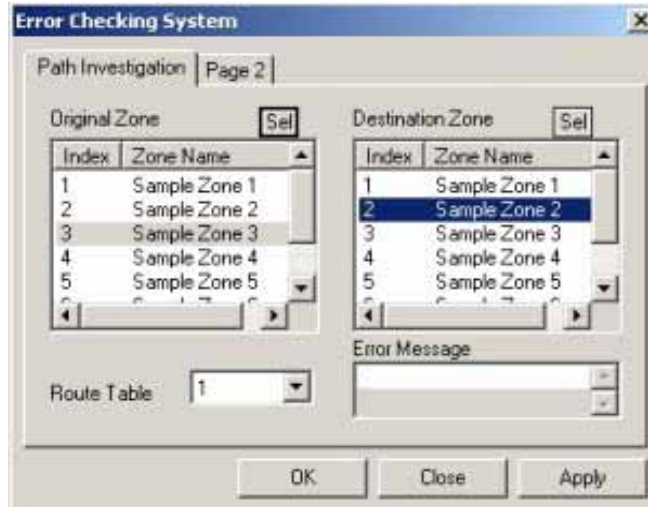


Figure 5-1 Network Connectivity Check Tool

Select OD pairs

The selection of any two zones of interest can be done in two ways.

First, a user can select the OD zones from the lists provided. When loading the NCC tool, all the zones with their names have been read from the Paramics Network into the “Origin zone” and “Destination Zone” lists (see Figure 5-1). The user can select an origin zone and click the “Sel” button. He/she may then select a destination zone in the “Destination Zone” list and click the “Sel” button. This will confirm the OD pair of interest.

The second method is to select a zone in the Modeller screen and then click “Sel” button as the corresponding origin or destination.

Either way will make the origin and destination appear as selected in the list box.

Connectivity Checking with Shortest Path

Once the “Apply” button is clicked, the shortest path from the origin zone to the destination zone is highlighted in white. The two zones are highlighted too. Figure 5-2 illustrates the shortest path from zone 3 to zone 2.

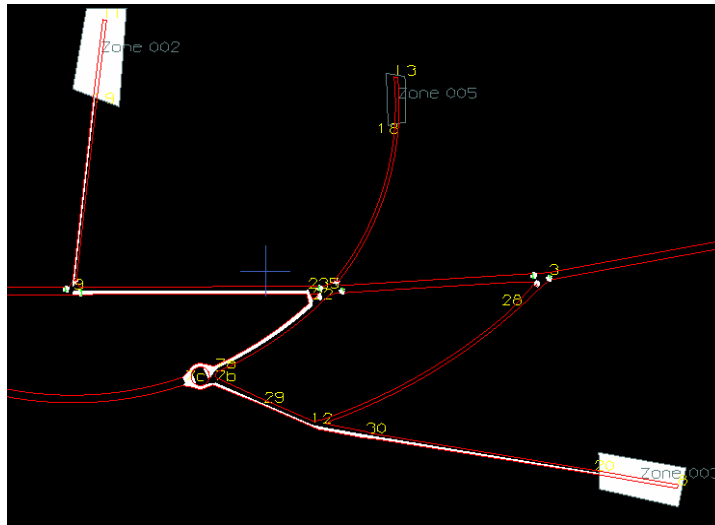


Figure 5-2 Highlighted Shortest Path from Zone 3 to Zone 2

Under some circumstances, a zone cannot be reached because the link associated with that zone is one-way in the opposite direction. Figure 3 shows such an example. The shortest path from zone 6 to zone 3 is highlighted in white. However, the link 32:33 and link 33:31 are one directional links from nodes 32 to 33, and nodes 33 to 31, respectively. Thus their opposing links, 33:32 and 31:33, are not available for travel in the reverse direction. Therefore, the barred link 31:33 and 33:32 are highlighted in yellow, while other available links are highlighted in white. Error messages about the barred links are printed in the error message box.

Clicking the “Close” button can turn off the highlighting effect of the links and zones in the shortest path. The entire highlight color will be removed and the property sheet is closed. If one wants to keep the links and zones highlighted, one just need to click the OK button. The property sheet is closed but the highlights on the associated links and zones are still shown. To turn off the highlights, one can open the property sheet again and click the Close button.

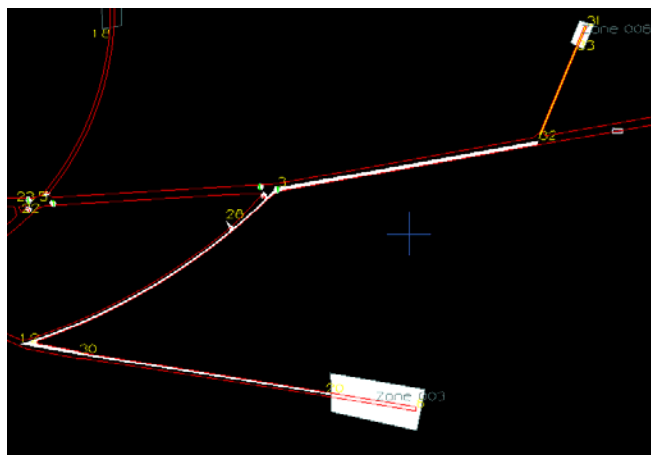


Figure 5-3 the Highlighted Shortest Path from Zone 6 to Zone 3 (with barred link painted in yellow)

5.3.2 Path Flow Diagnostics Tool

The PFD tool displays the distribution of flow on different paths between one origin and one destination in a real time manner as the simulation is running. In the Error Checking System dialog box, the PFD tool is on the tab titled “PF Diagnostics”.

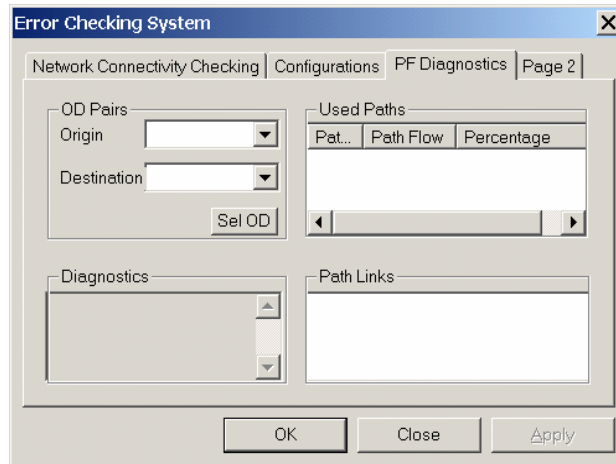


Figure 5-4 Path Flow Diagnostics Tool

Select OD pairs

In the PFD tool, the selection an origin zone and a destination zone can be through the “Origin” and “Destination” dropdown lists. When loading the PFD tools, all the zones in the Paramics network have been read into the “Origin” and “Destination” lists. Once a user has selected an origin zone and a destination zone and click the “Sel” button, the OD pair of interest is confirmed.

Used Paths

When one OD pair has been selected, the used paths connecting the OD pair will be shown, with their corresponding path numbers, number of completed trips at the time of selection, and percentages of all the completed trips.

By clicking any item in the “Used Paths” list, the selected path and the related links that make up the path, will be shown on the Modeller screen.

Diagnostics

When one OD pair is selected, the following diagnostics information will be displayed: the target demand between the OD zones that are supposed to be released, the completed trips at the time of activating the PFD tool (when the simulation is running), and the link list of the selected path.

Path Links

The list of links that make up the current path selected under the “Used Paths” will be shown, as in Figure 5-5.

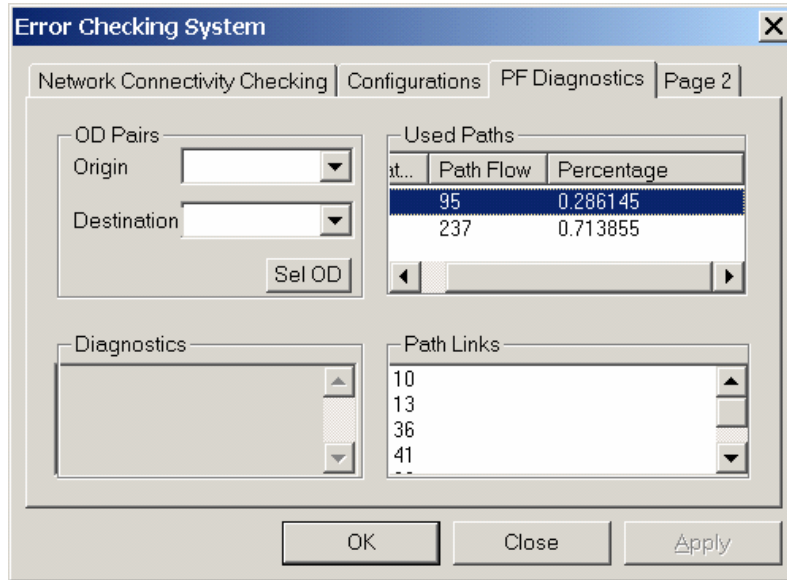


Figure 5-5 Path Information and Diagnostics

5.4 Technical Notes on Tool Kit Development

The calibration/diagnostic tool kit has been developed in the integrated development environment of Microsoft Visual Studio.net. Since the project is believed to be the first to use Microsoft Foundation Class (MFC) to integrate Paramics API with Windows dialogue box applications, the technical details are documented in this section to help other developers that need to adopt the same approach.

5.4.1 Tool Kit Architecture

Paramics Programmer provides four types of API functions, prefixed by `qpg`, `qps`, `qpo` and `qpx` (Quadstone 2003). The `qpo` functions are override API functions and the `qpx` functions are extension API functions. Override API functions allow users to define their own logics so as to replace the default ones that come with Paramics. On the other hand, extension API functions allow users to add more features to the existing simulation functions. Once an extension API function is called, the customized logic developed by the user will execute after the default logic has executed. These two types of API functions are sometimes called “API plug-ins”. They cannot be called directly by other API functions. The other two types of API functions, with `qpg` and `qps` prefixes, are used to get or set data values inside Paramics. They cannot be overridden or extended, but they can be called by any other API functions.

Paramics provides a template for each API function. Users are able to modify the templates into customized API functions when implement their own traffic models.

However, they will face difficulty in creating customized user interfaces using the MFC because the template shipped with Paramics is a Win32 Dynamic-Link Library (DLL) project, in which a MFC object cannot be added. Two different methods can overcome this difficulty: (1) by changing the API template (and function) to a MFC DLL project; or (2) by creating an external MFC DLL project and calling that MFC DLL project from the Paramics API function. Both are capable of activating the MFC framework so that all the Windows features (such as those available in a dialog box) can be introduced. In this project, the second alternative is chosen because of its simplicity and efficiency, that is, parallel development in both stand-alone Windows MFC development and Paramics API function are possible.

The architecture of the GUI-Based Paramics API is as follows. First, two terms need to be introduced in order to clearly present the working mechanism. The term “base DLL” refers to the binary output of the Paramics API function, and “MFC DLL” refers to the binary output of the user defined Windows MFC DLL project. When a network is loaded in the Paramics Modeller, the base DLL is also loaded. The customized menu item, “Error Checking”, is created by the base DLL (through the Paramics API function) and merged into the Paramics main menu system. At the same time, the user should manually activate the MFC DLL project to create a MFC DLL “handler” that corresponds with the Error Checking menu item. This handler serves as a bridge between the user created Error Checking menu item in the Paramics Modeller and the external MFC DLL object. Whenever the Error Checking menu item in the Paramics Modeller is clicked, the corresponding menu handler will be called. The menu handler then creates a separate user interface (UI) thread which is the Error Checking System dialogue box. This thread remains active as long as the dialogue box is opened. If the dialogue box is closed, the UI thread will be killed. The object (such as the dialogue box) created by the MFC DLL handler may contain any feature of a Windows program.

The base DLL and MFC DLL serve as functions that create a bridge between the Paramics Modeller and the Windows MFC environment. Once the bridge has been created, the Paramics Modeller is able to communicate directly with the Windows dialogue box.

5.4.2 Took Kit Implementation

In order to implement the abovementioned architecture, at least two Microsoft Visual Studio.NET projects are to be coded. The first one is called “modeler” project, originally shipped with Paramics as “base” project, while the other one is called “MFCBase” project, as defined by the authors. The modeler project generates the base DLL, while the MFCBase project generates the MFC DLL.

The functions of modeler project are to add menu entries to the Paramics Modeler, and call the proper menu handlers if any of the entries is clicked. To do this, the Paramics API template `qpx_NET_postOpen()` is extended to add the customized menu entries. The `qpx_GUI_tool()` template is also extended to respond to the menu selection. The menu entry, “Error Checking”, is added under the Tools menu in Paramics Modeller. If

this entry is clicked, its menu handler, `Start()`, will be called. This handler is earlier exported from the “MFCBase” project. The handle “`Start()`” activates a user interface (UI) thread. A handler can open at most one thread at any time. When the UI thread is being initialized, a dialogue box is created and customized items are added into the dialogue box. The UI thread keeps running until the dialogue box is closed.

Some technical obstacles were encountered but they have been overcome. For example, when text messages are to be printed on the Paramics message window, they could not be printed in time when the simulation was running. It was noticed that the message could only be printed out if the cursor hovers over the Paramics Modeller window. Therefore, the windows focus will always be reset to Modeler once some messages need to be displayed.

Another solution is adopted when highlighting the shortest path in the NCC tool. It is found that the shortest path could not be highlighted until an event forced the Paramics graphical window to refresh itself. For example, the path cannot be displayed until the window is moved or resized. To overcome this problem, the entire window was set to move left and then right by a tiny displacement (one pixel).

CHAPTER 6 SUMMARY AND FUTURE WORK

The work completed in the first year of this project complies with the proposed project timelines. An up-to-date review report summarizes the success stories of microscopic traffic simulation applications, and the state of the art in calibrating microsimulation models. A set of guidelines are presented for project planning/scoping, error checking and data collection. An analysis of the documented experiences further identified the urgent need of a systematic calibration framework.

Majority of the research efforts have been put into developing a set of calibration tools that assist users in the semi-automated calibration process. The research work in the first year covers three major steps in the proposed calibration procedure: global driving behavior model parameters, site specific adjustments for critical locations, and demand releasing pattern and users' route choice parameters. Genetic algorithm is used extensively in all the three steps. In addition, a set of calibration/diagnostics tools have been developed to assist users in error checking and calibration.

Continuing from the work done as reported here, the tasks for the next year are mainly investigating the interaction between users' departure time and route choice, and demand estimation. The traffic control in the simulation model will also be investigated and optimized to smooth the traffic flow over the network. After both parts have been accomplished, a calibrated simulation model is envisioned to have eliminated all possible errors, adjusted all possible aspects on both traffic demand and supply sides.

To consolidate the effectiveness of the developed calibration procedure and demonstrate the use of the tools, the research team proposes to be involved in ongoing simulation projects to assist their calibration efforts. A workshop meeting with Paramics users within Caltrans will be organized to demonstrate the calibration procedure and tools, as well as the real networks that have been calibration with the set procedure. It is anticipated that the project will help the users understand the proper calibration procedure and increase the efficiency of their calibration works.

APPENDIX GENETIC ALGORITHM TERMS AND OPERATING MECHANISMS

Gene Coding

The parameters to be optimized will be encoded before GA operation is applied, because GA works with an encoded parameter set rather than parameters themselves. Figure A-1 shows an example of encoding and decoding process. The coding method has a major impact on the GA's performance and may cause different accuracy and computation time(Pham 2000).

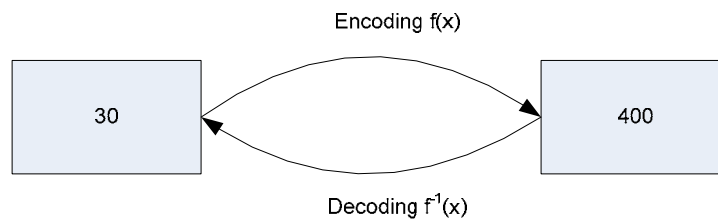


Figure A-1 GA Coding Illustration

Two popular coding methods have been reported. One is to encode values to binary numbers(Goldberg 1989; Kim 2004) and the other one is to transform it to a vector of unsigned integer digits (real-number coding)(Cheu 1998). Wright(Wright 1991) thoroughly compares the two coding methods and recommends the latter one. He summarizes its strengths as follows.

Increased efficiency: bit strings do not need to be converted to real numbers for every function evaluation;

Increased precision: since a real-number representation is used, there is no loss of precision due to the binary representation; and

Greater freedom to use different mutation and crossover techniques based on the real representation.

Therefore, the latter coding method is used in this project.

- Another issue of eliminating biases in gene coding need to be addressed. For example, assume a parameter Z ranges from 10 through 50, inclusively. Two digits are sufficient to cover the parameter space. The problem is values between 51 and 99 are invalid. Two approaches are available to solve this problem. One is to add condition

checking during the GA operations to guarantee that the each digit will always fall into valid space. It is straightforward but it is biased because some efforts to remove invalid GA operation results are involved.

- Alternatively, a scale method is used in this project. Before the scale method is introduced, the number of decimal digits should be determined to represent a parameter's encoded value. The length is fixed for a parameter and varies among parameters. Once the length, n , is determined, one can use the encoding function shown below to adjust actual parameter values so that they fit in the range of $[0, 10^n - 1]$.

$$f(x_j) = \frac{x_j - a_j}{b_j - a_j} \times (10^{n_j} - 1)$$

where:

x_j : natural value for the parameter j ;

a_j : lower boundary for the range of the parameter j ;

b_j : upper boundary for the range of parameter j ;

n_j : required length to represent encoded value of a parameter j .

The required length, n , is determined by the following formula:

$$n_j = \lg\left(\frac{b_j - a_j}{10^{c_j}} + 9\right)$$

where:

c_j : expected precision for the parameter j (number of places after a decimal point).

Similarly, to decode an encoded parameter value, a decoding function is applied.

$$f^{-1}(x_j) = \frac{f(x_j) \times (b_j - a_j)}{10^{n_j} - 1} \times a_j$$

After encoding function is applied, the natural parameter value is scaled from $[a, b]$ to $[0, 10^n - 1]$. Each digit in the encoded value will range from 0 through 9, inclusively. Whether a natural parameter value is an integer or not, the encoded value will be always an integer. Therefore, during GA operation, it is not necessary to worry about where a decimal point is.

Chromosome

Each parameter is encoded as a digit string using real-number coding. The digit strings for the parameters are concatenated together to form a single digit string called chromosome which represents the entire vector of parameters. Figure A-2 depicts a chromosome sample. There are four parameters encoded in this chromosome and each parameter takes three digits.

0 2 1	1 0 9	1 2 1	1 3 0
Param 1	Param 2	Param 3	Param 4

Figure A-2 Chromosome Illustration

Population and Generation

Basically, one can understand the population and generation as a two dimensional matrix. In this matrix, each row represents a generation. The number of rows means how many generations GA will go through. Each generation has a population which consists of a number of chromosomes. The population size may change from generation to generation. But in this project, it is a predefined GA control parameter before GA starts. Figure A-3 depicts the relationship between generation and population.

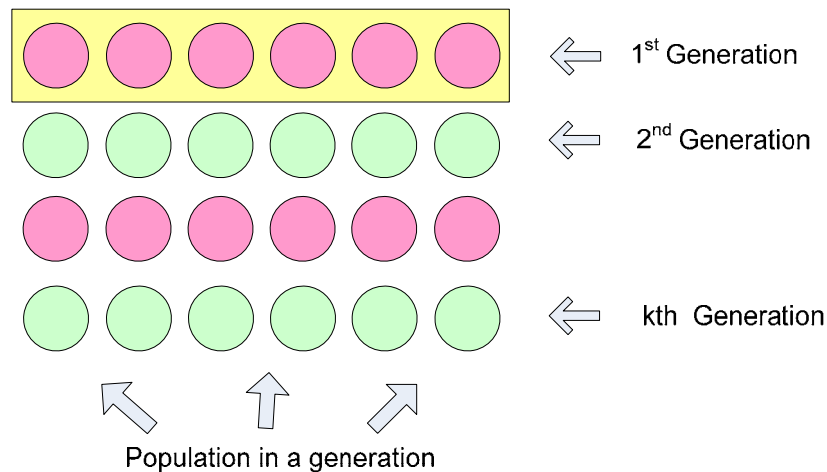


Figure A-3 Population and Generation Illustration

Fitness Function

Fitness function measures how close current parameter set is to the optimal solution. The fitness function can be constructed with either direct or indirect connection to the parameters to be optimized. The function should be monotonic. One of fitness functions

used in this project takes the form as follows.

$$F = \sum_{t=1}^T \sum_{i=1}^N [A_i \times GEH(x_i^t)]$$

where:

N: number of performance measurement variables;

x_i^t : the i-th measurement variable at t-th 5-minute interval;

T: number of 5-minute intervals in each simulation run;

A_i : a scalar.

$$GEH(x_i^t) = \sqrt{\frac{(x_t^{field} - x_t^{sim})^2}{\frac{x_t^{field} + x_t^{sim}}{2}}}$$

The fitness function given above is monotonically decreasing, therefore, the smaller the fitness value is, the closer the simulation result is to the field observation.

Reproduction

Generally, reproduction in evolution consists of at least four steps:

- Selection;
- Crossover;
- Mutation;
- Replacement

Selection defines a strategy to select two chromosomes from current generation. Usually selection is based on fitness value. In this project, since the defined fitness function is monotonically decreasing, the smaller fitness value a chromosome has, the higher probability it will be chosen to mate. To select a chromosome, a biased roulette wheel is created. Each chromosome in a generation has only one slot on the wheel and the slots on the wheel are exactly taken by population members in the generation. The wheel slot size is reversely proportional to fitness values. Assume the population size is M . The wheel is spun M times so that M chromosomes are selected. Since the wheel is weighted, some chromosomes with small fitness value (better solution) may be chosen multiple times, and ones with larger fitness value (worse solution) may be eliminated. The probability of a chromosome to be selected for mating takes the form as follows.

$$P_m^g = \frac{F_{M-m}^g}{\sum_{i=1}^M F_i^g}$$

where:

P_m^g : probability for the chromosome, in the g -th generation, whose fitness value is the m -th smallest to be selected;

M : population size;

F_m^g : fitness value associated with the m -th chromosome in the g -th generation.

Once two members in the population are selected, they will mate by crossover and mutation operations. Figure A-4 depicts a pair of chromosomes before and after crossover operation. Assume the chromosome length is L . Each digit in a chromosome is indexed from 1 to L starting from the leftmost. A position index, k , is randomly selected in uniform distribution in a range of $[1, L]$. Parent A and Parent B then swap all digits between $[k, L]$. Thus two new chromosomes are created.

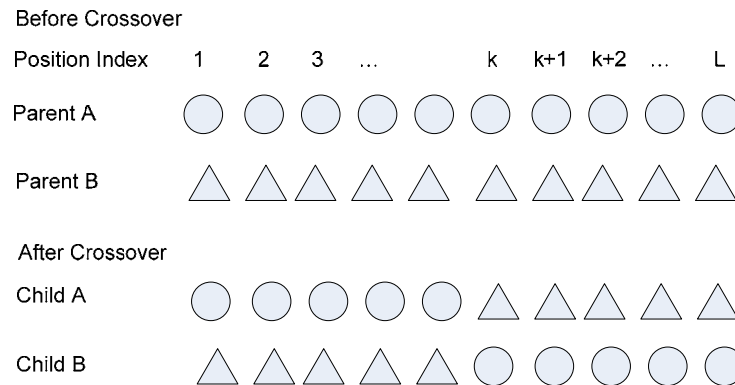


Figure A-4 Crossover Illustration

Although the information exchange in crossover operation gives GA much power to search in multi-dimensional space, occasionally it may lose diversity, which means GA will also lose potential useful information. To compensate for the loss, a mutation operation may be applied. Mutation operation will change one or more digit values in a chromosome with a small probability (also called mutation rate). Mutation can be implemented in different ways. Figure A-5 depicts the one used in this project. First a real number will be randomly generated in uniform distribution within $[0, 1]$. If the real number is greater than mutation rate, mutation operation will not apply to this chromosome. Otherwise, two more integer number, m and k , will be randomly generated in uniform distribution within $[1, L]$. The m -th item and k -th item in the chromosome are swapped afterwards.

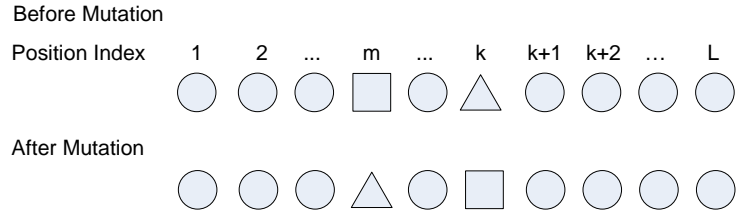


Figure A-5 Mutation Illustration

Mutation is a twofold sword. If the mutation rate is high, the “noise” will rise so that it prevents sufficient convergence in. Reducing mutation rate can definitely filter the noise but it may lead to premature convergence.

After crossover and mutation operations, new offspring will be generated. New offspring are kept in a mating pool until the pool size reaches population size, which means a new generation is completely created. Figure A-6 depicts selection and replacement operations.

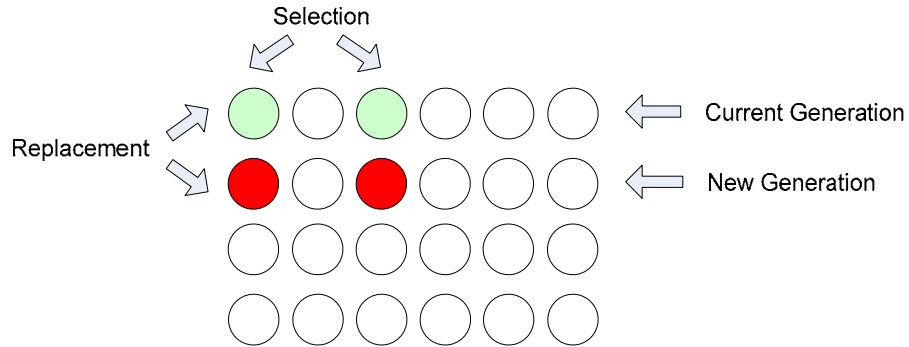


Figure A-6 Selection and Replacement Illustration

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