Paper # 03-4400

Optimization of the ALINEA Ramp-metering Control Using Genetic Algorithm with Micro-simulation

Lianyu Chu

California PATH, ATMS Center
Institute of Transportation Studies
University of California, Irvine
Irvine, CA 92697
Tel: 949-824-1876 Fax: 949-824-8385
Email: lchu@translab.its.uci.edu

Xu Yang

Institute of Transportation Studies
University of California, Irvine
Irvine, CA 92697
Tel: 949-824-1876 Fax: 949-824-8385
Email: xyang@translab.its.uci.edu

Submitted to 2003 TRB Annual Meeting

ABSTRACT

ALINEA, a local feedback ramp-metering strategy, has been shown to be a remarkably simple, highly efficient and easy application. This paper presents a hybrid method to optimize the operational parameters of the ALINEA algorithm, as an alternative to the difficult task of fine-tuning them in real-world testing. Genetic Algorithms (GA) are used for parameter optimization and micro-simulation is used for performance evaluation. Four parameters, including the update cycle of the metering rate, a constant regulator, the location and the desired occupancy of the downstream detector station, are considered in this optimization study. Simulation results show that the genetic algorithm is able to find a set of parameter values that can optimize the performance of the ALINEA algorithm.

1. INTRODUCTION

The ALINEA ramp-metering control strategy, proposed by Papageorgiou in 1990s, has been shown to be a remarkably simple, highly efficient and easily implemented ramp metering application based on the results of several field implementations in European countries (1)(2). Simulation-based evaluation studies on a number of adaptive ramp-metering algorithms conducted by the authors and their colleagues also showed the competitive performance of ALINEA compared to other ramp metering systems (3)(4). Because of the high performance of this algorithm, it is an excellent candidate for cost-effective ramp control as well as for being embedded into a coordinated ramp control or integrated control system.

The ALINEA ramp metering control is based on feedback control theory. It is a local traffic responsive strategy, aiming at maintaining the maximum throughput at the downstream merge area of the entrance ramp. A downstream detector station is required for the measurement of the traffic condition at the merge area. The successful application of ALINEA depends upon the correct determination of four parameters: the update cycle of metering control, a constant regulator used for adjusting the constant disturbances of the feedback control, the location and the desired occupancy of the downstream detector station. Calibration of these operational parameters is required during the pre-implementation phase. Current field tests of ALINEA have shown the adaptability of the algorithm to different combinations of parameter values, which were based on empirical analyses (1)(2). Studies show that significant benefits can be obtained from ramp metering only when implemented correctly and operated effectively (5). Therefore, calibration and optimization of the operational parameters of ALINEA ought be investigated in order to ensure the success of its implementation.

This paper presents a hybrid GA-simulation method to optimize the operational parameters of the ALINEA algorithm, as an alternative to the difficult task of fine-tuning them in real-world testing. Genetic Algorithms (GA), which have been increasingly regarded as a more effective method to find optimal combinations of parameter values, are used for parameter optimization. The micro-simulation is used for performance evaluation. Examples of microscopic models that could form the basis of such a method include PARAMICS, CORSIM, VISSIM, AIMSUN2, TRANSIM and MITSIM. These microscopic models are deemed more appropriate for ramp metering studies because the state of individual vehicles is continuously or discretely calculated and predicted based on vehicle-vehicle interactions. It is noted that MITSIM has been used in a previous calibration study of ALINEA; the calibration based on a traditional trial-and-error method (6). GA have been applied in a number of traffic simulation studies as the tool to solve optimization problems. Some recent works include: calibration of FRESIM model for Expressway flows in Singapore (7), calibration for PARAMICS in southern California (8) and CORSIM and TRANSIMS models in Texas (9).

This paper is organized as follows. Section 2 presents the methodology to calibrate and optimize the operational parameters of the ALINEA ramp-metering control algorithm using GA and micro-simulation. Section 3 describes the modeling of the studied network and the implementation of the ALINEA algorithm in the microscopic traffic simulation environment. The optimization study including the optimization results is given in Section 4. The optimization result is discussed in Section 5. Concluding remarks are presented in Section 6.

2. METHODOLOGY

2.1 Description of the ALINEA Algorithm

The ALINEA algorithm is a local feedback ramp metering control policy. The algorithm attempts to maximize the mainline throughput by maintaining a desired occupancy on the downstream mainline freeway. The metering rate during the time interval $(t, t+\Delta t)$ is calculated based on the following formula:

$$r(t) = \tilde{r}(t-\Delta t) + K_R \bullet (O^* - O(t)) \qquad (1)$$

where Δt is the update cycle of ramp metering implementation; O^* is the desired occupancy of the downstream detector station; $O(t)$ is the measured occupancy of time interval $(t\text{-}\Delta t,\ t)$ at the downstream detector station; $\tilde{r}(t-\Delta t)$ is the measured metering rate of the time interval of $(t-\Delta t,\ t)$, and K_R is a regulator parameter, used for adjusting the constant disturbances of the feedback control.

The ALINEA algorithm has four parameters to be calibrated: the location of the downstream detector station, the desired occupancy of the downstream detector station O^*, the update cycle of each metering rate Δt, and a constant regulator K_R. The following is a summary of parameter settings used in previous research and implementations (1) (2) (10).

1. The desired occupancy is set equal to or slightly less than the critical occupancy, or the occupancy value at capacity, which can be found in the volume-occupancy

diagram. Various values ranging from 18% to 31% have been found in previous applications.

2. Control results have been found to be insensitive for a wide range of values of the regulator K_R. In real-world experiments, the algorithm has been determined to perform well for $K_R = 70$.
3. The downstream detector should be placed at a location where the congestion caused by the excessive traffic flow originated from the ramp entrance can be detected. In reported implementations, this site was located between 40 m and 500 m downstream of the on-ramp nose.
4. A wide range of values for the update cycle of metering control has been used: from 40 seconds to 5 minutes. In theory, if the value is small, the location of the downstream detector station should be close to the entrance ramp. Otherwise, there is a risk of congestion build-up in the interior of the stretch from the ramp nose to the detector.

2.2 The GA-simulation method

The Genetic Algorithm is a heuristic optimization technique based on the mechanics of natural selection and evolution (11). In contrast to conventional optimization approaches, GA progresses toward the optimal solution from a population of points at each time step of a search, instead of a single point commonly found in conventional optimization approaches; thus, the robustness of the solution is enhanced. Traditional optimization algorithms are mostly categorized as gradient approaches (12). A major drawback of the gradient method is its lack of robustness, with only one feasible solution explored at a time. The use of multiple points in GA increases the robustness of the search in a complex space. The points are scattered in the solution space, reducing the likelihood of reaching a local optimum and increasing the probability of finding the global optimal solution. GA combines survival of the fittest among string structures with a structured, yet randomized, information exchange to form a search algorithm with some of the innovative flair of human search. In every generation, a new set of the artificial creatures (strings) is created using bits and pieces of the fittest of the last generation. An occasional new bit is introduced for added search breadth.

Gradients cannot be identified in such non-conventional modeling approaches as represented in microscopic traffic simulation models. Each individual vehicle is dynamically interacting with its neighboring vehicles, which makes it very difficult to find formulations to describe the system being modeled. Neither an analytically soluble form nor differentiable error function can be used to express the simulation model and its misfit function. The Genetic Algorithm has been found to be particularly effective and powerful in exploring and exploiting poorly understood or non-differentiable spaces for optimization and machine learning.

2.3 Framework of the optimization study

We choose PARAMCIS as the micro-simulator of this optimization study. PARAMICS

(PARAllel MICroscopic Simulation), is a scalable, high-performance microscopic traffic simulation package developed in Scotland. PARAMCIS can model ITS infrastructure, such as loop detectors and VMS. In addition, the most valuable feature of PARAMICS is its Application Programming Interface (API) library through which users can customize and extend many features of the underlying simulation model. As illustrated in Figure 1, the commercial PARAMCIS is enhanced through the complementation of two Advanced Transportation Management and Information system (ATMIS) modules, ramp metering controller and loop data aggregator. Both of them are developed in PARAMICS (13). The ramp metering controller is used for controlling the metering operations and the loop data aggregator API emulates the real-world loop data collection, typically with a thirty-second interval. The ALINEA control algorithm, also developed as a PARAMICS API module, is built on top of these two basic plug-in modules. During the simulation, the ALINEA API queries the required latest aggregated loop data through dynamic linking with loop data aggregation API. Then the metering rate for the next control interval is calculated. The new metering rate is implemented through the ramp controller API.

The capability-enhanced PARAMICS simulation is used to provide a simulated traffic system under ALINEA control in our study. The performance measure module, also developed in PARAMICS API, employs the gathering of the fitness value, or the measure of effectiveness (MOE). The fitness values of one generation will input to the GA algorithm in order to produce the next generation of parameter values.

3. SIMULATION MODELING

3.1 Study site

The study site is a 6-mile stretch of northbound freeway I-405, between the junction of freeway I-5 and Culver Dr., in Orange County, California. The network has seven entrance on-ramps, four off-ramps and one un-metered freeway-to-freeway ramp connecting I-405 with highway SR-133. The schematic representation of the study site is illustrated in Figure 2. The lines across the freeway lanes represent mainline detectors, whose locations are shown on the bottom by post-miles. There are also detectors located on entrance and exit ramps, which are not shown in the figure.

As a major freeway linking Orange County and Los Angeles, I-405 experiences heavy traffic daily. In this section, fixed-time ramp control is currently applied based on a one-car-per-green protocol during the morning and afternoon peak hours. For the purposes of the ALINEA calibration and optimization presented here, only on-ramp #5 is to be controlled by the ALINEA algorithm. Others will still be under fixed-time control.

The time-dependent OD demands, which are the inputs to PARAMICS simulation, are estimated based on the historical loop data. Loop data of May 22, 2001 are used for the calibration of our network model and our optimization study.

3.2 Calibration of PARAMICS

Micro-simulation models need to be calibrated carefully before being applied to a specific study. PARAMICS regards each vehicle in the simulation as a Driver Vehicle Unit (DVU). Simulation relies on characteristics of drivers and vehicles, the interactions between vehicles, and the network geometry as well.

In this study, the following aspects are considered in the calibration efforts:

- Accurate geometry of network and smooth coding of links, which are important since drivers' behaviors in PARAMICS are very sensitive to the network geometry;
- Proportion of each vehicle type on the studied section of freeway;
- Vehicle characteristics and performance, such as the acceleration and deceleration rate of each type of vehicle;
- Driving restrictions, such as the speed limits and driving lane restriction for trucks;
- The signposting setting for links, which defines the location of the vehicle weaving area if there are more than one links connecting with the downstream end of the link or there is geometry change at the downstream end of the link.
- The mean target headway and driver reaction time, which are the key user specified parameters in the car-following and lane-changing models, can drastically influence overall driver behaviors of the simulation. The calibrated values of the two parameters are 0.9 sec and 0.6 sec in this study.

Since local arterial streets are not included in the studied network, route choice is not considered in this calibration process.

The calibration process is an iterative process with the object function to minimize the difference of traffic counts at measurement locations. Measurement locations include detector stations at all on-ramps and off-ramps, and major mainline detector stations, located at post-mile 1.93, 3.04, 3.86, and 5.55 (one station at each junction). The simulation model is well calibrated. As an example, we demonstrate the calibration results at the loop detector station at post-mile 3.04. The comparison of the observed and simulated traffic counts at 5-minute intervals over the whole simulation period is shown in Figure 3. The Mean Abstract Percentage Error (MAPE) error between simulation and observation is 8.7%. The volume-occupancy plots based on simulations and observations are shown in Figure 4, which show that both curves have the similar trend, whose threshold occupancy at capacity is in the neighborhood of 20%.

3.3 Implementation of the ALINEA algorithm in PARAMICS

Figure 5 shows the detector configurations of a ramp meter under ALINEA control. Basically, two detector stations are required for the implementation of the ALINEA algorithm. The first one is located on the mainline freeway, immediately downstream of the entrance ramp, used for measuring the mainline traffic condition. The second one is on the downstream end of the entrance ramp for counting the on-ramp volume. Besides those, a queue detector, located at the upstream end of the entrance ramp, is also required for an implemented ramp metering system for detecting excessive queue length. When the occupancy value of the queue detector exceeds a certain threshold, the ramp metering will operate at a maximum metering rate in order to prevent the queuing traffic spillback onto arterials. This is called queue override strategy. In this study, the queue detector is located at the ¾ total length of the entrance ramp and the occupancy threshold is set to 50%. In addition, an on-ramp volume restriction is employed that limits the calculated metering rate to be within some pre-defined maximum and minimum values (300 and 1200 veh / hour in our study).

4. OPTIMIZATION STUDY

4.1 Optimization objective

Ramp metering control involves balancing the interests between local (arterial) and through (freeway) traffic. The MOE from simulations, or the fitness function in GA used to evaluate the goodness of parameter optimization for the ALINEA algorithm should consider the whole freeway system, which includes not only the mainline freeway condition but also on-ramp delays. Total vehicle travel time (*TVTT*) is used in our study, which can be formulated as:

$$TVTT = \sum_{\forall i,j} D_{i,j} \bullet \left(\sum_{k=1}^{N_{i,j}} T_{i,j}^{k} / N_{i,j}\right) \quad (2)$$

where $N_{i,j}$ is the total number of vehicles that actually traveled between origin i and destination j; $D_{i,j}$ is the travel demand from origin i to destination j for the whole simulation time ($D_{i,j}$ is not equal to $N_{i,j}$ because of the randomness of the micro-simulation); and $T^k_{i,j}$ is the travel time of the kth vehicle that traveled from origin i to destination j.

Therefore, the optimization objective of our study is to minimize TVTT. The smaller value of TVTT means the better parameter combination for the ALINEA algorithm performance.

4.2 GA implementation

The GA process is employed to optimize all four parameters of the ALINEA algorithm according to the MOE (fitness value). The ranges of these four parameters are shown in Table 1. Due to the scattered and random natural selection of the GA process, wider ranges for each parameter are selected for the GA process, compared to ranges in former research and implementations that were discussed in section 2.

In each generation of the GA process, a number of parameter combinations are produced to form the population. Simulations are needed for each parameter combination. It takes approximately 15 minutes for each simulation run to test the three and one half hour ALINEA application in the study network. Since 30 different random seeds are generated for simulation for each unique parameter combination, a total of 450 minutes are needed to produce one fitness value for each individual combination. Because of this relatively long computation time, it is necessary to select appropriate combinations of population size and number of generations. Various combinations have been investigated focusing on the search of "depth" and "breadth" (7). The population size for each generation and the number of generations for simulation are set to 10 and 10, because "depth" and "breath" are considered with the same importance in our search procedure. The convergence criterion is satisfied when simulations and GA process stop. Several input parameters required by the GA process are shown in Table 2.

4.3 Optimization results

The convergence of the GA is shown in Figure 6, in which the best, worst and average fitness values, i.e., *TVTT* in this paper, of each generation are displayed. All of these indices decreased in accordance with the number of generations, which shows the effectiveness of the GA optimization.

After the GA process, all four optimized ALINEA parameters converge to much smaller ranges than their initials. Table 3 shows final results for optimized ALINEA parameters based on the GA process. Based on Figure 6, the average *TVTT* of the first generation is almost the same as that of the fixed-time metering case. After the optimization, the average *TVTT* of the last generation (generation 10) is further reduced 2.5% compared to that of generation 1.

5. RESULT ANALYSIS

When the regulator K_R, used for adjusting the constant disturbances of the feedback control, is within the range from 70 to 200, the metering system is found to perform well. This result is consistent with that from previous field tests, the system performance is not sensitive to the variation of K_R.

The optimal location of the downstream detector is found to be between 120~140 meters downstream of the on-ramp nose in our simulation study. This location in the real world, which depends on the peculiarities of each individual entrance ramp, may not be the same. As we discussed in section 2, the downstream detector should be placed at a location where the congestion caused by the excessive traffic flow originated from the ramp entrance can be detected. However, this location is not easily specified because ramp metering is being implemented in heavy traffic scenarios in which the traffic condition is not stable. The estimation of optimal location for the downstream detector station from the analytical method will dictate further traffic flow studies on the freeway merge areas.

The update cycle of the metering rate implementation gives the best system performance when it ranges from 30 to 60 seconds in our study. When the update cycle is small, the metering rate changes rapidly, which can lead to turbulence in the freeway mainline traffic stream. When the value is large, the metering rate cannot respond to the real-time traffic conditions in time in order to adjust its value to maintain the optimal traffic condition on the freeway mainstream. This explains that there is a correlation between the location of the downstream detector station and the update cycle of metering rate.

The desired occupancy of the downstream detector station is found to be within two ranges, either from 19% to 21% or from 30% to 31%. The performance of the metering control system can reach its optimum at these two different levels of downstream occupancy. The first optimized range 19%~21%, is easily understood and explained because 20% is the percent occupancy at capacity based on the volume-occupancy plots at the downstream detector location, shown in Figure 7. The existence of the second optimized range 30%~31% implies that the ramp control system can also perform well under the condition of higher density (or percent occupancy). This can be also explained by Figure 7, which shows that when the desired occupancy equals to 30%, its volume is only 20% less than its capacity (corresponds to the occupancy value of 20%). The volume drops dramatically if the occupancy is higher than 30%.

The following two reasons can be used for further explaining why there are two ranges of occupancy values. The first reason is that the queue override strategy is integrated in the implementation of our ALINEA algorithm. The current demand pattern shows that the peak-hour demand from on-ramp #5 is as high as 1100 vehicles per hour. As a result, a smaller value of the desired occupancy is prone to trigger the override strategy, which will set the metering rate to its maximum value. This override strategy causes an unstable traffic condition on the downstream of the entrance ramp, i.e. more vehicles merging into the freeway in a short time period, which deteriorates system performance. On the contrary, a larger value of the desired occupancy makes the traffic system work under the condition of lower speed and higher density, which causes “smoother” changing of the metering rate and the override strategy to be triggered less often.

Another reason comes from the MOE (fitness) selected in this study to evaluate the system performance, i.e., the total vehicle travel time. The vehicle-time on the freeway mainstream and the waiting-time on the entrance ramps are included in this MOE. Therefore the value of the desired occupancy will be used for balancing the interests of local (arterial) travelers and through (freeway) traffic. The smaller desired occupancy value benefits vehicles from entrance ramps and the larger value benefits vehicles of freeway mainstream. As a result, the effects of metering control reach equilibrium at two occupancy levels.

In order to find which occupancy range can generate better benefits, we introduce another performance measurement index, the reliability of the network, which is defined as the standard deviation of the total vehicle travel time (std_TVTT) of multiple runs. The smaller value of std_TVTT means more reliable of the scenario. Two scenarios are compared. They have the same downstream detector location (i.e. 120 m), update cycle (i.e. 30 sec), and regulator constant (i.e. 70 vph); but have different desired occupancy, 20% and 30%, respectively. We run each scenario for 30 times and results show the scenario with the desired occupancy of 20% (std_TVTT = $1.6*10^5$ sec) has a lower value of std_TVTT than that of the scenario with the desired occupancy of 30% (std_TVTT = $2.6*10^5$ sec). This implies that the higher desired occupancy (30%-31%) scenario is more unreliable than the lower desired occupancy (19%-21%) scenario. Therefore, we can pick the occupancy at capacity (19%-21%) as the optimized desired occupancy value.

6. CONCLUDING REMARKS

This paper presents a hybrid GA-simulation method to find the optimized parameter values the ALINEA ramp-metering control in order to improve its performance. Based on our simulation results, the ranges of four parameters of ALINEA have been given. We find the control performance is not sensitive to the variation of K_R. When the update cycle ranges between 30 to 60 seconds, mainline detector is placed between 120~140 meters downstream of the on-ramp nose, and the desired occupancy is set to 19% to 21%, the ALINEA control can produce the best performance in our testing network.

The desired occupancy is the most sensitive parameter among all four selected parameters in our study. Choosing a suitable value for the desired occupancy is essential to optimize the performance of ALINEA control. Simulation results show that the occupancy at capacity at the mainline downstream detector station is the best value to select. Practitioners can use our optimization results as a basic operational reference if they implement ALINEA control to the real world.

This study shows that micro-simulation can be used to calibrate and optimize the operational parameters of ramp metering control. Potentially, micro-simulation may also be used to fine-tune parameters for various other ITS strategies.

REFERENCES

1. M. Papageorgiou, H. Hadi Salem, and J-M. Blosseville (1991) "ALINEA: A Local Feedback Control Law for On-Ramp Metering," *Transportation Research Record*, vol. 1320, pp. 58-64.
2. M. Papageorgiou, H. Hadi Salem and F. Middleham (1997) “ALINEA Local Ramp Metering: Summary of Field Results,” *Transportation Research Record*, vol. 1603, pp.90-98.
3. L. Chu, X. Liu, W. Recker and H. M. Zhang (2002) “Performance Evaluating of Adaptive Ramp Metering Algorithms”, accepted by *ASCE Journal of Transportation Engineering*.
4. H. M. Zhang, T. Kim, X. Nie, W. Jin, L. Chu and W. Recker (2001), “Evaluation of On-ramp Control Algorithm,” *California PATH Research Report, UCB-ITS-PRR-2001-36*, University of California, Berkeley.

5. Pearce, V (2000) "What Have We Learned About Its? Chapter 2: What Have We Learned About Freeway Incident And Emergency Management And Electronic Toll Collection?" *Technical Reports & Papers*, US Department of Transportation.
6. M. Hasan (2000), "*Evaluation of Ramp Control Algorithms using a Microscopic Simulation Laboratory*," MIT, Master thesis, Massachusetts Institute of Technology.
7. R-L. Cheu, X. Jin, K-C. Ng, Y-L. Ng, and D. Srinivasan (1998) "Calibration of FRESIM for Singapore Expressway Using Genetic Algorithm," *Journal of Transportation Engineering, ASCE*, vol. 124(6), pp. 526-535.
8. D-H. Lee and X. Yang (2000) "Parameter Optimization for PARAMICS Using Genetic Algorithm," *Proceedings of the 6th ASCE AATT International Conference*, Singapore.
9. K-O. Kim and L. R. Rilett (2001) "Genetic-Algorithm-based Approach for Calibrating Microscopic Simulation Models," *Proceedings of 4th IEEE Intelligent Transportation Systems Conference*, Oakland, CA.
10. M. Papageorgiou, J-M. Blosseville and H. Hadj Salem (1990) "Modeling and Real-time Control of Traffic Flow on the Southern Part of Boulevard Peripherique in Paris: Part II: Coordinated On-ramp Metering," *Transportation Research*, vol. 24A, no. 5, pp. 361-370.
11. D. E. Goldberg (1989), *Genetic Algorithms in Searching Optimization and Machine Learning*, Addison-Wesley Publishing Co., Reading, Mass.
12. C. S. Beightler, D. T. Philips and D. J. Wilde (1979), *Foundations of Optimization*, 2nd ed., Prentice-Hall, Inc., Englewood, N.J.
13. H. Liu, L. Chu and W. Recker (2001), "PARAMICS API Development Document for Actuated Signal, Signal Coordination and Ramp Control," *California PATH working paper UCB-ITS-PWP-2001-11*, University of California, Berkeley.

LIST OF FIGURES

LIST OF TABLES

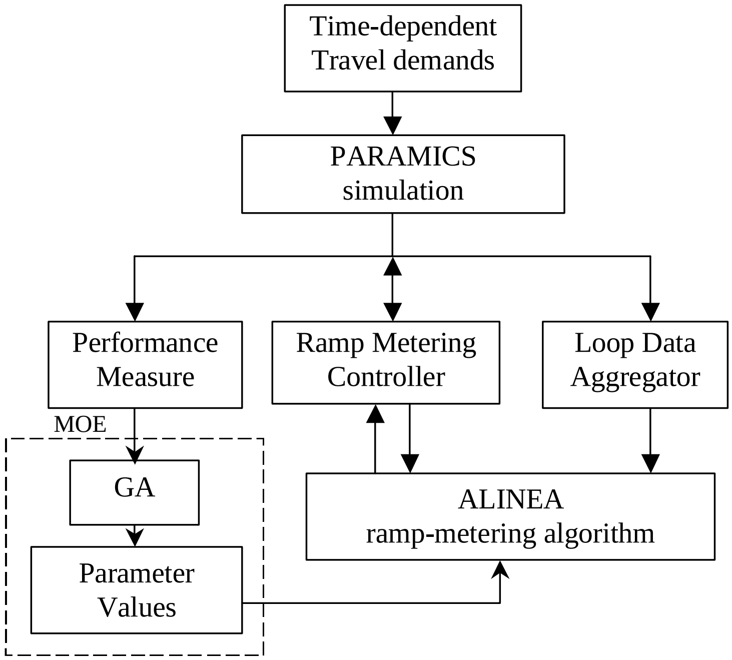


Figure 1. Framework of the optimization study

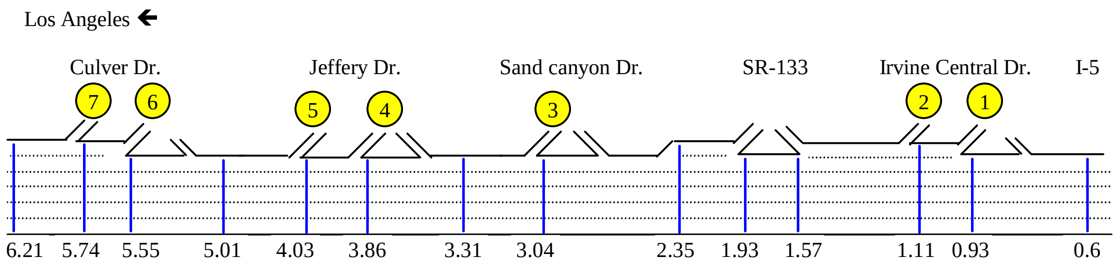


Figure 2. Schematic figure of the study site including seven on-ramps

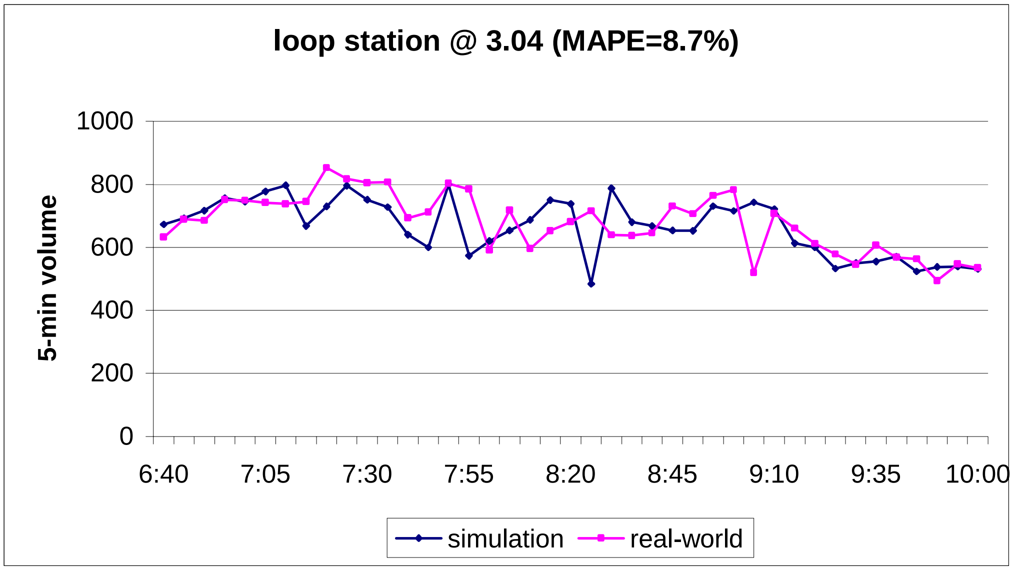
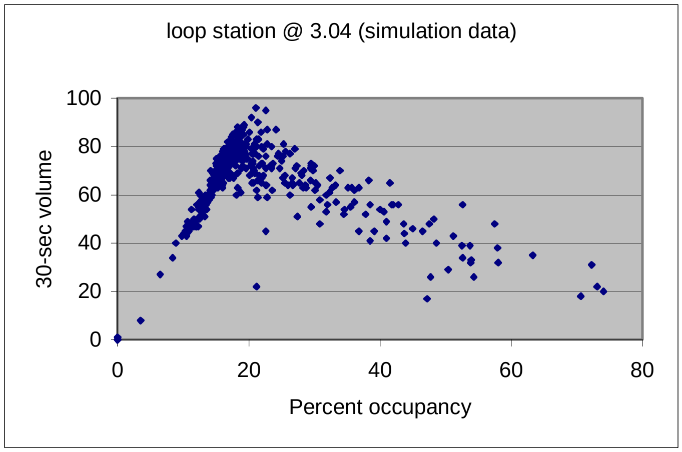


Figure 3. Comparison of traffic counts between simulation and observations



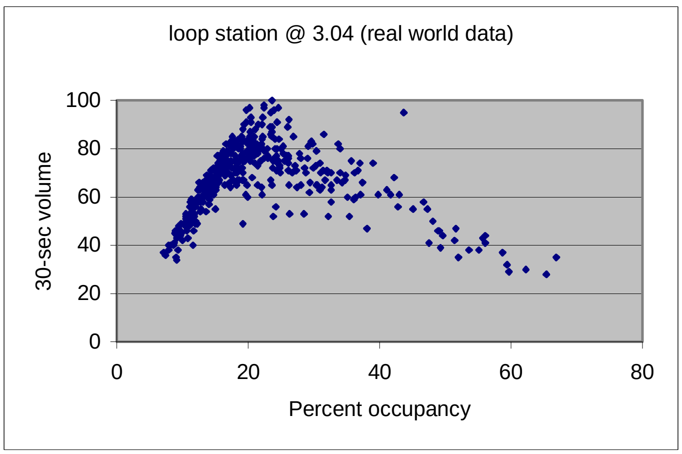


Figure 4. Volume-occupancy plots of loop station at post-mile 3.04

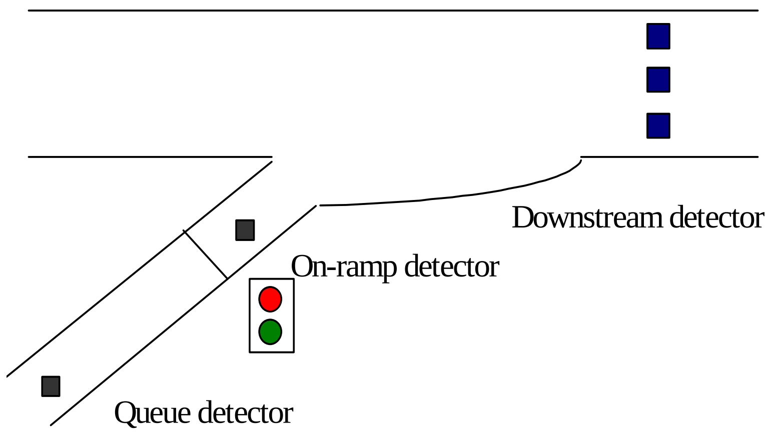


Figure 5. Detector layout for the implementation of the ALINEA strategy

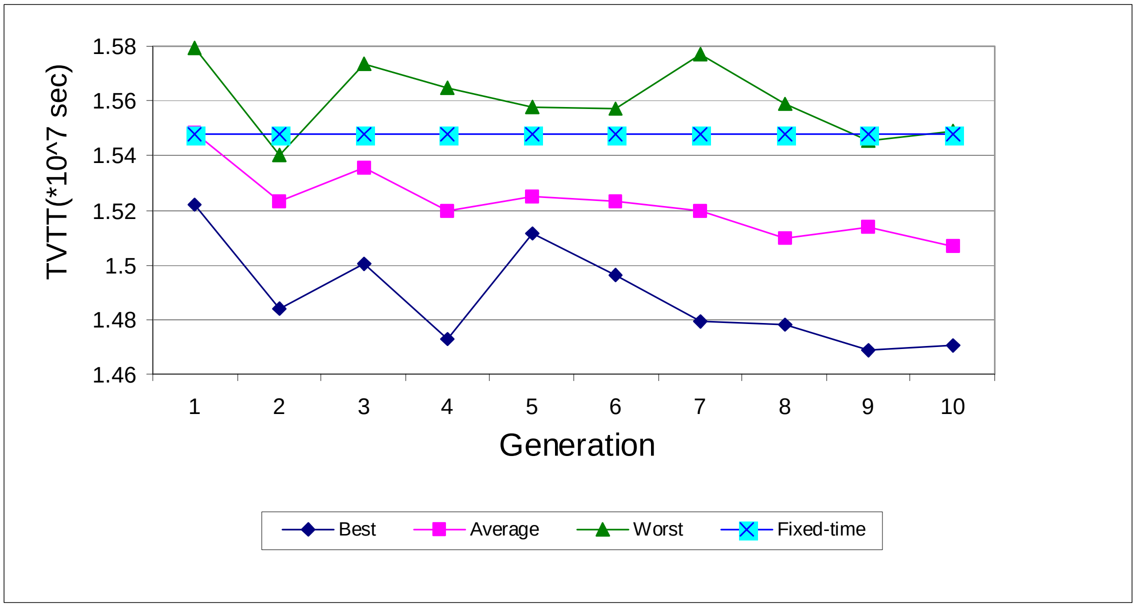


Figure 6. Convergence of the best, worst and average fitness values of each generation

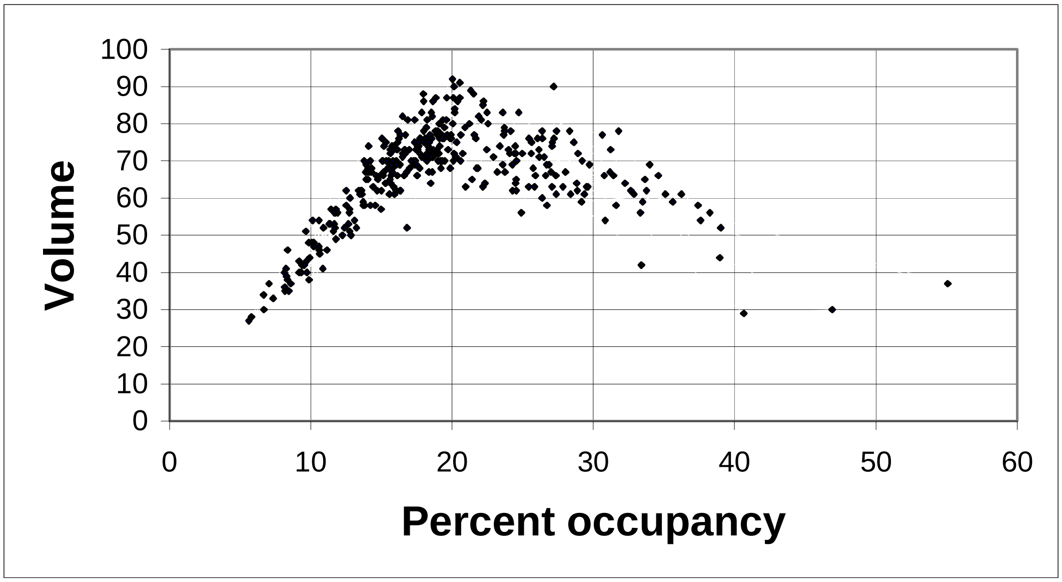


Figure 7. Volume-occupancy plots of the downstream detector station

Table 1 The range of calibrated ALINEA parameters in GA

Parameter	Range
Regulator K_R	10 ~ 300
Desired occupancy	10% ~ 40%
Update cycle of metering rate	10~300 sec
Location of downstream detector	0~600 m

Table 2 Control parameters for the GA

Number of parameters	4
Number of bits per parameters	8
Number of citizens in the population	10
Random number seed	100
Elitism flag	1
Jump mutation rate	0.02
Creep mutation rate	0.32

Table 3 Optimized ALINEA parameters

Parameter	Range
Regulator K_R	70~200
Desired occupancy	19~21%, 30~31%
Update cycle of metering rate	30~60 sec
Location of downstream detector	120~140 m