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

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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) is used for parameters 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 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

Based on the results of several field implementations in European countries [1][2], 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. 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 coordinated 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.

Implementation of ALINEA depends on four parameters: the update cycle of the metering rate, a constant regulator, 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 [16]. Therefore, calibration and optimization of the operational parameters of ALINEA ought be investigated in order to ensure the success of the 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 has been increasingly regarded as a more effective method to find optimal combinations of parameter values, is 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 that considered three factors: the location and desired occupancy of downstream detector station, and different override strategies [5]. GA has 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 [6], calibration for PARAMICS in southern California [7] and CORSIM and TRANSIMS models in Texas [8].

This paper is organized as follows. Section 2 presents the methodology to calibrate and optimize the control parameters of the ALINEA ramp-metering control algorithm using GA and micro-simulation. Section 3 describes the simulation modeling of the model network and the implementation of the ALINEA algorithm. Simulation 4 is the optimization study. The optimization results and analysis are given. Concluding remarks are presented in Section 5

2. METHODOLOGY

2.1 Problem description

The ALINEA algorithm is a local feedback ramp metering control policy. The algorithm attempts to maximize the mainline throughput by maintaining a desired (or optimal) 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 (typically, it is set equal to or slightly less than the critical occupancy) of the downstream detector station; $O(t)$ is the measured occupancy of time interval $(t-\Delta t, t)$ 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.

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] [9].

1. The desired occupancy can be equal to or around the occupancy value at capacity, which can be also found in the volume-occupancy diagram. Various values ranging from 0.18 to 0.31 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, used for adjusting the constant disturbances of the feedback control. 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 ramp-metering rate have 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 [10]. 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 [11]. 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

Figure 1 illustrates the framework of this optimization study. The core of the study framework is the micro-simulator, PARAMICS (PARAllel MICroscopic Simulation), which 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.

The PARAMICS simulation is used to provide a simulated traffic system under ALINEA control in our study. Two complementary Advanced Transportation Management and Information system (ATMIS) modules, including ramp metering controller and loop data aggregator, are used for enhancing the capabilities of PARAMICS in order to emulate the real traffic system. These ATMIS modules are implemented through API programming [12]. The entrance ramp signals in the simulation network are controlled by the ramp metering API, through which metering rates can be queried and set by other API modules. The loop data aggregator API emulates the real-world loop data collection, typically with a thirty-second interval, and stores the aggregated loop data into MYSQL database continuously.

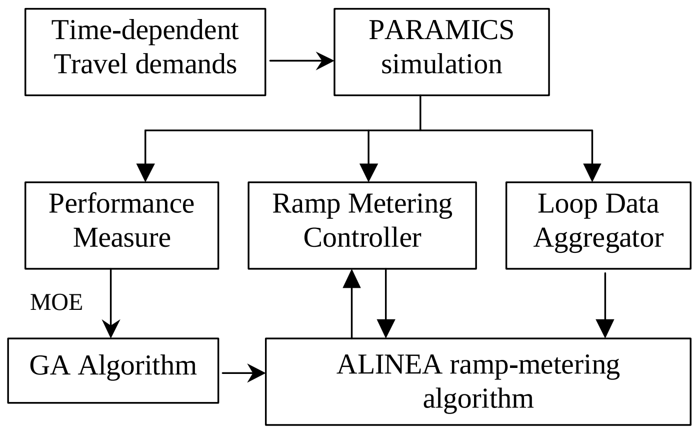

Figure 1 Methodology of the optimization study

The ALINEA control algorithm, also developed as a PARAMICS API, 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. After the simulation runs, the fitness value, or the measure of effectiveness (MOE), calculated by the performance measure module is fedback to the GA algorithm in order to produce the next generation of parameter values.

3. SIMULATION MODELING

3.1 Study site and data acquisition

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.

Time-dependent travel demand data for the morning peak-hour are estimated for this optimization study, based on planning demand data and real-world loop data from May 22, 2001 to June 4, 2001.

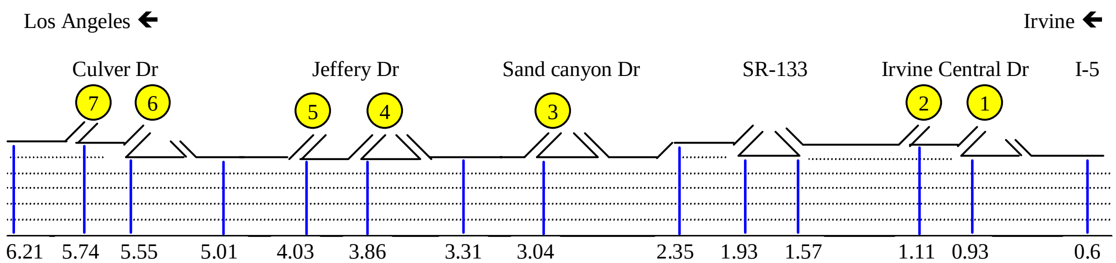

Figure 2. Schematic figure of the study site including seven on-ramps

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. Some previous efforts have focused on the model calibration and validation of PARAMICS [13][14][15].

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 PARAMCIS 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 and 0.6 in this study.

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

As shown in Figure 3 and Figure 4, volume-occupancy plots and traffic counts at a major loop station to demonstrate the calibration results have a good match with the real world loop data.

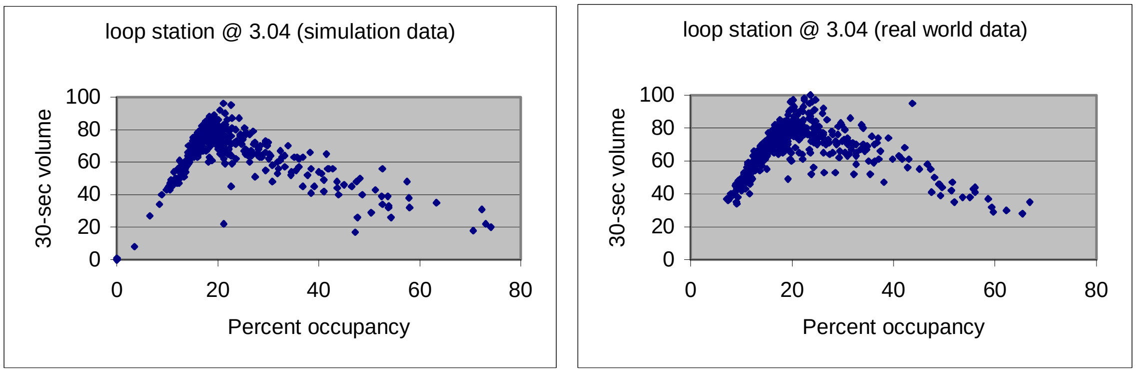

Figure 3 Volume-occupancy plots at loop station 3.04

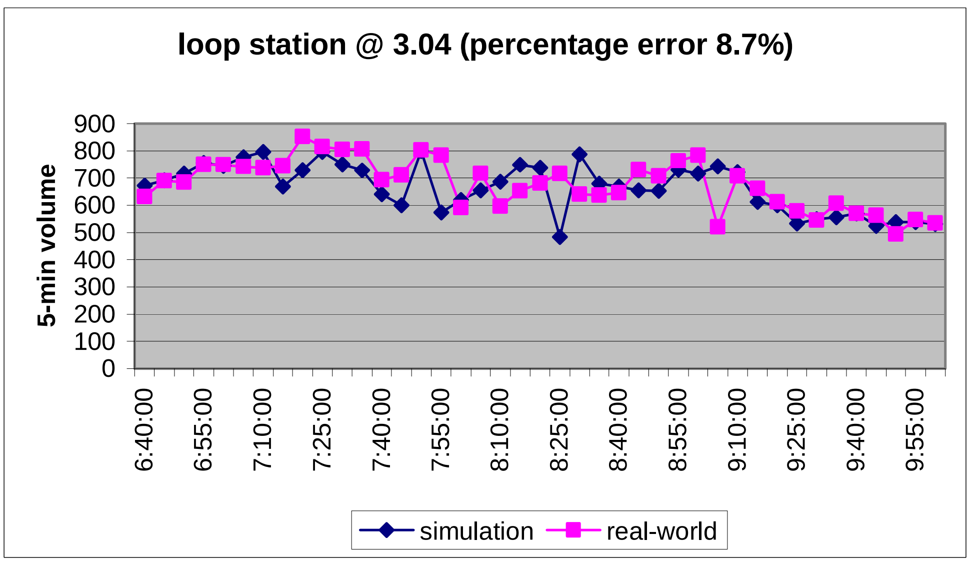

Figure 4. Comparison of volume data from simulation and real world

3.3 Implementation of the ALINEA algorithm in PARAMICS

Three detector stations, shown in Figure 5, are required for real-world implementation of the ALINEA algorithm. The first one is located on the mainline freeway, immediately downstream of the entrance ramp. The second one is on the downstream end of the entrance ramp for counting the on-ramp volume. The third one, located at the upstream end of the entrance ramp, is the queue detector, which is used for detecting excessive queue length in order to avoid interference with the arterial traffic.

In this study, the queue detector is placed at a location equal to ¾ maximum length of the on-ramp links. When the occupancy of the detector exceeds a certain threshold (50% in this study), the metering rate is set to a maximum value (1200 veh/h) in order to avoid interference with surface street traffic. 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).

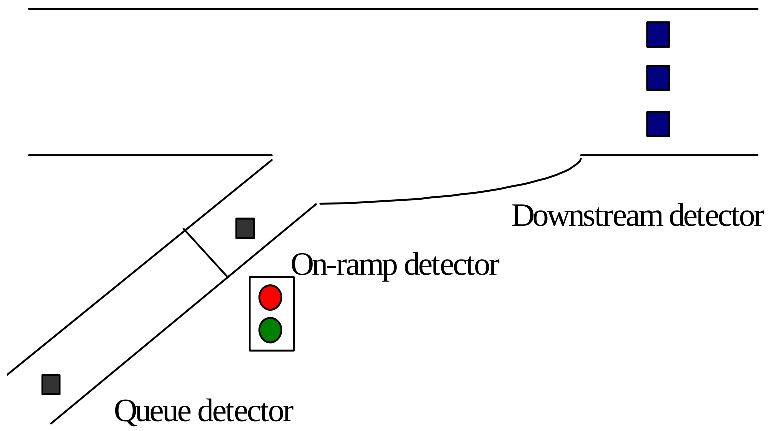

Figure 5 Detector layout for the implementation of the ALINEA strategy

4. OPTIMIZATION STUDY

4.1 Measure of effectiveness (MOE)

Total vehicle travel time (*TVTT*), which is a measure of system performance for the whole network, is the fitness function used to evaluate the goodness of parameter optimization of the ALINEA algorithm in this paper. The performance measure module in the simulation laboratory calculates and outputs this measure. All vehicles, including those having finished their journey and those currently simulated, are all considered in this measure. This measure can be expressed as:

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

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.

4.2 Setup the range of calibrated parameters for ALINEA

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.

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

4.3 GA implementation

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" [6]. 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.

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

4.4 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 system performance index

(*TVTT*) of generation 1 is only slightly better than fixed-time metering case (less than 1%). After the optimization, *TVTT* of the last generation in the GA process reduces 2.5% compared to that of generation 1.

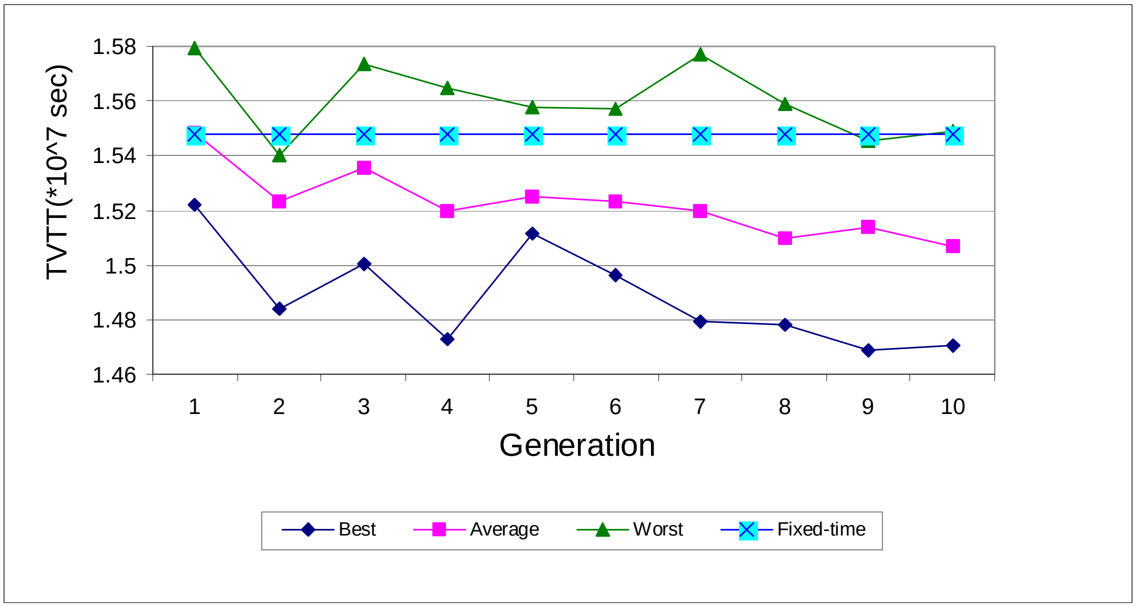

Figure 6 Convergence of the best, worst and average fitness values of each generation

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

4.5. 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 around 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 from 30% to 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 downstream detector station 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%.

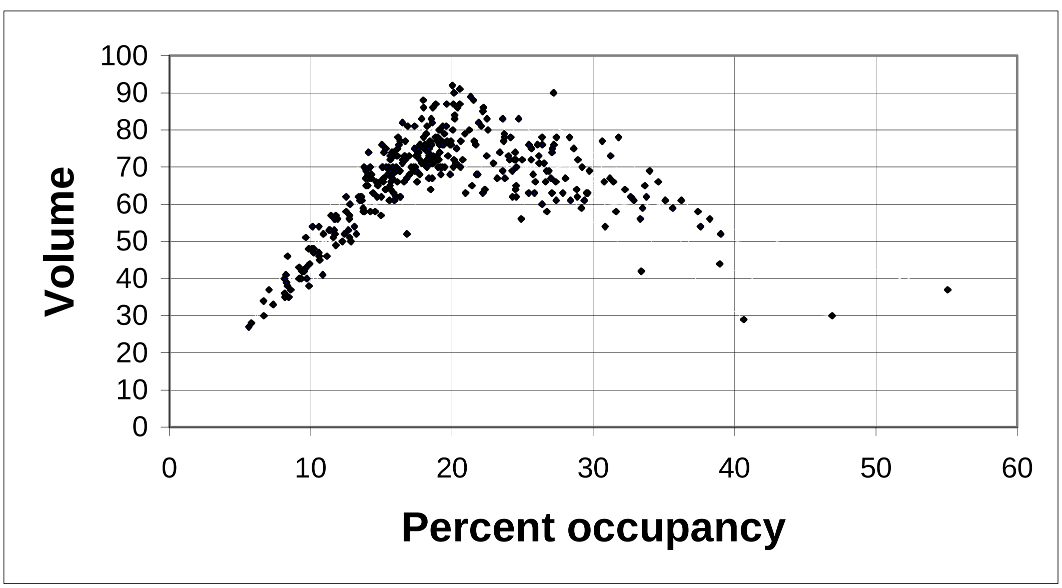

Figure 7 Volume-occupancy plots of the downstream detector station

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. Therefore, we can pick the occupancy at capacity as the desired occupancy value based on the volume-occupancy diagram at the downstream detector station.

In order to know which occupancy range can generate the better benefits, we need to use another performance measure, the reliability of the network, which can be calculate as the standard deviation of the total vehicle travel time (std_TVTT) of multiple runs. We run each scenario for 30 runs and result show the 19-21% (std_TVTT = $1.6*10^5$ sec) is better than 30-31% (std_TVTT = $2.6*10^5$ sec). This explains that the traffic condition that the occupancy value is larger than the occupancy value at capacity is not reliable.

5. CONCLUSION 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 parameters. The use of a good desired occupancy is essential to the optimization of the performance of ALINEA control. Simulation result shows that the occupancy at capacity at the mainline 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.

Micro-simulation shows the capabilities to calibrate and optimize the operational parameters of ramp metering control in this study. Potentially, various ATMIS strategies can use micro-simulation to fine-tune their parameters.

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